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Collaborative Models for Supply Networks Coordination and Healthcare Consolidation

Shima Mohebbi
University of Tennessee - Knoxville, smohebbi@vols.utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Shima Mohebbi entitled "Collaborative Models for Supply Networks Coordination and Healthcare Consolidation." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Industrial Engineering.

Xueping Li, Major Professor

We have read this dissertation and recommend its acceptance:

Mingzhou Jin, Oleg Shylo, Hamparsum Bozdogan

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Collaborative Models for Supply Networks Coordination and Healthcare Consolidation

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Dedication

To my parents, and brother for their support and encouragement

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Abstract

This work discusses the collaboration framework among different members of two complex systems: supply networks and consolidated healthcare systems. Although existing literature advocates the notion of strategic partnership/cooperation in both supply networks and healthcare systems, there is a dearth of studies quantitatively analyzing the scope of cooperation among the members and its benefit on the global performance. Hence, the first part of this dissertation discusses about two-echelon supply networks and studies the coordination of buyers and suppliers for multi-period procurement process. Viewing the issue from the same angel, the second part studies the coordination framework of hospitals for consolidated healthcare service delivery.

Realizing the dynamic nature of information flow and the conflicting objectives of members in supply networks, a two-tier coordination mechanism among buyers and suppliers is modeled. The process begins with the intelligent matching of buyers and suppliers based on the similarity of users profiles. Then, a coordination mechanism for long-term agreements among buyers and suppliers is proposed. The proposed mechanism introduces the importance of strategic buyers for suppliers in modeling and decision making process. To enhance the

network utilization, we examine a further collaboration among suppliers where cooperation incurs both cost and benefit. Coalitional game theory is utilized to model suppliers' coalition formation. The efficiency of the proposed approaches is evaluated through simulation studies.

We then revisit the common issue, the co-existence of partnership and conflict objectives of members, for consolidated healthcare systems and study the coordination of hospitals such that there is a central referral system to facilitate patients transfer. We consider three main players including physicians, hospitals managers, and the referral system. As a consequence, the interaction within these players will shape the coordinating scheme to improve the overall system performance. To come up with the incentive scheme for physicians and aligning hospitals activities, we define a multi-objective mathematical model and obtain optimal transfer pattern. Using optimal solutions as a baseline, a cooperative game between physicians and the central referral system is defined to coordinate decisions toward system optimality. The efficiency of the proposed approach is examined via a case study.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction and Overview

1.1 Motivation of the Study

Collaborative approaches among different entities of complex systems have recently emerged as a new paradigm, leading to tremendous performance gains and efficient delivery of services. The idea is that competing parties, individuals or organizations, being mindful of potential retaliatory actions of their counterparts in future interactions, are willing to engage in collaboration and such relationship can induce optimal gains for both parties (Wu et al., 2010). Hence, such approaches emphasize the inclusion of diverse perspectives and knowledge, equality and shared responsibility while decision-making power is redistributed amongst a broad range of stakeholder or partners (Aveling and Martin, 2013).

While it has been proven that integrated systems have the capacity to address the quality deficiencies resulting from the lack of coordination (Cutler and Morton, 2013), the scope of the collaboration to align and synchronize the contributions of the independent/autonomous members in such complex systems still needs to be addressed deeply. As a matter of fact, each member in such systems may still act as an individual entity with its own culture and operations. The coexistence of cooperation and conflict objectives of members is becoming a challenging issue as the effectiveness and efficiency of such consolidated systems depend on the extent to which global performances are obtained. Thus, it can be inferred that there are a couple of key factors affecting the success of such systems:

- realizing the dynamic nature of information flow and capturing its benefits in decision making process,
- proper cooperation mechanisms among members/partners ensuring the longterm functioning of collaboration structures.

Supply networks (SNs) and consolidated healthcare systems are two main complex systems having adopted the concept of collaboration/partnership. Numerous supply chain partnerships existing in retail and service industries have been introduced and examined in the literature. For instance, the Walt Disney Company partnered with eBay to build a co-branded shopping website in 2000; and Yahoo partnered with Microsoft's Bing in 2010 to use its search engine. As for the healthcare industry, from 2007 to 2012, 432 hospital merger and acquisition deals were announced in the United States (Cutler and Morton, 2013); as a result, consolidation projects have attracted scholars' attention. It has also been demonstrated that there is considerable room for industrial organization theorists to contribute to the understanding of healthcare markets (Katz, 2013). The effect of coopetitive relationships and coordination mechanisms on quality and performance are interesting areas for both supply networks and consolidated healthcare systems, as there are common issues needing to be addressed from system modeling perspectives.

1.2 Methodology

In this work, we define new services taking into account the aforementioned concepts. These services are categorized into three overlapping groups as shown in Fig. 1.1. All of the proposed services including feasibility analysis, system optimality, and coordination are based on information sharing concept. The service of feasibility analysis facilitates the selection of qualified partners or service providers based on the similarity of profiles in a multidimensional space defined by attributes. *Multi-criteria decision making* methods are utilized to investigate all possible relations among members and choose the most promising ones. In order to ensure system optimality, i.e. fulfilling all members' objectives, *Optimization* techniques are applied which also serve as a baseline to direct the coordination mechanism towards global optimality. *Cooperative game theory* is ultimately utilized to tackle the potential misaligned activities among the competing members of such systems. It provides a formal analytical framework to strengthen the commitments of partners through fair sharing of risk, profit or cost and moving the strategies/actions toward a better global performance. Throughout the past, game theory has made revolutionary impact on a large number of disciplines ranging from engineering, economics, political science, philosophy, or even psychology (Myerson, 1991). Recently, there has been significant growth in research activities using game theory for analyzing supply chains and healthcare systems.

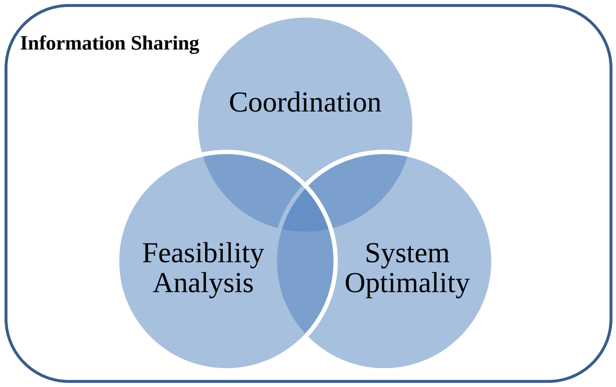


Figure 1.1: Proposed service categories

1.3 Structure of Dissertation

The remainder of this dissertation is organized as follows. Chapter 2 motivates the concept of cooperation and addresses long-term partnership among buyers and suppliers in e-supply networks for multi-period procurement processes. Chapter 3 presents another layer of collaboration among suppliers to maximize the network capacity utilization. Chapter 4 reviews the background of partnership in healthcare systems and addresses the coordination of hospitals for consolidated healthcare systems. Ultimately, Chapter 5 summarizes the contributions of this work and presents future research directions.

Chapter 2

Designing Intelligent Agents to Support Long-Term Partnership in Two Echelon e-Supply Networks

Abstract

Realizing the dynamic nature of information flow and the conflicting objectives of members play vital role in effective design of e-Supply Networks (e-SN). While there are some research in the SN literature proposing different dynamic and intelligent coordination mechanisms, the impact of the proper definition of data structure and long-term relationship in modeling both coordination and negotiation mechanisms have not been addressed deeply. In this chapter, we propose three overlapping services including intelligent matching of partners, proposal generations, and long-term contract management. The process begins with the selection

of qualified partners based on the similarity of users profiles in a multidimensional space defined by network attributes. Then, a coordination mechanism for long-term agreements is proposed such that the generated proposals in e-SN encourage buyers to reveal their demand in advance. The proposed mechanism introduces the importance of strategic buyers for suppliers in modeling and decision making process. To illustrate the model efficiency, a prototype system has been modeled and is compared to the traditional tendering mechanism. The validation results confirm the model efficiency in providing long-term decisions in a dynamic environment.

2.1 Introduction

Recent Internet-based technologies such as web services provide us with additional opportunity to deal with complex supply chains. For instance, information technology provides an infrastructure for integrating the internal and external activities of a company so that it connects the geographically distant supply chain members together to form a network system. In the same vein, electronic markets have eliminated the geographical obstacles and provided opportunities for the meaningful investigation of the buyer-supplier relationships in supply chains. Hence, the traditional linear supply chains are converted into an electronic supply network (e-SN) in which collaboration among partners, real-time decision making, and automation of conventional activities are improved.

e-SN is an electronic-based, dynamic, and distributed supply system (Mohebbi et al., 2011) comprised of many transactional echelons where the membership, the structure of interaction, and the nature of network attributes as represented by informational flow change dynamically over time (Mahdavi et al., 2009). Indeed, an e-SN is comprised of independent input nodes, such as buyers with their corresponding information, influencing on each output node, i.e. suppliers, so that according to the input layer attributes and output layer capabilities in terms of the scope of work and available capacity different flows can be obtained. Thus, it can be inferred that there is a couple of key factors affecting the success of an e-SN: a) realizing the dynamic nature of information flow in a web-based environment and, b) a proper cooperation mechanism among distributed supply network members.

In an e-SN, new buyers and suppliers join, existing buyers and suppliers may move out, and new products are introduced or replacing existing ones; hence, the network structure is dynamically altering in terms of relations among nodes (arcs) which are mainly due to changes in preferences and performances over time. Such situations, i.e. the sheer number of participants and difficulties to rapidly identify suitable partners, reinforce the idea that the definition of information structure, the way we acquire and maintain the information, and the governing rules have critical roles in the success of the system (Cho et al., 2011). In other words, while it is well-accepted by supply chain executives that information sharing can lead to enhanced supply chain performance (see La Londe and Ginter (2004)), the source, potential magnitude, and the allocation of the improvements across channel members are not clear (Sahina and Robinson, 2005).

Today's global e-marketplaces have changed their way of thinking to mitigate one of the most important failures of their ancestors: the "chicken and egg" problem. Buyers do not desire to commit to an e-market unless there are a substantial number of suppliers connected to it, and vice versa. One of the best examples of such rethinking is the MFG.Com, an online-based global sourcing marketplace for the manufacturing industry, which instead of using transaction-based fee, allows the buyers to freely utilize the service while the suppliers should pay a subscription fee. According to Mitch Free, founder and CEO of MFG.com, the user rating system is their core which rates the suppliers' quality, timely delivery and customer service, and buyers' timely payment, quality of technical data and ease of doing business. In addition, public e-marketplaces such as Amazon and eBay, unlike their consortium specific cousins, have felt the financial success through the years. Here, the concept of information sharing, reviewing previous buyers comments and ratings also looks to be amazing to the buyers. In other words, product reviews possess critical information regarding buyers concerns and their experience with the product which is essential to firms business intelligence for the purpose of conceptual design, personalization, product recommendation, better buyers understanding, and finally attract more loyal customers (Zhan et al., 2009).

As addressed before, the second factor affecting the success and performance of an e-SN is designing a proper cooperation/coordination mechanism. SN coordination can be defined as the coordination of the distributed decisions of organizations or participants on material flow, information flow and financial flow. Indeed, the internationalization and globalization of markets, and customer orientation of B2B and B2C sectors, as well as the emergence of the knowledge society, require new patterns of cooperation among suppliers, trading partners and customers in supply chain to successfully respond to the e-business demands (Manthou et al., 2004). Paradigm of agility also advocates cooperation as a route for gaining competitiveness (Wadhwa et al., 2010).

Generally speaking, coordination consists of horizontal coordination (Andersen and Christensen, 2005) and vertical coordination (Fiala, 2005). Horizontal coordination refers to the mechanism where the member of one echelon, such as buyers, share their experience and information to transfer the effect of interaction among themselves. The vertical information sharing implies that the upstream (i.e., supplier) and downstream (i.e., buyers) participants of the supply chain share information. Thus, the suppliers have access to the collective information that is required to coordinate the supply chain and each buyer has also access to the suppliers setups and holding cost information.

The coordination of a supply chain, however, requires accurate and timely information about the operational decisions and activities to be shared among all members to deal with uncertainties (Li and Wang, 2007). Such information is those which the parties are willing to share with their partners and hence does not include the member's confidential information. It can be, therefore, concluded that the main issue on SN coordination is to establish a suitable structure of information which should be shared among the network members (**?**). Intelligent agents are an alternative technology to perform business activities in e-SN such as collecting information from both sides, tracing the data exchange between layers and within nodes, and assisting the network members in decision making. One of the advantages of the intelligent agents is that they facilitates information sharing via the network leading to an effective decision making while preventing the parties to access the undesired information of each other. A multi-agent system means that the real system of interest is modeled as a set of interacting agents in a defined environment (i.e., as an agent system) and implemented in a simulation software (Lattila et al., 2010).

In this study, we define new services taking into account the aforementioned key concepts for designing e-SN and then implement an agent-based e-supply network. The proposed system uses service oriented architecture (SOA) in the core. All of the proposed services including intelligent matching of partners, proposal generations, and long-term contract management are based on information sharing concept. The service of intelligent matching facilitates the selection of qualified partners based on the similarity of users profiles in a multidimensional space defined by network attributes. The process begins with smart classification of the attributes and then the concept of discrepancy between the performances of nodes for meeting the buyers needs along with an improved weighting process is utilized. After determining the most promising partners, a coordination mechanism for long-term agreements are proposed such that the generated proposals in e-SN encourage buyers to reveal their demand in advance. The mechanism introduces the importance of strategic buyers for suppliers in modeling and decision making process. This approach allocates the benefits of the mechanism to all partners and optimizes the network global objective function as well.

The remainder of the work is organized as follows: In Section 2.2, the literature on the use of intelligent agents in e-supply network coordination is reviewed. In Section 2.3, a detailed mechanism for the model is presented. Section 2.4 describes the implementation details for the simulation and gives results on the performance of the model. Finally, the conclusions are given in Section 2.5.

2.2 Literature Review

The multi-agent systems (MASs) are alternative technologies for automated decisions and coordination in SNs because of the certain features such as distribution, collaboration, autonomy, and intelligence. An agent is a software entity, which is characterized with environment awareness, ongoing execution, autonomy, adaptiveness, intelligence, mobility, anthropomorphism and reproduction. Thereby, a MAS consists of a number of agents, which interact with each other in order to carry out tasks through cooperation, coordination and negotiation (Wooldridge, 2002). They can monitor and retrieve useful information, and do transactions on behalf of their owners or analyze data in the global markets (Xue et al., 2007). Therefore, the major challenge of the agent-based supply coordination is to find a global solution for the composite service such that all agents find the solutions that satisfy not only their own constraints but also inter-agent constraints (Liu et al., 2002).

Researchers have taken various perspectives including MASs when investigating coordination and information sharing within a SN. Sadeh et al. (2003) introduced MASCOT, Multi-Agent Supply Chain Coordination Tool, which is an architecture that aims at providing a framework for dynamic selection of supply chain partners and for coordinated development and manipulation of planning and scheduling solutions at multiple levels of abstraction across the supply chain. Hadikusumo et al. (2005) suggested using electronic purchasing agent for searching, selecting the supplier and preparing purchase order. Wang et al. (2008) proposed an agent-mediated approach to on-demand e-business supply chain integration. Each agent works as a service broker, exploring individual service decisions as well as interacting with each other for achieving compatibility and coherence among the decisions of all services. Lee et al. (2009) introduced an agent-based procurement system aiming to improve the current subjective practice of supplier selection, price negotiation and supplier evaluation by deploying the agent technology and OLAP (online analytical processing). Indeed, their main contribution was the investigation of interaction of agent technology and OLAP in the whole purchasing cycle. Based on the fuzzy inference theory, Lin et al. (2011) proposed an agent-based price negotiation system for on-line auctions. Mainly, three agents are used in the study: a seller agent, a buyer agent, and a mediator agent. Mohebbi and Shafaei (2012) proposed an agent-based mechanism for effective coordination and negotiation among buyers and suppliers in e-SN which is fully automated, global goal-oriented, multi-attributes, mediated, and time-dependent, and its structure is double-sided multilateral negotiation. Their proposed integrated model begins with finding most promising partners based on the similarity of buyers and suppliers profiles and the negotiation process among the feasible partners is then established using some rules such that the goodness of the generated proposals at each round of negotiation is evaluated through a global optimization model. Cho et al. (2011) utilized intelligent agents to simulate buyers and suppliers behaviors in e-SN and facilitate horizontal and vertical information sharing. They demonstrated that information sharing in SN can be effectively established if the barriers of information access and information effects are wisely defined.

Given the plethora of research in the SN literature proposing different agent-based coordination mechanism from various perspectives, the impact of long-term relationship in modeling both coordination and negotiation mechanisms has not yet been deeply addressed.

Therefore, in this study, we have changed the viewpoint of "a one-shot purchase to a multi-period demand" which can be delivered in separated packages in different periods. In the next section, we will illustrate how the interaction of the proposed services in e-SN supports the long-term contract management.

2.3 Analytical Modeling

Finding suitable partners from a large number of suppliers and making the right decision in satisfying the organization's demands are common concerns for the most modern firms. Here, the service of intelligent matching facilitates the selection of qualified partners. Supply and product selection in the proposed system is based on the different kind of attributes so that values are assigned regarding to several predefined rules and the attribute types. Our proposed system utilizes two sets of attributes to define the requirements, similarities, and properties: critical attributes and bilateral attributes (Table 3.1). The former is the attribute defining the overall goals of buyers and suppliers companies so that any decisions and making contracts should be compatible with the critical attribute. The latter is the attribute assigned to the suppliers as a common viewpoint about the properties of the product and are divided into two subsets: qualitative and quantitative. While the critical attribute values

Table 2.1: Critical and bilateral attributes

Bilateral Attributes		**Critical Attributes**
Qualitative	*Quantitative*	
After sale services	Price	Regulatory conflicts
Credit and brand	Transportation cost	Technological cooperation
Quality	Lead time	Export/Import taxes

are computed by the network agent based on buyers' and suppliers' viewpoints, the bilateral attribute values are initiated by the supplier but automatically updated by the system. The process of updating the bilateral attributes has a key role in the firm fairness and the validity of offers made by the system. Updating bilateral attribute values is accomplished by considering the previous buyers of the products. Most existing work about processing online customer reviews focuses on opinion mining which aims to discover reviewers' attitudes, whether positive or negative, with respect to various features of a product, e.g. the weight of laptops and the picture quality of a digital camera (Hu and Liu, 2004; Popescu and Etzioni, 2005).

This classification of attributes helps effectively design agents that can specify the requirements and restrictions of suppliers/buyers in the network. These classes are used in methods that we explain later on. The administrator can break down each attribute into sub-attributes. For instance, regulatory conflicts involve political and geographical issues. The initial set of bilateral and critical attributes is defined by the system administrator for each group of products, but both buyers and suppliers can offer new attributes for a specific product group or for critical attributes.

The system acts in a continuous manner; hence, the system receives the buyers demand through the time and helps buyers to choose among long-term contracted suppliers as well as other suppliers registered in the network. This means the system always have an estimation of supply and demand for the future. To effectively describe the system, we will explain both the data structure and the methods used to achieve the previously described goals

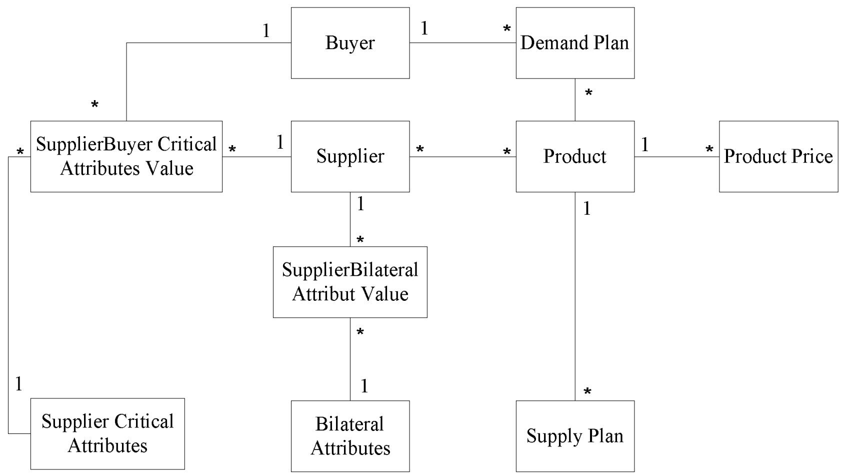


Figure 2.1: Simplified Class Diagram

of system. Figure 2.1 shows a class diagram * illustrating a simplified version of the data structure the system uses. Although supplier and product entities are separately shown in the class diagram, to simplify the notations we utilize a supplier-product couple in the formulas explained in this work. Products are categorized and different bilateral attribute sets can be defined for each product. As the figure shows, a bilateral attribute of a supplier has a common value among all the buyers while the value of a critical attribute is just meaningful between one buyer and one supplier. For example, if a buyer cannot easily interact with a supplier in a specific region because of regulation problems or high export/import taxes, the assigned value for this supplier is only valid for that specific buyer.

* A class diagram in the Unified Modeling Language (UML) is a type of static structure diagram describing the structure of a system by showing the system's classes, their attributes, and the relationships among objects.

2.3.1 Intelligent Matching of Buyers and Suppliers

To tackle the process of connecting/matching the members of two parties, i.e. buyers and suppliers in a supply network, most studies have taken the advantage of intelligent agents and customized multi-criteria decision making (MCDM) methods. Analytical hierarchy process (AHP), developed by Saaty (1977), and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), developed by Hwang and Yoon (1981), are two most commonly applied MCDM techniques in the literature. The AHP accommodates absolute measurement by allowing the decision maker to design ranges of intensity scales (e.g., Poor, Fair, Good, Very Good, Excellent) for each criterion, assign relative weights to each intensity, and evaluate each alternative/option by rating it on the intensity scale under each criterion (Millet and Saaty, 2000). TOPSIS defines an index called similarity (or relative closeness) to the positive-ideal solution and the remoteness from the negative-ideal solution. Then, the method chooses an alternative/option with the maximum similarity to the positive-ideal solution. Another major category of MCDM models includes outranking methods and the ELECTRE, the most popular one, whose main idea is the proper utilization of the outranking relations (Wang and Triantaphyllou, 2008). The fuzzy counterparts of these methods have also been developed in the literature, as fuzzy linguistic models permit the translation of verbal expressions into numerical ones, thereby dealing quantitatively with imprecision in the expression of the importance of each criterion (Kahraman et al., 2007).

The aforementioned methods generally treat all attributes/criteria in the same way for sorting out the alternatives/options, while some attributes have critical role in the selection process and need to be treated in a binary format. Hence, we improve the attributes' weighting process and utilize the classification of criteria and fuzzy numbers to effectively design agents and the governing rules. The overall process is summarized in the following steps.

Step 1(Start State): Suppliers/buyers enter their estimation of the supply/demand at each period. The suppliers reserved price that should be entered to the system is collected in this phase as well.

Step 2 (Information Collection): The buyer is asked to answer the following questions and reveal the importance value using linguistic terms introduced in Table 2.2. These numbers are adopted from Kahraman et al. (2007).

- What is your geographical location?
- Do the credit and brand of suppliers affect your transactional decisions?
- Do you desire to collaborate with suppliers?
- What degree of quality do you require for the product?

The network agent then creates the array of the order for each buyer which contains of 6 elements: ID number of the buyer which is associated with the product; entry time and geographical location; importance degree of credit and brand of the supplier; buyer's tendency for collaboration with suppliers; and desired quality for the product.

Step 3 (Matching Buyers and Suppliers): Based on the available information about suppliers, the network agent finds the similar profiles for buyer i as follows:

Table 2.2: Sample triangular numbers representing the importance degree for different attributes

Importance	**Value**
Very Low	(0,0,20)
Low	(0,20,40)
Medium	(30,50,70)
High	(60,80,100)
Very High	(80,100,100)

I. According to the geographical location of buyer i, the network agent search all available suppliers and calculate the weight of the d^{th} attribute, w_{ij}^{d}, for buyer i and supplier j as follows:

- In case of $d = \{regulatory\ conflicts,\ technological\ cooperation\}$, $w_{ij}^{d} = 0$ if transaction between two regions is restricted and $w_{ij}^{d} = 1$ otherwise. Such restrictions are initially determined by suppliers or system administer.

- In case of $d = \{export/import\ taxes,\ transportation\ cost\}$, the network agent constitutes the buyer-supplier attribute vector as $B_i^d = [\widetilde{V_{ij}}]_{1\times|J|}$, $\forall i, d$, where $\widetilde{V_{ij}} = (a_{ij}, b_{ij}, c_{ij})$ represents the fuzzy triangular number of the d^{th} attribute for the i^{th} buyer who transacts with supplier j. a_{ij} is the optimistic value of taxes or transportation cost and c_{ij} is the pessimistic ones. The network agent then normalizes vector using the following formula:

$$N_i^d = [\widetilde{r_{ij}}]_{1\times|J|}, \quad where\ \widetilde{r_{ij}} = \widetilde{V_{ij}^{-}}(/)\widetilde{V_{ij}}, \quad \forall i,\ d \tag{2.1}$$

$\widetilde{V_{ij}^{-}}$ represents the minimum fuzzy number in the corresponding vector. Afterwards, in order to obtain the weight for each supplier, the network agent calculates the rank of each component of the N_i^d vector, $\widetilde{r_{ij}} = \left(a'_{ij}, b'_{ij}, c'_{ij}\right)$, using Lee and Li (1998) method and considers these values as the weight of the d^{th} attribute for supplier j. Indeed, this helps convert the triangular number into a crisp value. The ranking of each fuzzy number can be computed as follows:

$$w_{ij}^d = \frac{{a'_{ij}}^2 + {c'_{ij}}^2 - a'_{ij}.b'_{ij} + c'_{ij}.b'_{ij}}{3(-a'_{ij} + c'_{ij})}, \quad \forall i,\ j \tag{2.2}$$

II. The network agent calculates weighted distance between qualitative attributes of the i^{th} buyer and the j^{th} supplier using the following formula:

$$\Omega_{ij} = \sum_{d=1}^{n_{ql}} w_{ij}^d \times L_{ij}, \quad \forall i,\ j \tag{2.3}$$

where, n_{ql} is the number of qualitative attributes, and w_{ij}^d denotes the weight of the d^{th} attribute for the j^{th} supplier from the perspective of the i^{th} buyer. L_{ij} represents the dissimilarity between the importance value of the d^{th} criteria for the i^{th} buyer, $\mu_{V_d^i} = (\alpha_i, \beta_i, \gamma_i)$, and the fuzzy value for the j^{th} supplier in satisfying the d^{th} attribute, $\mu_{R_d^j} = (\alpha_j^+, \beta_j^+, \gamma_j^+)$. It is assumed that the values of the j^{th} supplier capabilities in satisfying the corresponding criteria are known so that they are initially determined by suppliers and/or system administrator. L_{ij}, can be calculated using the following formula (Kahraman et al., 2007):

$$L_{ij} = \begin{cases} 1 - \frac{\gamma_i - \alpha_j^+}{\beta_j^+ + \gamma_i - \alpha_j^+ - \beta_i} & \text{for } (\beta_i < \beta_j^+) \\ 1 - \frac{\gamma_j^+ - \alpha_i}{\beta_i + \gamma_j^+ - \alpha_i - \beta_j^+} & \text{for } (\beta_j^+ < \beta_i) \end{cases} \tag{2.4}$$

The fuzzy value for suppliers will be updated in the system by considering buyers' attitudes about the suppliers' performance at previous rounds as follows. The buyer of a specific product from the j^{th} supplier can vote for the bilateral attribute d of the product at the period t. Votes are considered to be linguistic terms (Table 2.2) and 0 for no vote. Then, through weighting the votes and calculating the average of at least two successive periods, the performance of each supplier can be obtained.

III. The network agent sorts the existing suppliers for each buyer based on the following formula:

$$\Theta_{ij} = \begin{cases} \left(\Omega_{ij} \times w_{ij}^d\right) & \text{If } \nexists d \text{ such that } w_{ij}^d = 0 \\ \mathcal{C} & \text{Otherwise} \end{cases} \tag{2.5}$$

where $\mathcal{C}$ is a large number. In some cases, if $\Omega_{ij} = 0$, then the network agents considers it as a small value, i.e. ϵ , and calculates Θ_{ij}. Ultimately, suppliers are ranked for each buyer such that the lower Θ_{ij} leads to better matching of buyers and suppliers.

2.3.2 Proposal Generation and Long-Term Partnership

Review of the literature reveals that most studies have focused on the design of different proposal engines on the basis of the bargain on prices where the goodness of the generated offers is evaluated using a utility function. In practice, a supplier sells products to many buyers and a buyer may distribute its demand among many suppliers. Therefore, the issue of quantity can complicate the decisions of proposals evaluation - since it generally interacts with other issues such as price (Cheng et al., 2006) and lead time. Hence, Mohebbi and Shafaei (2012) proposed a mechanism where the price proposal is considered to be dependent on lead time and the goodness of the proposals is evaluated in terms of the material flow and total welfare of the supply network. In this study, we advocate such an approach as the suppliers' offered lead time is often based on their capacity and operational constraints. In some cases, based on the buyers requirements and the importance degree for the price attribute, the suppliers may be capable to deliver the products earlier with early delivery fee. In contrast, in order to decrease the workload in specific periods, some suppliers may offer a discount to the buyers such that agree to extend the lead time. The next sub-sections describe how to generate an offer at a certain stage leading to long-term contracts.

After sorting suppliers for each buyer, the network agent delivers a message to buyers to receive the profile of each buyer's demand during different time periods represented as $D_i = \{d^1, d^2, \ldots, d^t\}$. By receiving the corresponding information of buyers and suppliers agents, the network agent will generate offers to find mutually compatible solutions and evaluate the proposals.

Let $\Gamma_i^t = \langle P_B^i, P_{max}^i, \zeta_R^i \rangle$ and $\Lambda_j^t = \langle P_S^j, P_{min}^j, \zeta_{min}^j \rangle$ denote the set of private information of buyer i and supplier j at the period t, respectively. P_B^i and P_S^j are the reserved price of the i^{th} buyer and the j^{th} supplier, respectively. P_{max}^i and ζ_R^i are the buyer's maximum price and lead time that she can offer; any proposal higher than it should not be accepted. For the supplier, similarly, P_{min}^j and ζ_{min}^j are the seller's minimum price and lead time such that for any reduction in the reserved lead time, higher price will be charged. The rest of notations are as follows.

- I: Set of buyers
- J: Set of suppliers
- F_i: Subset of feasible suppliers for buyer i
- T: Set of planning periods
- S_j^t: Supply of the j^{th} supplier at period t
- D_i^t: Demand of the i^{th} buyer at period t
- $\triangle\, T$: Discrepancy of suggested lead times for the j^{th} supplier and the i^{th} buyer
- $\triangle\, P$: Increment/reduction in price for each unit of $\triangle\, T$
- φ_{ij}: The value giving the importance of buyer i for supplier j. It gets values greater than 1 if buyer i is a strategic customer for the j^{th} supplier and gets values lower than 1 otherwise.
- P_{ij}^t: The purchase price of the i^{th} buyer from the j^{th} supplier at period t

- X_{ij}^t: The decision variable giving the quantity of products which the i^{th} buyer purchases from the j^{th} supplier at period t

- f_b^*: Optimal value of buyers' objective function before negotiation

- f_s^*: Optimal value of suppliers' objective function before negotiation

In order to calculate the value of φ_{ij}, the network agent constitutes a contract matrix at the end of each period as $\psi^t = [X_{ij}^t]_{|I|\times|J|}$. After a specified number of periods, the network agent calculates the purchase share of buyer i from the total supply of the j^{th} supplier as $S_P^i = \frac{\sum_{t=1}^{T} X_{ij}^t}{\sum_{t=1}^{T} S_j^t}$. Then, based on a threshold value which may be specified by suppliers, φ_{ij} can be determined. According to the aforementioned concepts, we propose the following function for generating price proposals:

$$\mathbb{P}_{ij}(t) = P_R^j + \left(P_R^j \left(\frac{P_R^j + \triangle\, P}{P_R^j} \right)^{\triangle T} - P_{min}^j \right) \left(1 - \frac{t}{T} \right)^{\varphi_{ij}} \quad \forall i,\ j \in F_i,\ t \qquad (2.6)$$

The above function implies that if buyer i reveals its demand in advance for different periods, she will pay lower for any increase in t. Indeed, the network agent first checks the desired lead time of buyer i, ζ_R^i, with the value of ζ_{min}^j for the j^{th} feasible supplier. If the buyers' suggested lead time is equal or greater than the suppliers' lead time, then it generates price offers; otherwise it removes the feasibility of transaction between those partners. As it is illustrated in Figure 2.2, the relation between the price and lead time is described exponentially. Although the relationship between these two variables has usually been considered as a step function in discrete states, the increment in price does not reveal

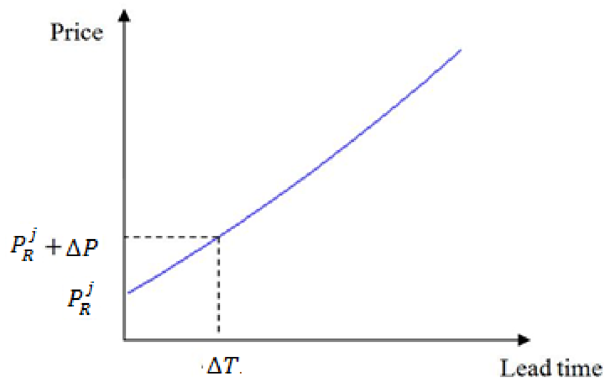


Figure 2.2: Price and lead time relationship

linear behavior in real market situations. It is also worth mentioning that for strategic buyers, where φ_{ij} is greater than 1, suppliers are more conceder and go quickly towards their reservation value. In order to propose the offers for each negotiation round that are likely to be accepted by both buyers and suppliers, we applied the following mechanism:

$$P_{ij}^t = Rand\left[\mathbb{P}_{ij}(t), P_{ij}^{t-1}\right] \quad \forall i,\ j \in F_i,\ t \tag{2.7}$$

where, $Rand[a, b]$ is a random number between a and b, and $P_{ij}^0 = \mathbb{P}_{ij}(1) + (P_{max}^i - \mathbb{P}_{ij}(1))\left(1 - \frac{\tau}{\tau_{max}}\right)$. τ denotes the negotiation rounds and τ_{max} is the time deadline for the bargaining process. The term $\left(1 - \frac{\tau}{\tau_{max}}\right)$ is the concession degree for suppliers. A concession is the difference between the supplier's two neighboring offer prices (Cao et al., 2015). Our model is based on Faratin's time-dependent concession model indicating that an agent is likely to concede more rapidly if it needs to reach an agreement by a deadline (Faratin et al., 1998).

Mathematical Model

In order to preserve social welfare, i.e. fulfilling all participants objectives, in a multi-agent system and establishing long-term contract in terms of price and quantity of products in each period, we define a mathematical model with global objective function which is the minimization of sum of the relative "errors" of all agents. For the sake of mathematical simplicity, we eliminate the index of product types and consider one product in the supply network. The bi-objective function is presented as follows. Using weighting method to formulate a single objective function, optimal solutions can be obtained.

$Z = Min\left[R^b(X), R^s(X)\right],$

where,

$R^b(X) = \sum_{t,i,j\in F_i} \frac{f_b^* - f_b(X_{ij})}{f_b^*},$

$R^s(X) = \sum_{t,i,j\in F_i} \frac{f_s^* - f_s(X_{ij})}{f_s^*}.$

Indeed, f_b^* and f_s^* can be computed by solving the constrained optimization problem locally for each agent before coordination in the network. The operational constraints for the model can be defined as below.

- $\sum_{j\in F_i} X_{ij}^t = D_i^t, \quad \forall i,\ t$
- $\sum_i X_{ij}^t \le S_j^t, \quad \forall j \in F_i,\ t$
- $X_{ij}^t \ge 0, \quad \forall i,\ j \in F_i,\ t$

The constraints are considered to satisfy the demand and supply of each period. The value of S_j^t is considered so that when new buyers enter the system in the next periods, suppliers can also meet their demands. In other words, suppliers reserve some of their capacities for the new buyers to benefit from the existence of different buyers with different willingness to pay.

Rule of Bargain

The network agent evaluates the proposals through the presented global objective functions. At time τ, the agent generates new offers and continue this process until the end of the negotiation round, τ_{max}. We summarize the automated negotiation process in following steps:

- Step 0: Set the negotiation round to $\tau \leftarrow 0$.
- Step 1: If $\tau \leq \tau_{max}$, generate new offers. Otherwise, go to the final step.
- Step 2: Run the global objective function. Accept the offers if it is improving the objective function with respect to previous round. Set $\tau \leftarrow \tau + 1$ and proceed to Step 1.
- Step 3: Send the best outcomes to marketplace according to optimal solutions and stop.

The negotiation among interacting counterparts would be withdrawn if there is no joint area in suggested intervals for price or the offers are infeasible for a certain number of successive negotiation rounds. In the next section, we first apply the proposed model in a network scenario and then evaluate its performance using simulation model.

2.4 Validation and Performance Evaluation

In order to validate and evaluate the proposed system, an agent-based simulation was designed using Microsoft Visual Studio. The agents including *buyers*, *suppliers*, and *a network coordinator*, have some behaviors and attributes in common with the ones used in the system process. Although decision making in industrial markets is known to be more rational and mostly affected by product attributes and technical specifications, but we considered Jager et al. (2000) model to design the psychological part of selection behavior of the agents. We also considered a scenario in which the sellers sell a specific product. Customers send request for quotation (RFQ) and announce their demand for one or several periods(s). Then, suppliers bid on them depending on the critical attributes and their ability to satisfy the customers delivery dates and prices. The starting assumption is that first suppliers register in the network by informing their capacities in different periods (it is not mandatory for all suppliers to declare their supply capacity for several periods) and other attributes such as location, product scope and their specifications and so on. Thereby, their information will be set before simulation. It is also assumed that the demand should be fulfilled even in the course of backlog orders.

At the initiation stage, a set of buyers are created. These buyers are assumed to have a random demand (within a slowly changing range) during the time, and a set of slowly changing critical and bilateral attributes. The "repetition or habit" mode of Jager et al. (2000) work is in effect here, causing the buyers to select products having good experience with during several rounds. We also consider the production planning as "make to order". The total cost of SN entities is composed of suppliers unutilized capacity and backlog orders.

In the following part of this section, we conduct the experiments to validate the proposed long-term coordination mechanism for the SNs. We then compare the performance of the proposed model with the tendering process which is being practiced by the most industries. The comparison is conducted in terms of the total network cost, and the agreed price in a contract based on the strategic index of the buyer. Here, the following hypotheses are considered:

- H_1: The proposed long-term coordination mechanism outperforms the traditional tendering process in terms of the total cost.
- H_1: The proposed long-term coordination mechanism outperforms the traditional tendering process in terms of considering the strategic index of buyers for making a contract.

The statistical analyses of the above addressed hypotheses are performed through one-way ANOVA.

2.4.1 Performance Evaluation

In this study, two scenarios have been investigated. In the first scenario, the proposed approach is considered. This includes a dynamic decision making whereby product attributes are changed randomly throughout the rounds, while the known attribute values follow the rules introduced previously. It means that the experienced attributes may be different from the ones really sensed by the buyers. As a consequence, buyers may vote positively or negatively to the purchased products.

The second scenario follows a more traditional method in which suppliers offer products to the buyers at a certain price. Buyers have concerns about the product attributes and the supplier of the product. Selection among the offers is mostly influenced by the price. The buyers' assumptions about the products and suppliers are just updated by their experience, and so at the first buy, the buyer can just rely on the information provided by the supplier. In addition, attributes are just updated after a transaction. This means that in this method, decisions are made separately by the suppliers/buyers and information sharing does not exist systematically. The parameters used in the simulation model are given in Table 2.3.

Table 2.3: Parameters in the simulation model

Parameter	**Value**
Maximum buyer demand period (t)	12
Demand (D_i)	Uniform [50, 300]
Supply (S_j)	Uniform [70, 400]
for $\triangle\, T > 0$	$\triangle\, P = 5\%$
Unutilized capacity unit cost (per period)	100
Backlog order unit cost (per period)	150
Number of buyers	Uniform [2, 15]
Number of suppliers	10

The performance of the both scenarios is measured using total network cost (Figure 2.3), and average agreed price in terms of buyers strategic index (Figure 2.4) for 200 simulation rounds. It should be noted that the SN cost is aggregated through all the players and also the strategic index of a buyers is normalized between 0 and 1. It means that for a more strategic buyer, the index is closer to 1.

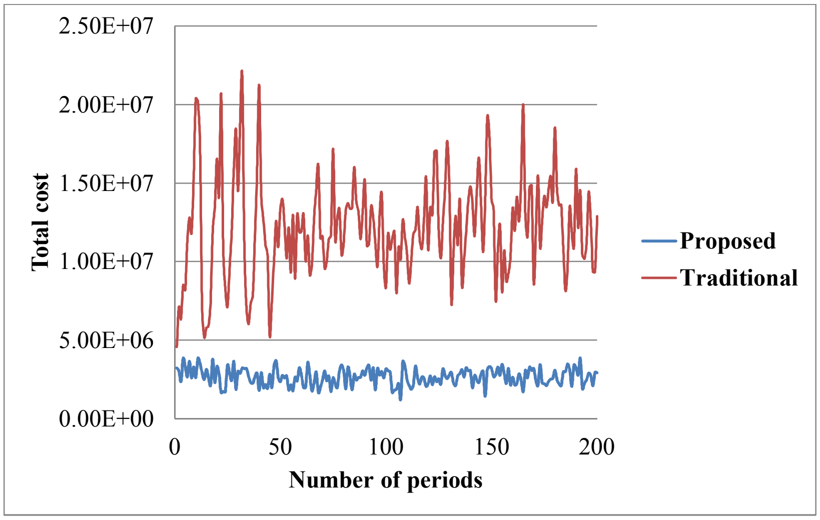


Figure 2.3: Total Cost curve of proposed long-term mechanism vs. traditional tendering process

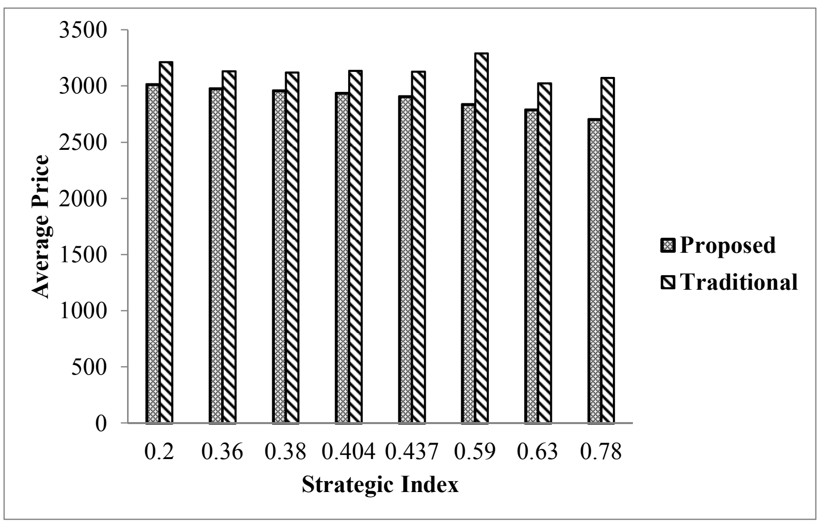


Figure 2.4: Average agreed price of the proposed long-term mechanism vs. traditional tendering process

2.4.2 Discussion and Analysis

Figures 2.3 and 2.4 demonstrate the performance of the proposed approach and that of the traditional tendering process in terms of the total network cost and agreed contract based on the strategic index of buyers, respectively. The results indicate that the proposed approach for making long-term partnership outperforms the traditional tendering process. This is mainly due to the intelligent behavior of the proposed approach for making long-term contracts where both the horizontal information sharing among buyers and negotiations among buyers and suppliers have been taken into account. In order to investigate the significance of the presented hypotheses in Section 4, the one-way ANOVA is applied. The results as presented in Table 2.4, supports both hypotheses. Since the null hypothesis in ANOVA is rejected at the significance level of 0.05, it is desired to have a pair-wise comparison of factor level means in order to investigate the factor effects. Considering the obtained confidence intervals for the differences between the factor level means $((\mu_{agent} - \mu_{tender}))$, normal tendering process leads to higher mean costs in the network. These outcomes approve that the proposed approach leads to both reliable and higher performance than that of the normal tendering approach.

Table 2.4: One-way ANOVA

Performance	F-Statistics	P-value	Confidence Interval
Total Cost	1770.44	0.000	$(-1.001 \times 10^7, -0.9116 \times 10^7)$
Price-Strategic Index	28.03	0.0001	$(-351.285, -148.715)$

2.5 Conclusions

In this study, we designed an agent-based e-SN while the distributed and dynamic nature of the decision making process has been taken into account. The proposed system uses service oriented architecture such that each of the defined services addresses one of the confronting challenges in e-SNs. The first and foremost contribution of this study is the facilitation of the long-term partnership in an e-SN. While most of the existing works in the literature consider one-shot purchase processes, we established a framework for a multi-period procurement process such that both buyers and suppliers benefit from this mechanism. Such an approach enabled us to define the buyers strategic index and consider its impact on the contract terms. Our second contribution is associated with the intelligent matching of buyers and suppliers through defining suitable data structures for the agents. This process is designed using the categorization of the influencing attributes on a long-term contract and a novel weighting algorithm. Evaluation process of the generated proposals through a global objective function while both price and quantity are decision variables is the next contribution of this study. The presented model encourages buyers to reveal their demand in advance through proposing lower prices.

Chapter 3

Coalitional Game Theory Approach to Modeling Suppliers' Collaboration in Supply Networks

Abstract

Suppliers' collaboration is a new paradigm to improve the utilization of collective intelligence in supply networks. Although existing literature advocates the notion of cooperation in supply networks, there is a dearth of studies quantitatively analyzing cost and benefit of cooperation. In this study, we first develop a model for suppliers' dynamic coalition formation using coalitional game theory. The proposed cost structure, including operational costs, influences the utility of each possible coalition and restricts the coalition size and search space for finding possible coalitions. To distribute the profit earned by cooperation in a

fair manner, a criterion named *Shared Capacity Index* is developed according to suppliers' capacity share in the corresponding coalition. A suppliers' cooperation algorithm is then proposed to resolve possible conflicts among network members whereby each supplier is able to explore coalition structures autonomously. The efficiency of the proposed approach is evaluated through simulation studies and compared to other solution methods, including Shapley value and Proportional Fairness. Results demonstrate that long-term cooperation among suppliers leads to enhanced average individual profit in the network.

3.1 Introduction

Strategic partnership among competing members of supply networks to benefit from collaborative synergy has altered the functionality of e-supply networks (SNs). The idea is that competing parties, individuals or organizations, being mindful of potential retaliatory actions of their counterparts in future interactions, are willing to engage in collaboration and such relationships can induce optimal gains for both parties (Wu et al., 2010).

It is no longer the case that firms perform all vital functions in-house to build and maintain competitive advantages; rather, they form alliance with other firms to execute some of the business activities (Zhang and Frazier, 2011). Hence, a proper cooperation mechanism among distributed supply network members affects the success of SNs. While it is well accepted by supply chain scholars that dynamism and decisions in a distributed manner are two main sources of complexity in designing SNs, the dynamic network structure in terms of relations among nodes/members, and the scope of cooperation to align and synchronize the contributions of the independent members in e-SNs are not addressed deeply.

It has been proven that buyers mandate co-opetitive interactions between suppliers by applying purchasing leverage (Wu et al., 2010). In other words, the paradigm of agility advocates cooperation as a route for gaining competitiveness (Wadhwa et al., 2010). Zhang and Frazier (2011) have introduced numerous supply chain partnerships existing in retail and service industries. For instance, Amazon developed an innovative IT-enabled supply chain and Borders sought to leverage it instead of trying to match it. The Borders Group partnered with Amazon under a long-term contract in 2001. Under the agreement, Amazon provided design and underlying technology to its rival bookseller's Web site, took over customer service and order fulfillment, and was compensated by sharing a portion of the sales from Borders. The Walt Disney Company partnered with eBay to build a co-branded shopping website in 2000; and Yahoo partnered with Microsoft's Bing in 2010 to use its search engine.

From buyers' perspectives, the use of common suppliers that deliver identical parts and/or similar services can also be a source of efficiency Dubois and Fredriksson (2008) as this approach can lead to the reduction of risk while increasing the flexibility. Although in certain conditions limited stock-out is allowed, under these conditions the buyer requires a certain degree of reliability from the enterprise towards the fulfillment of stock-out demand. Such a case is a typical concern for agile enterprises. Hence, further coordination among suppliers is highly important in order to maximize the network capacity utilization especially when the suppliers are geographically decentralized. The purpose is to fulfill buyer's stock-out demand by a cooperative mechanism through which these demands are pooled out to another node.

This approach leads to fulfill these demands within a smaller time-period as investment in production capacity is often a critical decision for several manufacturing sectors such as the semiconductor, consumer electronics, and telecommunication industries.

The collaborative relationship, however, may not always sustain (Zhang and Frazier, 2011). For example, Borders ended the collaboration with Amazon and launched a new Web site for its online customers in early 2008. Disney ended their partnership with eBay and moved the Disney Auction website under its own banner as of fall of 2006. As a result, we agree with the idea argued by Bengtsson and Kock (2000) that, in situations in which two firms both compete and cooperate, "it is of crucial importance to separate the two different parts of the relationship to manage the complexity and thereby make it possible to benefit from such a relationship". In the presence of competitive risk, suppliers may not desire to cooperate with one another. The main reasons are due to the use of company credit and brand, the transfer of technological knowledge to other companies, and the improvement of the competitive situation of rival suppliers. This case mainly occurs when the cooperation domain of technological knowledge among suppliers is considerably high and includes the core competencies of the company. In such a situation, the cooperation among suppliers is not recommended; hence, the coordination is limited to the areas where suppliers are willing to share the information and there is no conflict in interest between the parties (Mohebbi et al., 2011). In addition, to ensure the long-term functioning of collaboration structures among independent members, an appropriate profit sharing scheme for partners should be generated in the collaboration process. Such considerations are of major concern in game theory which is divided into non-cooperative/strategic and cooperative/coalitional games.

Cooperative game theory seems more appropriate to analyze a supply network in its design stage, as it is characterized by many possibilities for enterprise coalitions and allocation patterns for tasks and rewards (Hennet and Mahjoub, 2010). As a matter of fact, the complexity of centralized approaches and the need for distributed solutions have sparked a huge growth in the coalition formation literature that aims to find low complexity and distributed algorithms for forming coalitions (Arnold and Schwalbe, 2002). Coalition formation games encompass coalitional games where, unlike cohesive games, network structure and cost for cooperation play a major role. In many cases, forming a coalition requires a negotiation process or an information/material exchange process that can incur costs, thus, reducing the gains from forming the coalition. Coalition formation games can be classified into two categories: static and dynamic games. In the former, an external factor imposes a certain coalitional structure and the objective is to study this structure, while the latter is a richer framework and the main objectives are to analyze the formation of a coalitional structure through players' interaction, and to study the properties of this structure (Saad et al., 2009b).

In SNs, it is desirable that the coalition formation process among suppliers takes place in a distributed manner, whereby they have autonomy on the decision to whether or not join a coalition. Hence, in this study, we model suppliers' collaboration for multi-period demand via coalitional game theory such that cooperation incurs both cost and benefit. The purpose is to maximize the network capacity utilization via a cooperative mechanism through which backlog orders are pooled out to other suppliers. Since SN members have their own objectives and can be in conflict with one another, we derive a fair and practical cooperation algorithm such that the decision to cooperate does not degrade the performance of any of the cooperating suppliers. The proposed algorithm enables suppliers to self-organize into independent disjoint coalitions while the cost structure influences the utility of each possible coalition and restricts the coalition size.

The remainder of the work is organized as follows: In Section 3.2, the literature on the application of the cooperative game theory in SNs is reviewed and the contributions of this study are highlighted. In Section 3.3, a detailed mechanism for the proposed model is presented. Section 3.4 describes the implementation details for the simulation and gives results on the performance of the model. Finally, conclusions are given in Section 3.5.

3.2 Literature Review

Game theory can be divided into two branches: non-cooperative and cooperative game theory. Non-cooperative game theory studies the strategic choices resulting from the interactions among competing players, where each player chooses its strategy independently for improving its own performance (utility) or reducing its losses/costs (Saad et al., 2009b). For solving non-cooperative games, several concepts exist such as the celebrated Nash equilibrium (Basar and Olsder, 1999). The main idea for Nash equilibrium is to calculate the best response/utility function of each player and then find the profile of actions such that no player can profitability deviate, given the actions of the other player (Osborne and Rubinstein, 1994).

While non-cooperative game theory studies competitive scenarios, cooperative game theory provides analytical tools to study the behavior of rational players when they cooperate (Saad et al., 2009b). The main branch of cooperative games describes the formation of cooperating groups of players, referred to as coalitions (Myerson, 1991), that can strengthen the players positions in a game. Cooperative and non-cooperative approaches, though different in their theoretical content and the methodology used in their analysis, are really just two different ways of looking at the same problem (Nagarajan and Sosic, 2008). The main idea is that if the individual goal of each player is only to maximize his gain or to minimize his loss, the agreements obtained by negotiation may be fragile and will not generally guarantee global optimality for the whole system. For these reasons, much effort has been recently devoted to conceiving contracts strengthening the commitments of partners through risk, profit or cost sharing, and/or moving the equilibrium state of the game toward a better global performance (Hennet and Arda, 2008).

Two key aspects are of importance in cooperative games (Saad et al., 2009b): a) finding a payoff allocation which guarantees that no group of players have an incentive to leave the grand coalition, and b) assessing the gains that the grand coalition can achieve as well as the fairness criteria that must be used for distributing these gains. For solving cooperative games, the literature presents a number of concepts including core, and Shapley value (Myerson, 1991). The core of a game is directly related to the grand coalition's stability while Shapley value takes into account the marginal contribution of each player within a coalition.

There is a growing number of research efforts utilizing cooperative game approach for modeling the behavior of members in a supply chain. For instance, Smirnov and

Cortes (2004) studied cooperative game configuration using fuzzy coalitions. Based on the framework, they proposed an approach that considers configuring as: (a) coalition formation, and (b) product and resource allocation tasks in a multi-agent environment. Wang and Efstathion (2004) introduced a two-echelon, cooperative supply chain model. Jin and Wu (2006) have shown that in online reverse auctions there is one unique strongly stable suppliers' coalition allowing for maximizing profit. Charles and Hansen (2008) have applied the cooperative game theory to global cost minimization and cost allocation in an enterprise network. Hennet and Arda (2008) evaluated the efficiency of different types of contracts between the industrial partners of a supply chain. Their proposed model combines queuing theory for evaluation aspects and game theory for decisional purposes. Zhang et al. (2013) investigated the cooperative advertising problem by taking reference price effect into account for supply chain coordination.

In the light of cooperative game theory, a supply network can also be modeled as a coalition of partners pooling their resources and sharing the same utility function/profit (Hennet and Mahjoub, 2010). Leng and Parlar (2009) analyzed the problem of allocating cost savings from sharing demand information in a three-level supply chain with a manufacturer, a distributor, and a retailer. Hennet and Mahjoub (2010) investigated the possibility of combining the requirement of coalition stability with a fair allocation of profits to participants. Zhang and Frazier (2011) studied dynamic alliance formation among competing firms with a multi-period model. In each period, there is a two-stage game of co-opetition. In Stage 1, two competing firms decide on forming a partnership by negotiating a contractual agreement; and in Stage 2, all firms in the market engage in price competition. Renna and

Argoneto (2011) proposed a coordination mechanism for a network of independent plants such that the approach is based on Owen's theorem. Using simulation, they demonstrated that plants gain considerable benefits through participating in a network supported by the proposed cooperative mechanism.

Among the research studies utilizing the cooperative game theory, Saad et al. (2009b) proposed a taxonomy for classifying coalitional games based on game properties including canonical/cohesive games, coalition formation games, and coalitional graph games. Cohesive games are the most popular category that have widely been understood, formalized, and have clear solution concepts. The main characteristic of cohesive games pertains to the mathematical property of superadditivity, implying that the formation of large coalitions is never detrimental to any of the involved players. Hence, the grand coalition of all players is an optimal structure and is of major importance.

Unlike the cohesive games class, coalition formation games encompass coalitional games such that network structure and cost for cooperation play a major role. There are three main characteristics making a game a coalition formation game (Saad et al., 2009b): a) forming a coalition brings gains to its members, but the gains are limited by a cost for forming the coalition; hence, the grand coalition is seldom the optimal structure, b) the objective is to study the network coalitional structure, i.e., answering questions like "which coalitions will form?", "what is the optimal coalition size?", and "how can we assess the structure's characteristics?", and c) the coalitional game is subject to environmental changes such as a variation in the number of players, a change in the strength of each player, or other factors that can affect the network's topology. Consequently, it can be inferred that the important

Table 3.1: Summary of recent studies utilizing cooperative games in supply chains

Authors	Game type	Problem	Game solution
Charles and Hansen (2008)	Cohesive game	Global cost minimization in an enterprise network	Core
Hua and Li (2008)	Nash bargaining	Profit sharing between a manufacturer and a retailer	Nash solution
Leng and Parlar (2009)	Cohesive game	Allocating cost savings from sharing demand information	Core
Hennet and Mahjoub (2010)	Cohesive game	Possibility of combining the coalition stability with a fair allocation of profits	Core, Shapley value
Drechsel and Kimms (2010)	Cohesive game	Computing core allocations for cooperative procurement	Core
Zhang and Frazier (2011)	Nash bargaining	Dynamic alliance formation between two competing firms	Nash solution
Renna and Argoneto (2011)	Linear assignment	Capacity sharing in a network of independent factories	Core
Lozano et al. (2013)	Cohesive game	Allocating benefits of horizontal cooperation	Shapley value, minmax core, least core

characteristic classifying a game as a coalition formation game is the presence of a cost for forming coalitions. In cohesive games, as well as in most of the literature, there is an implicit assumption that forming a coalition is always beneficial (i.e. through superadditivity).

Here, we summarize some of the recent works in the literature in terms of the type of the proposed game, the underlying problem, and the game solution (Table 3.1). Reviewing the literature reveals that since the number of possible coalitions grows exponentially with the number of partners, most of the studies have considered coalitions with two or three suppliers or as a control parameter such that it is pre-defined within computational studies (see Renna (2010), Kutanoglu and Wu (2007)). The formation of the grand coalition is another limiting assumption for real-world supply chains. As a result, such approaches cannot be implemented for SNs with a large and variant number of players. Furthermore, in practice, based on the capability of suppliers and their commitments, it is desired to have long-term supplier agreement (LTSA) contracts among suppliers. Therefore, in this study, we have changed the viewpoint of static coalition structures to dynamic coalition formation enabling each supplier to explore possible coalition structures autonomously for multi-period demands. In the next section, we illustrate how the proposed cost structure influences the utility of each possible coalition and restricts the coalition size, and search space for finding optimal coalitions.

3.3 Analytical Modeling

The SN acts in a continuous manner; hence, the system receives buyers' demands through the time and suppliers who wish to sell their products are invited to register their related products/services. This means the system always has an estimation of supply and demand for the future. It is also assumed that each product consists of a number of operations and each supplier can perform all operations of the products.

Here, we skip the process of matching buyers and suppliers and refer readers to Mohebbi and Li (2012). Hence, we assume that demand for each supplier k during time period τ is given as $D_k = \{d^1, d^2, ..., d^\tau\}$. We dichotomize k suppliers so that the first class includes k_f suppliers who have backlog orders and highly utilized capacity and the second class includes

k_s suppliers who are not facing with the backlog order but are having unutilized capacity (i.e., $k_f + k_s = k$). The unutilized capacity for each process associated with each supplier is then recorded in a database called Spared Sharing Capacity. This includes the name of the process, the supplier name, and the corresponding technical capability of the supplier. In order to reduce the backlog orders, we ask suppliers belonging to the first class to propose process(es) they desire to outsource. These are normally the bottleneck processes causing the backlog orders. Afterwards, the issue is to find the feasible structure/coalition of suppliers, belonging to the second class, to satisfy the backlog orders of each over-loaded supplier. The rest of the notations are as follows:

- I: Set of suppliers in the first class
- J: Set of suppliers in the second class
- τ: Number of periods
- V_i: Supplier i belonging to the first class
- W_j: Supplier j belonging to the second class
- $U_{j\tau}$: Unutilized capacity of the j^{th} supplier at period τ
- $B_{i\tau}$: Backlog order of the i^{th} supplier at period τ
- C_{ij}: Unit transportation cost between the location of the i^{th} supplier and supplier j
- ψ_{ij}: Discrepancy of lead times for the i^{th} overloaded supplier and the j^{th} supplier with unutilized capacity

- $I_{j\tau} = \begin{cases} \psi_{ij} & \text{if } \psi_{ij} \geq 0 \\ 0 & O.W. \end{cases}$

- α: Fixed penalty for the late delivery of products

- R^i_τ: Profit earned by delivering backlog orders of supplier i at period τ

- Z^i_T: Longterm cost incurred by the formation of coalition T to satisfy backlog orders of supplier i

- $X^i_{j\tau}$: Decision variable giving the quantity of backlog orders assigned to the j^{th} supplier at period τ for supplier i

3.3.1 Coalitional Game Model

A coalitional game can be defined as $< N, v >$ such that

- N: the set of players,

- v: the characteristic function assigning to each coalition T the profit earned by the members of T as a result of their joint efforts.

A group of players $T \subseteq N \backslash \{\emptyset\}$ is called a coalition and $v(T)$ is called the value of this coalition. Let |N| be the cardinality of a finite set N. A payoff vector or allocation (ϕ_1, ..., ϕ_n) of a coalitional game $< N, v >$ is an $|N|$-dimensional vector describing the payoffs of the players, such that each player $j \in N$ receives ϕ_j. The existing literature has not deeply addressed the impact of cost structures on determining possible coalitions in SNs.

While some studies have discussed about collaboration costs for the coalition reformation in updated circumstances (see Seok and Nof (2014)), we utilize the cost structure to reduce computational burden to explore all possible coalitions in the SN. Hence, in order to define the characteristic function, we first define the cost structure for the formation of a coalition.

Cost of a coalition

Denote $N = \{1, ..., k_s\}$ as the set of all members in the second class, and $T \subseteq N$ as a coalition consisting of $|T|$ members ($|\cdot|$ represents the cardinality of a set). For a cooperating coalition T, we first define the cost of a coalition from the perspective of a supplier in the first class. This cost function is aggregated through different time periods.

To form a coalition, members need to exchange their semi- or final products. Furthermore, in order to maintain customer satisfaction, lead times need to be consistent while suppliers outsource some of the processes to avoid bottleneck and backlog orders. Hence, we define a bi-objective problem to estimate operational costs and determine material flows such that a coalition tends to have suppliers with the least lead time differences and transportation costs. For the sake of mathematical simplicity, we eliminate the index of process types and consider one product in the SN. The objective functions and constraints are defined as follows.

$Min\ Z_T^i = [\ \sum_{\tau,\ j \in T \subseteq N} X_{j\tau}^i.C_{ij}\ ,\ \sum_{\tau,\ j \in T \subseteq N} \alpha.I_{j\tau}.X_{j\tau}^i\ ],$

s.t.

$\sum_{j \in T \subseteq N} X_{j\tau}^i \leq B_{i\tau} \quad \forall \tau$

$X_{j\tau}^i \leq U_{j\tau} \qquad \forall j \in T \subseteq N,\ \tau$

$X_{j\tau}^i \geq 0 \qquad \forall j \in T \subseteq N,\ \tau$

The constraints are considered to satisfy backlog orders and capacity limits at each period, respectively. Note that the model introduced above is of a general form and some additional constraints may be added when dealing with some particular cases of practical relevance. In addition, the model can be elaborated by considering the type of vehicles and routs for transporting products. It is obvious that there is no need to solve the above model when the coalition size is equal to 1.

Characteristic function

Based on the defined cost function for each coalition $T \subseteq N$, the characteristic/utility function, $v(T)$, can be defined. However, without considering this cost, the grand coalition would be the optimal solution. It is worth mentioning that when the coalition size increases, the cost of making a coalition increases accordingly. In the same vein, the main purpose of the coalition formation is to satisfy backlog orders. Hence, we desire to have equal or near equal amount of unutilized capacities and backlog orders in a coalition. Considering the aforementioned concepts, we propose the following characteristic function for the described coalitional game:

$$v^i(T) = \sum_{\tau} R^i_{\tau} - Z^i_T \cdot \left(\frac{|T|}{|N|} \right)^{P^i_T}, \tag{3.1}$$

where, $P^i_T = \frac{\sum_{\tau} \sum_{j \in T} U_{j\tau}}{\sum_{\tau} B_{i\tau}}$.

In equation 3.1, R^i_{τ} is the profit earned by delivering backlog orders at the right time during different time periods τ, Z^i_T is the long-term cost incurred by the formation of coalition

T. $\left(\frac{|T|}{|N|}\right)^{P_T^i}$ is the supplier's concession degree, and P_T^i is the ratio of unutilized capacities, $U_{j\tau}$, and backlog orders, $B_{i\tau}$, in coalition T. Our concession strategy is in accordance with Faratin et al. (1998) and Cao et al. (2015) models indicating that suppliers concede more when they reach to the final stage, i.e. the formation of a grand coalition. This coefficient modifies the cost such that when P_T^i is greater than 1 (the amount of unutilized capacities exceed backlog orders), it gets larger value for the coalition with greater size. As a result, it increases the cost and avoids including more members in the coalition. When P_T^i is lower than 1 (backlog orders has not yet been satisfied by the members of a coalition), it gets larger value for small coalitions with respect to the case that the coalition size increases and satisfy the whole backlog order. Therefore, the model encourages adding members to a coalition to satisfy all backlog order instead of some portion of it. In other words, suppliers make a small concession at the beginning and a bigger one will be made when all backlog orders are satisfied.

3.3.2 Game Properties

To model cooperation in SNs, some research studies proved/assumed that the grand coalition of all members can form (see Chen and Larbani (2005), Drechsel and Kimms (2010), Yuh-Wen et al. (2010)), and then investigated its stability. In the proposed coalitional game, however, the grand coalition will seldom form and, instead, disjoint coalitions will form in the network.

- **Definition 1**: A payoff vector $\phi^v = (\phi_1^v, ..., \phi_{|N|}^v)$ for dividing the value v of a coalition is said to be group rational if $\sum_{j \in N} \phi_j^v = v(N)$. A payoff vector ϕ^v is said to be individually rational if the player can obtain the benefit no less than acting alone, i.e. $\phi_j^v \geq v(j)$, $\forall j$. An imputation is a payoff vector satisfying the above two conditions.

- **Definition 2** (Saad et al. (2009a)): An imputation ϕ^v is said to be unstable through a coalition T if $v(T) > \sum_{j \in T} \phi_j^v$, i.e., the players have incentive to form coalition T and reject the proposed ϕ^v. The set $\mathcal{C}$ of stable imputations is called the core. i.e.,

$$\mathcal{C} = \{\phi^v : \sum_{j \in N} \phi_j^v = v(N) and \sum_{j \in T} \phi_j^v \geq v(T) \ \ \forall T \subseteq N\}. \tag{3.2}$$

  A non-empty core means that the players have an incentive to form the grand coalition.

- **Remark**: *The core of the proposed coalitional game $< N, v >$ is empty.*

  In the proposed model, the costs of cooperation for coalition T increase in cases that the amount of unutilized capacities exceed backlog orders and the number of members in the coalition increases. In particular, for a grand coalition, several coalitions $T \subseteq N$ have an incentive to deviate from this grand coalition and form independent disjoint coalitions. Consequently, duo to the cost, an imputation that lies in the core cannot be found, and the core of the coalitional game $< N, v >$ is generally empty.

- **Definition 3**: A coalitional game $< N, v >$ with transferable utility is said to be supper-additive if for any two disjoint coalition $T_1, T_2 \subseteq N$, $v(T_1 \cup T_2) \geq v(T_1) + v(T_2)$.

- **Proposition**: *The proposed coalitional game with characteristic function $v(T)$ is not super-additive.*

  Proof: Consider two disjoint coalitions $T_1 \subset N$ and $T_2 \subset N$ with function $v(T_1)$ and $v(T_2)$ where the size of the coalition T_2 is equal to one. Assume that the member in coalition T_2 is geographically far from the members of coalition T_1, and also because of tax and import/export regulations, the dissimilarity cost between this supplier and the i^{th} supplier in the first class, that members of coalition T_1 are satisfying his/her backlog orders, is high enough. In this case, $v(T_1 \cup T_2) < v(T_1) + v(T_2)$. Hence, the game is not super-additive.

3.3.3 Stabilizing Coalitional Structure

In order to have stable coalitional structures such that none of the members desire to leave the coalition, we need to distribute the profit earned by cooperation fairly. The common approach is to design a distribution mechanism based on each member's power/contribution in the corresponding coalition. We first review two popular fairness criteria in the literature, Proportional Fairness and Shapley value, and then present a new criterion named *Shared Capacity Index* for the underlying problem.

Proportional Fairness

This criterion, developed by Kelly (1997), divides the extra benefit in weights according to the members' non-cooperative utilities. Thus, the utility of member j is

$$\phi_j^v = w_j \cdot \left(v(T) - \sum_{\acute{j} \in T} v(\{\acute{j}\}) \right) + v(\{j\}), \quad \forall j \tag{3.3}$$

where $\sum_{j \in T} w_j = 1$ such that $\frac{w_j}{w_{\acute{j}}} = \frac{v(\{j\})}{v(\{\acute{j}\})}$. Therefore, qualified members (in terms of non-cooperative utility) deserve more benefit.

Shapley Value

Another fairness criteria, developed by Shapley (1953), takes into account the random-ordered joining of members in the coalition. Hence, it is interpreted as the members' expected marginal contribution when they join the coalition. Shapley (1953) provided four axioms, including efficiency, symmetry, dummy, and additive, and showed that there exists a unique mapping, Shapley value, that satisfies these axioms given by

$$\phi_j^v = \sum_{T \subseteq N : j \in T} \frac{(|T|-1)!(|N|-|T|)!}{|N|!} [v(T) - v(T \setminus \{j\})], \quad \forall j \tag{3.4}$$

Shared Capacity Index

As discussed earlier, Proportional Fairness assigns more benefit to suppliers with higher non-cooperative utilities while the suppliers sharing more capacity during coalition formation process deserve more benefit. Shapley value is also under the assumption of randomly-ordered joining and it might not be individually rational for a non-superadditive game (Saad et al., 2009a). Hence, we develop a fairness criterion, Shared Capacity Index, for the underlying problem in which the extra benefit is divided according to the suppliers' capacity share as follows:

- **Step 1:** Constitute a contract matrix for each period as $\Omega_\tau = [X^i_{j\tau}]_{k_f \times k_s}$. Then, we calculate the capacity share of supplier j from the total backlog of the i^{th} supplier at period τ as $\rho^i_{j\tau} = \frac{X^i_{j\tau}}{B_{i\tau}}$.

- **Step 2:** Extract the minimum, average, and maximum values of $\rho^i_{j\tau}$ for each supplier j through time period τ and constitute the fuzzy triangular number of supplier j's capacity share as $\widetilde{\rho^i_j} = \left(a^i_j, b^i_j, c^i_j\right)$. a^i_j is the minimum value of capacity share and c^i_j is the maximum one.

- **Step 3:** Calculate the rank of $\widetilde{\rho^i_j}$ using Lee and Li (1998) method and consider this value as the contribution of supplier j in coalition T. The ranking of each fuzzy number can be computed as follows:

$$w^i_j = \frac{{a^i_j}^2 + {c^i_j}^2 - a^i_j.b^i_j + c^i_j.b^i_j}{3(-a^i_j + c^i_j)}, \quad \forall j \in T \tag{3.5}$$

- **Step 4:** Compute the payoff vector ϕ^i as below:

$$\phi^i = (w^i_1.v^i(T), ..., w^i_j.v^i(T)), \tag{3.6}$$

  where, $\sum w^i_{j\in T} = 1$. Therefore, suppliers receive benefit based on their capacity share in the coalition.

3.3.4 Coalition Formation Algorithm

The steps of the proposed coalition formation mechanism for suppliers are represented in Algorithm 1. We define three main procedures including *Distributed search*, *Conflict resolution*, and *Fair distribution of profit*. While it is proven that finding optimal partition by exhaustive search is mathematically and computationally intractable for large number of players (Saad et al., 2009a), this algorithm enables suppliers to self-organize into independent disjoint coalitions. The distributed search procedure enables each overloaded suppliers to explore and find potential partners belonging to the second class autonomously. As a result, each supplier from the first class explores available suppliers in the second class and computes the characteristic function for each $T \subseteq N$. Afterwards, based on the utility obtained from $v^i(T)$, each supplier selects the best partners and the first network partition can be obtained.

The conflict resolution procedure first checks if all members are partitioned such that all coalitions are pairwise disjoint set. If so, we have reached the feasible structure for the SN and proceed to the fair distribution procedure. Otherwise, for each supplier j belonging to two or more coalitions, compute his/her utility in those coalitions, $w_j^i.v^i(T)$, separately. Supplier j belongs to the coalition providing higher profit. Hence, supplier j will be removed from the set N, and the i^{th} supplier in the first class that supplier j is eliminated from his/her coalition needs to re-compute the utility/characteristic functions and proceed to the distributed search procedure.

Initialization: l=0, $|T| = 1$, $v_l^i(T) = 0$

Procedure: Distributed search

---

while *Characteristic function,* $v^i(T)$*, is improving* **do**
  for *all coalitions with size* $|T|$ **do**
    $l \leftarrow l + 1$;
    Select a coalition ($T \subseteq N$);
    Compute the cost structure;
    Compute characteristic function $v^i(T)$;
    if $v_{l+1}^i(T) \geq v_l^i(T)$ **then**
      Update partner list
    end
  end
  $|T| \leftarrow |T| + 1$;
end

Procedure: Conflict resolution

---

if *Coalitions are not pairwise disjoint* **then**
  Send offers to the second class suppliers;
  Compute payoff vectors, ϕ^i, for coalitions with joint suppliers;
  Select the coalition providing higher profit;
  Update set N for supplier i ;
  Repeat the "Distributed Search" procedure;
else
  Proceed to "Fair Distribution of Profit" procedure;
end

Procedure: Fair distribution of profit

Send offers to the second class suppliers;
Compute contribution of each supplier (w_j^i);
Compute payoff vectors for all coalitions (ϕ^i).

Algorithm 1: The proposed algorithm for suppliers' collaboration

Table 3.2: Parameters in the simulation model

Parameter	**Value**
Maximum demand period (τ)	12
Demand distribution for suppliers	Normal (400, 150)
Suppliers' total capacity at any time τ	Uniform (200, 500)
Unit transportation cost (C_{ij})	\$5
Positive lead time discrepancy ($I_{j\tau}$)	Uniform [0, 10]
α	\$10

The fair distribution procedure first computes the contribution of each supplier within the corresponding coalition, w_j^i, and then calculates the payoff vector, ϕ^i, based on the rules given in Section 3.3.3.

3.4 Validation and Performance Evaluation

To examine the performance of the proposed model, a prototype system is implemented and simulated. The starting assumption is that suppliers register in the network by informing their capacities and other attributes such as location, products scope and their specifications, and so on. Thereby, their information is set before simulation. We assume that suppliers execute "make to order" policy. The parameters used in the simulation model are given in Table 3.2. It is assumed that suppliers' demand follows normal distribution and their capacity is constant at time period τ. Since demand for each supplier at time period τ is given, suppliers can be dichotomized based on their workload and parameters $B_{i\tau}$ and $U_{j\tau}$, to be fed to the optimization model, can be computed. It is also assumed that each item's value is \$100 for suppliers in the second class.

We then define four performance measures to investigate the capability of the proposed mechanism including the average coalition size, the number of iterations, the average concession degree of suppliers, belonging to the first class, and the average profit for each member. Depending on the chosen fairness criteria for the payoff division, the resulting network topology changes as the conflict resolution process becomes different.

To illustrate the fairness impact on the network structure, the final structure and individual payoffs for one instance using different fairness criteria including *Proportional Fairness*, *Shapley value*, and *Shared Capacity Index* are given in Table 3.3. In this instance, five suppliers are considered in the second class. It can be observed that for all fairness types, supplier 1 and supplier 5 form a coalition. For the Proportional Fairness, supplier 2 merges with this coalition as it assigns a higher weight to suppliers with the best non-cooperative utility. For the Shapley value, the newly formed coalition $\{2, 3\}$ improves the payoff for supplier 2 with respect to the other fairness criteria. In the same vein, Shared Capacity Index provides high individual payoff for all suppliers except for supplier 2.

For each combination of the experimental levels, ten random instances were generated. We initially ran the model for 10 replications and used the half width of the confidence interval, h, for the average individual profit as a baseline to determine the number of replications. The required number of replications is approximately equal to $n_0 \cdot \frac{h_0^2}{h^2}$ where n_0 is the number of initial replications, h_0 and h are the initial and desired half widths respectively. Reducing the half width from $h_0 = \$950.38$ to $h = \$200$, a total of 225 replications have been conducted and solved using the proposed algorithm with different fairness criteria.

Table 3.3: Network structure and individual payoffs for different fairness criteria

Criteria	Proportional Fairness	Shapley value	Shared Capacity Index
Network structure	{{1,5,2},{3},{4}}	{{1,5},{2,3},{4}}	{{1,5},{3,4},{2}}
Member 1	2649.4	2730.2	2715.4
Member 2	2406.6	2505.4	2090.8
Member 3	1830.4	1658.8	1964.6
Member 4	2949.8	2889.6	3025.4
Member 5	1773.2	1825.4	1813.2

Figure 3.1 illustrates the resulting average coalition size for the different number of suppliers in the network and different fairness criteria. The number of clustered coalitions is equivalent to the number of suppliers in the first class. For all fairness criteria, the average number of members per coalition increases with the availability of more suppliers in the network. This is mainly due to the existence of more partners to form coalitions. However, after a specific number of suppliers, the average coalition size does not change. This demonstrates the model capability to control the coalition size based on the amount of backlog order and incurred cost for cooperation, simultaneously. In addition, it can be observed that Shapley value and Shared Capacity Index yield the largest and smallest average coalition size, respectively.

Figure 3.2 shows the average number of iterations for the proposed algorithm against different number of suppliers in the network for different fairness criteria. It can be found that the number of iterations decreases with the availability of more suppliers to form coalitions for all criteria. In addition, the Shared Capacity Index outperforms other criteria for the lower number of suppliers in the second class.

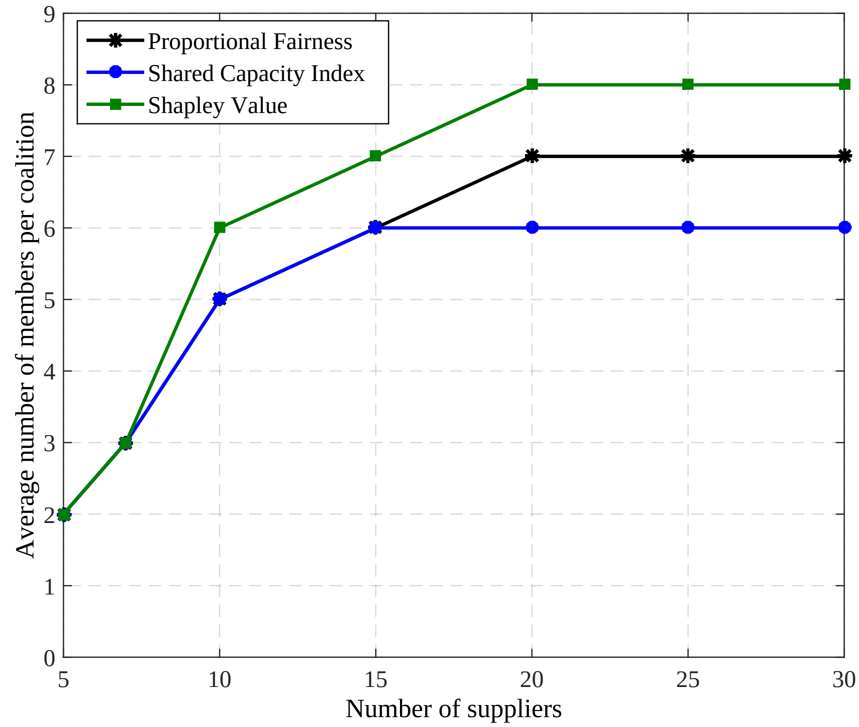


Figure 3.1: Average coalition size for different number of suppliers

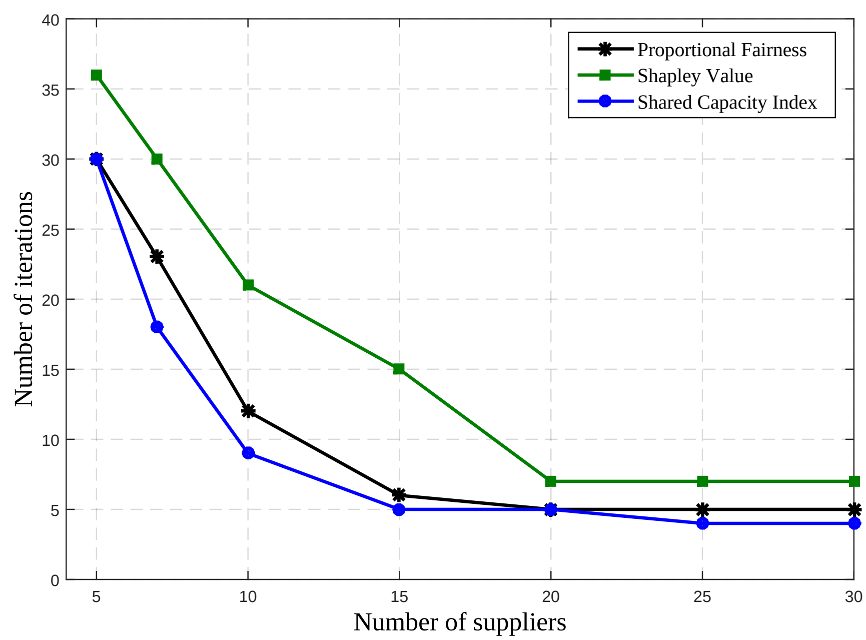


Figure 3.2: Average number of iterations

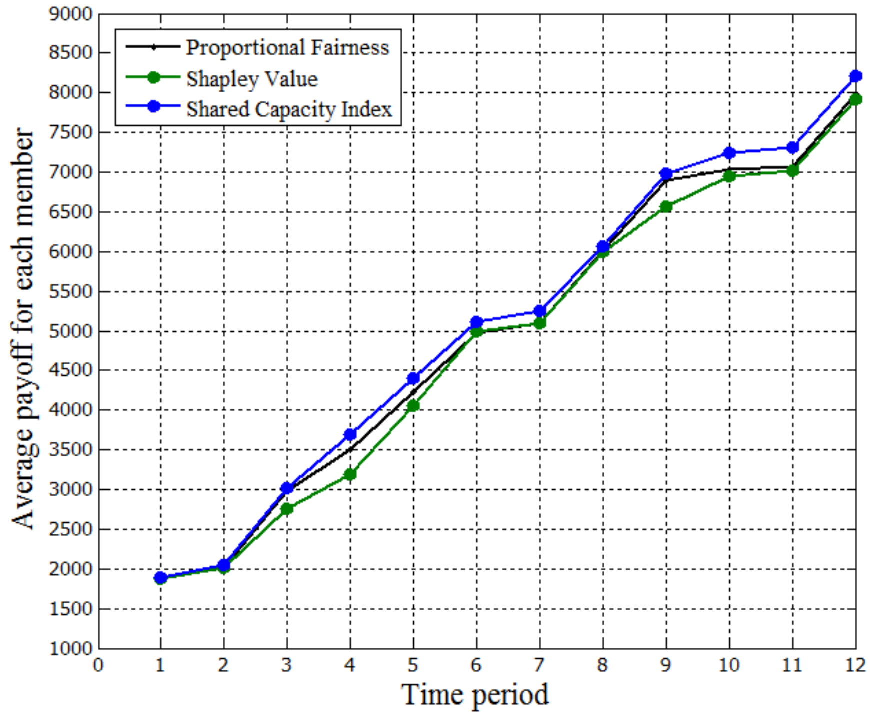


Figure 3.3: Average individual payoff for different time periods

In Figure 3.3, the average individual payoff is depicted for different time periods and fairness criteria. The results indicate that long-term partnership or LTSA improves the average supplier's profit. This is mainly due to including long-term costs, incurred by the formation of coalitions, in the proposed characteristic function for multi-period demands.

Figure 3.4 presents the concession degree of suppliers in the first class for different values of P_T^i, and the ratio of coalition size, $|T|$, and total number of suppliers, $|N|$. It can be observed that suppliers make a bigger concession with the increase of P_T^i, the ratio of unutilized capacity to backlog orders within a coalition, and lower coalition size. In other words, this figure illustrates the performance of the proposed characteristic function to meet the main goals of the coalition formation process.

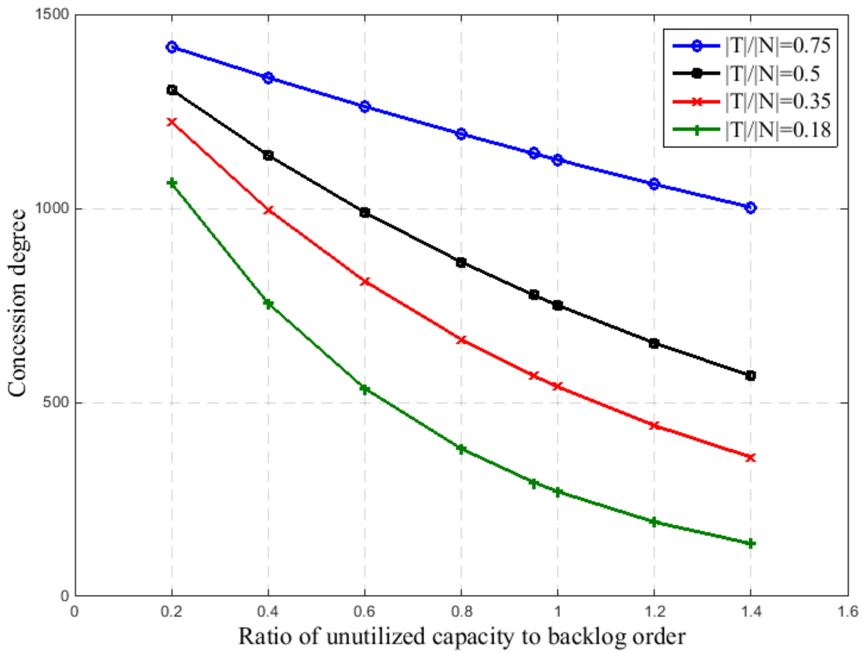


Figure 3.4: Concession degree of suppliers in the first class

To examine the impact of unit transportation cost, C_{ij}, on the average individual profit, Figure 3.5 illustrates the profit achieved for different unit transportation cost and fairness criteria when $k = 30$. This figure shows that as the cost increases, the gains decrease and ultimately converge towards the non-cooperative gains at high cost.

In Figure 3.6, we present the average individual supplier's profit achieved during the cooperation mechanism for different fairness criteria against the number of suppliers in the network. We also compare the performance of the proposed algorithm to that of the non-cooperative case. For the cooperative mechanism, the average member's profit increases with the number of suppliers since the possibility of finding cooperating partners and satisfying backlog orders increases. It should be noted that the average profit reaches to a constant value after a specific number of suppliers for all fairness criteria. This is an expected result

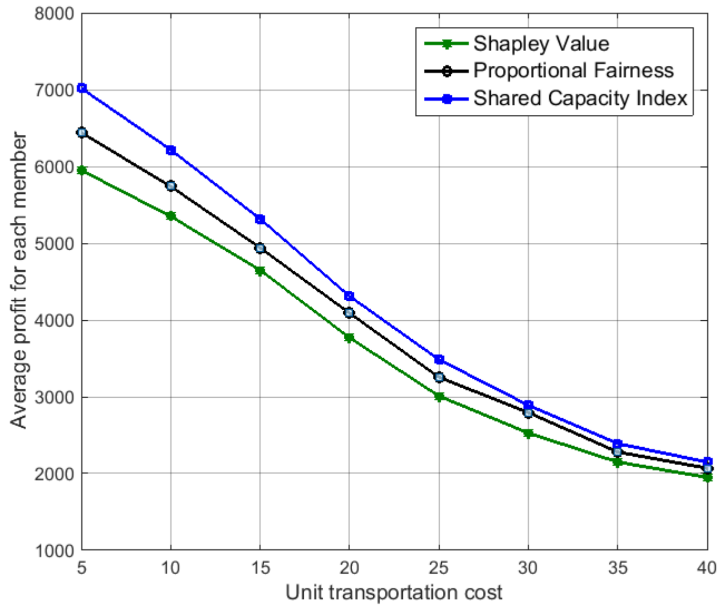


Figure 3.5: Average individual profit for different unit transportation costs for a network having 30 suppliers

as increasing the number of suppliers in the second class does not influence on the network structure after a cutoff point. In contrast, the non-cooperative approach presents an almost constant performance level with different number of suppliers.

The cooperation mechanism provides a significant advantage over the non-cooperative case in terms of the average individual utility/profit. To investigate the statistical significance, the one-way ANOVA is applied. The obtained p-value, i.e. 0.0001, supports the hypothesis that the proposed long-term cooperation among suppliers outperforms the non-cooperative case. Since the null hypothesis in ANOVA is rejected at the significance level of 0.05, it is desired to have a pairwise comparison of factor level means in order to investigate the factor effects. The obtained confidence interval, i.e. $(2.72 \times 10^3, 5.13 \times 10^3)$, for the difference between the factor level means $(\mu_{cooperation} - \mu_{non-cooperation})$ reveals that

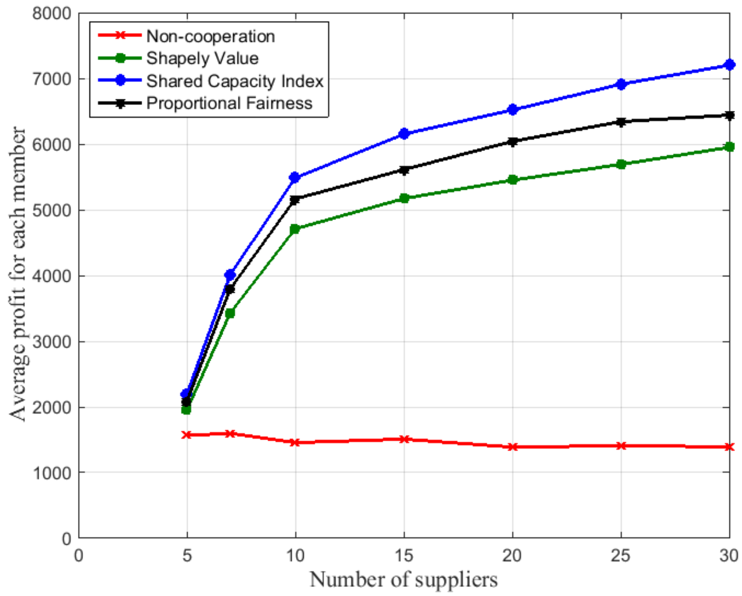


Figure 3.6: Average individual profit achieved by the proposed cooperation mechanism

the proposed approach leads to both reliable and higher performance than that of the non-cooperative approach. In addition, the t-test results among different fairness criteria when the number of suppliers in the network is greater than 10 are summarized in Table 3.4. It can be observed that the choice of fairness criteria significantly influences on the average individual profit for the large number of suppliers.

Table 3.4: T-test results among fairness criteria for $k > 10$

Criteria	Proportional Fairness	Shared Capacity Index
Shapley Value	*	**
Proportional Fairness	-	*

*: statistically significant at $\alpha = 0.05$; **: statistically significant at $\alpha = 0.01$

3.5 Conclusions

Cooperation among suppliers in e-SNs contributes to maximizing the network capacity utilization and taking the advantages of collaborative synergy to improve competitive situations. In this paper, we developed a framework for suppliers' collaboration in e-SNs while the distributed and dynamic nature of the decision making process has been taken into account. Dynamic coalitional game theory is utilized to analyze the formation of coalitional structures through suppliers' interaction where firms both compete and cooperate. The first and foremost contribution of this study is the facilitation of creating dynamic coalitional structures in e-SNs. While most of the existing works in the literature consider static coalitional structures, we proposed a model enabling each supplier to find optimal coalitional structures autonomously for multi-period demands. Defining the cost structure, including operational costs, for the coalition formation process is our second contribution. Although cooperation provides gain/profit to its members, the gains are limited by the cost for forming coalitions. The proposed cost structure not only restricts the coalition size and determines material flows in the SN but also reduces computational burden to explore all possible coalitions. The third contribution is associated with developing the fairness criterion, *Shared Capacity Index*, and the cooperation algorithm to resolve possible conflicts among suppliers. The proposed algorithm enables suppliers to self-organize into independent disjoint coalitions and distribute obtained profit in a fair manner. The simulation results also demonstrated that the proposed approach is superior to other solution methods, including Shapely value and Proportional Fairness.

Chapter 4

Designing an Incentive Scheme within a Cooperative Game for Hospitals Coordination

Abstract

This study investigates the collaboration framework of hospitals, for consolidated healthcare service delivery. Although existing literature advocates the notion of strategic partnership in healthcare systems, there is a dearth of studies quantitatively analyzing the co-existence of cooperation and conflict objectives of members. We concentrate on the coordination of hospitals such that there is a central referral system to facilitate patients transfer. Three main players are considered including physicians, hospitals managers, and the referral system such that the interaction within these players will shape the coordinating scheme to improve

the overall system performance. To come up with the incentive scheme for physicians and aligning hospitals activities, we develop a multi-objective mathematical model to obtain the optimal transfer pattern. Using such optimal solutions as a baseline, a cooperative game between physicians and the central referral system are defined to coordinate decisions toward system optimality. Indeed, this approach allows for intervening physicians' perceived cost function and encourages them to accept requested transfers. The feasibility of the proposed approach is examined via a case study with real world datasets.

4.1 Introduction

Partnership among healthcare providers and the dynamic nature of the involved interactions have altered the way healthcare services are delivered and used. Basically, health or social care networks are characterized by dynamic, flexible, and evolving methods of working that rely on horizontal, and self-governing networks to deliver a range of services (Rummery and Coleman, 2003).

From 2007 to 2012, 432 hospital merger and acquisition deals were announced (Cutler and Morton, 2013); as a result, consolidation projects have attracted scholars' attention in healthcare industry. Consolidation has the potential to fulfill patients' needs in the right time and an integrated manner, as investment in treatment technologies and facilities is often a critical decision for healthcare providers. Here, the term healthcare providers refers to hospitals setting prices for the delivered services.

From patients' perspective, consolidation provides the opportunity to coordinate the care process across different layers of providers. Even under particular conditions, patients require a certain degree of reliability from the providers towards the fulfillment of their needs. Hence, a further coordination among providers is also highly important in order to maximize the network capacity utilization and enhance patients' satisfaction. While it has been proved that integrated health systems have the capacity to address the quality deficiencies resulting from the lack of coordination (Cutler and Morton, 2013), the scope of the coordination to align the contributions of the independent providers in healthcare systems are not addressed deeply. In other words, each provider in such systems may still act as an individual entity with its own culture and operations; however, the efficiency of the system depend on the extent to which global performances are obtained.

The literature also highlights many challenges to partnership in practice. Internationally, healthcare costs are increasing, due to, amongst other things, advances in medical and technological treatments, an aging population, changing public expectations and evolving patterns of diseases (Acerete et al., 2011). There are several empirical studies discussing about cost savings resulted from consolidation. The most recent work, presented by Harrison (2011), sheds light on the fact that economies of scale are present for merging hospitals and they realize these cost savings immediately following a merger; however, cost savings decrease over time and the proportion of hospitals experiencing positive cost savings declines.

In addition to hospitals' managers, physicians play a key role in the decision making process and their contribution needs to be well considered and modeled. While managers and physicians may have different objectives, physicians' decision to admit patients and requested transfers from other hospitals influence considerably on the global performance. As a result, in order to ensure the long-term functioning of collaboration structures among healthcare providers and physicians, an appropriate incentive scheme for physicians should also be generated in the collaboration process.

The remainder of the work is organized as follows: In Section 4.2, the literature on the partnership in healthcare industry is reviewed. In Section 4.3, a detailed mechanism for the proposed model is presented. Section 4.4 describes the implementation details for the case study and gives results on the performance of the model. Finally, the conclusions are given in Section 4.5.

4.2 Literature Review

There are growing numbers of research efforts discussing and examining the notions of partnership and consolidation in healthcare industry. Although the existing literature is somehow patchy, partnership in healthcare can be classified into three categories. The first category mainly explores the potentials of partnership between private and public sectors. Better risk management, clearer government policies, more appropriate financial analysis, revealed critical success factors, and improved maturation of contracts are discussed as the advantages of various aspects of public-private partnerships(Tang et al., 2010).Aveling and Martin (2013) synthesized the literature and proposed an analytical distinction between instrumental and transformative partnerships for delivering healthcare services.

The second stream in the literature discusses about academic-service partnerships whereby a new and interprofessional roles need to be defined to facilitate the collaborative partnership. Warner and Burton Warner and Burton (2009) investigated the policy and politics of such emerging relationship and emphasized on the necessity of new thinkings for evolving healthcare systems.

The third category deals with IT-enabled healthcare systems and the involved interactions and collaborations to deliver health services. Many studies (e.g. see Wu et al. (2009)) have empirically investigated the benefits of applying information technology for healthcare partnership. Horizontal collaboration, e.g. hospitals with other hospitals, and vertical collaboration, e.g. hospitals with other healthcare providers; or different divisions of a healthcare organization, are two main consequences that can be achieved in practice as the result of applying IT-enabled healthcare systems and sharing real-time information.

Scholars have taken various perspectives on modeling and investigating partnership among healthcare providers which mainly rely on non-cooperative game approach among main players in healthcare systems. It is well accepted that hospitals are a product of multiple groups with converging or conflicting interests interacting within the organization (Galizzi and Miraldo, 2011). Hence, Custer et al. (1990) analyzed the effects of a prospective payment system on hospital production, focusing on the relationship between the hospital and its medical staff. Other studies that account for different incentives within the hospital model hospitals' internal relations by means of take-it-or-leave offers made by one of the parties, which amounts to assuming that only the proposer has decision power. Boadway et al. (2004) proposed a model with managers and doctors as decision makers and develop a two-stage agency problem in which contracts are designed to elicit information. Their approach is extended by Galizzi and Miraldo (2011) via introducing strategic negotiations between doctors and managers within the hospital in the spirit of non-cooperative bargaining. They also compared the effects of different interactions within the hospital on the contracts offered by the government. Other studies in the literature have emphasized on the patients involvement in decision-making processes. Moreno et al. (2010) considered a decision theory approach for treatments comparison based on the cost-effectiveness of treatments. Clayman et al. (2012) investigated a shared decision making coding system for the analysis of patient-healthcare provider encounters.

While the literature advocates the involvement of different players in modeling health-related decisions, it appears that coordinating hospitals and physicians, as two main players, in consolidated systems needs to be addressed quantitatively to improve global performance and revenue.

4.3 Analytical Modeling

Here, we study the coordination of hospitals, consolidated for healthcare delivery, such that there is a central referral system to facilitate patients transfer. As it is illustrated in Fig. 4.1, the referral process begins with receiving a call, i.e. request for transfer, from referring hospitals. The central referral system processes the request by collecting some clinical info and filling out a form. Afterwards, the corresponding agent in the referral system needs to identify/assign suitable physician and hospital based on the health status of the patient.

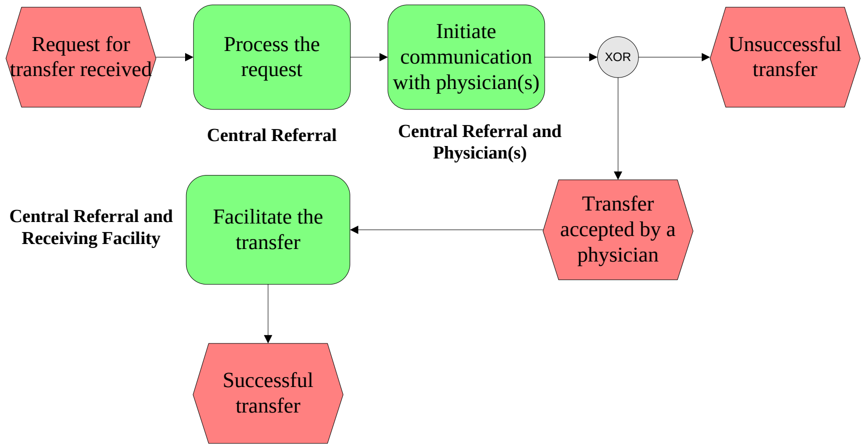


Figure 4.1: Event-driven process chain diagram for the healthcare referral system

This initial decision, to be made by the referral system, can considerably influence on the transfer process and the global performance in terms of quality of care. In practice, different protocols have been designed for each hospital spelling out different decision rules in terms of physicians and specialties.

Based on the existing protocols, the central referral system initiates communication with physician(s) leading to two states: a) a physician accepts the patient, or b) they do not accept the transfer due to some reasons like no need for higher level of care. The cases falling into the second category are considered as unsuccessful transfers, which are not desirable for the high level managers of the consolidated system.

In current practice, the central referral system assigns transfers based on geographical distances and/or referring physician's suggestion. In order to reduce the number of rejected transfers by physicians, the referral system may try to handle such cases thorough administrator involvement. The idea is to contact the receiving hospital's manager to facilitate the transfer process through further communication with physicians, which turns out to be time consuming in many cases. Nonetheless, it has been demonstrated that there is a considerable percentage of lost/unsuccessful transfers influencing on the quality of care, provided by the consolidated system to patients, and the overall market share. Unlike the current studies in the literature, we are not aiming to investigate the problem in a contract design level between hospitals and physicians as physicians are contracted and the consolidated system does not have direct control over the contracts' terms. Instead, we take one step forward to formalize the problem in such a way that facilitates analyzing the contribution of different players toward system optimality.

In this study, we consider three main players including physicians, hospitals' managers, and the referral system which acts on behalf of the leadership team to guarantee the global optimality of the consolidated system. Hospitals' managers aim at maximizing their expected financial budget, whereas physicians are mostly contracted by a third party, and the central referral system considers improving the overall healthcare status of their patients. As a consequence, the interaction within these players will shape the coordinating strategies to improve the overall system performance.

For each hospital, there are several physicians providing treatments to patients suffering from specific illnesses. For each specialty, we dichotomize H hospitals such that the first class includes H_f hospitals providing high technology therapy and the second class includes H_s hospitals with low technology treatment. The literature advocates that the benefit of using high technology therapy in the treatment of a patient increases with the patient's disease severity (see Galizzi and Miraldo (2011)). Hence, high illness-severity patients should be treated with high technology therapy.

To analyze the described system, cooperative game theory in conjunction with optimization techniques seems appropriate as it is characterized by many possibilities for allocating tasks and rewards. Hence, we first adopt the intelligent matching process to identify potential physicians for patients based on health attributes. To come up with the coordinating contract and incentive scheme for physicians and aligning hospitals activities, we define a multi-objective mathematical model, to be fed by historical data, and obtain optimal transfer pattern. Using optimal solutions as a baseline, a cooperative game between physicians and the central referral system will be defined to coordinate decisions toward system optimality. Indeed, this approach allows for intervening physicians' perceived cost function and encourage them to accept requested transfers. To collect pilot data and verify the proposed model, we collaborate with an undisclosed Healthcare system in Tennessee which includes nine hospitals with more than 10,000 healthcare professionals.

This section formalizes the proposed mechanism for facilitating patients transfer when the central planner seeks a system-wide optimum that is more consistent with global health goals.

4.3.1 Matching Patients and Physicians

Receiving a call (request for transfer), the central referral system needs to identify/assign a suitable physician and hospital based on the health status of the patient. In practice, different protocols have been designed for each hospital spelling out different decision rules, which are mainly based on specialties and physicians. Hence, we adopt the intelligent matching algorithm to facilitate the selection of qualified physicians for patients based on some health attributes. This classification of attributes helps effectively specify the requirements and restrictions of transfers in the network.

After reviewing some protocols being used in practice, we propose utilizing two sets of attributes to define the requirements, similarities, and properties: critical attributes and bilateral attributes (Table 4.1). The former include the attributes defining exclusive criteria related to the scope of the hospitals' services so that any decisions should be compatible with the critical attributes. The latter are the attributes assigned to the physicians as a common viewpoint about their level of specialty and quality of the services they provide. The overall process is summarized as follows.

Table 4.1: Critical and bilateral health attributes

Bilateral Attributes	**Critical Attributes**
Hospital location	Specialty scope (Trauma, pediatrics, etc.)
Level of medical care	Established communication with specific physicians

Step 1(Start State): We create the set of specialties, K, such that there are n_k physicians in different hospitals.

Step 2 (Information Collection): We create the array of the service for each patient as follows:

$$S_i = [P_i, k, L_i, \rho_i], \quad \forall i \tag{4.1}$$

S_i represents the requested service for the i^{th} patient which contains of 4 elements: P_i denotes the ID number of the patient; k and L_i denote the required specialty and geographical location of the i^{th} patient (the location of the referring facility) respectively; ρ_i denotes the severity of illness based on the reported symptoms. It gets values larger than 1 if the health status of the patient is critical and gets values lower than 1 otherwise. The more precise definition of this parameter will be given in the next section.

Step 3 (Matching Patients and Physicians): Based on the available information about physicians and patients, we explore all available physicians and calculate the weight of the d^{th} attribute, w_{ij}^d, for patient i and physician j as follows:

- In case of $d = \{specialty\ scope\}$, $w_{ij}^d = 0$ if the requested services cannot be offered by the physician and $w_{ij}^d = 1$ otherwise. Such restrictions are initially determined by the central referral system in protocols.

- In case of $d = \{established\ communication\}$, $w_{ij}^d = 1$ if patient i has been previously visited by the j^{th} physician. Otherwise, we ignore this attributes for the rest of computation.

- We calculate the weighted distance between bilateral attributes of the i^{th} patient and the j^{th} physician using equation 2.3. It is assumed that the membership function for $d = \{location,\ level\ of\ medical\ care\}$ are determined by linguistic terms given in Table 2.2. These values are initially determined by the central referral specialists.

- The potential physicians for each patient can be sorted out using equation 2.5. Ultimately, physicians are ranked for each patient such that the lower Θ_{ij} leads to the better matching of patients and physicians.

4.3.2 Optimal Transfer: System Problem

The central referral system is interested in optimizing the financial and health costs of the system as a whole. These costs, as defined by the summation of perceived costs from the perspective of hospitals' managers and the referral center, determine the system problem to optimize global health outcomes. The parameters and decision variable are presented as follows:

Sets and Parameters

- I: Set of patients
- J: Set of physicians
- F_i: Subset of feasible physicians for patient i
- H: Set of hospitals
- $\mathcal{T}$: Set of time blocks within the planning horizon
- ρ_{is}: Random variable representing the illness severity for patient i in scenario s. It gets values larger than 1 if the health status of the patient is critical and gets values lower than 1 otherwise.
- ψ_{hk}: Average cost of losing a potential patient at hospital h for specialty k during each time block
- p: Average penalty cost due to not using a high technology therapy

- Δp: Increment of the penalty cost (in percent) due to not using a high technology therapy when severity of illness, ρ_{is}, increases

- B_h^τ: Number of beds available at hospital h at time block τ

- m_j: Maximum number of patients to be assigned to physician j at each time block

Decision Variables

- $X_{ijh}^\tau = \begin{cases} 1 & \text{if patient } i \text{ is accepted by physician } j \text{ at hospital } h \text{ during time block } \tau \\ 0 & \text{otherwise} \end{cases}$

Global Objective Function

$Min\ Z = \alpha H(X) + (1-\alpha)R(X),$

where,

$H(X) = \sum_\tau \mathbb{E}_\rho \left[\sum_{k,\ h \in H_s,\ i,\ j \in F_i} \left(p \left(\frac{p+\triangle p}{p} \right)^{\rho_{is}} \cdot X_{ijh}^\tau \right) \right],$

$R(X) = \sum_{\tau,\ h,\ k,\ i,\ j \in F_i} \left(1 - X_{ijh}^\tau\right) \psi_{hk}.$

The first objective function penalizes the assignment of patients with severe illness to the hospitals in the second class. While it is demonstrated that the benefit of using high technology therapy increases with the patient's illness severity (Galizzi and Miraldo, 2011), increasing patients throughput is another goal needing to be achieved in consolidated systems via proper patients referral/transfer. The latter particularly influences on the length of stay, lost transfers, and the number of trips between hospitals. While modeling the cost structure considering the aforementioned elements is complicated, the proposed cost function is designed in such a way that for the lower value of severity, $\rho_i < 1$, the penalty cost is negligible while it increases exponentially as ρ_i gets larger. Mathematically, this parameter can take any large value and gives the flexibility to model the non-linear behavior of the cost increment for different scenarios and specialties. The average penalty cost, p, can be estimated based on the potential lost opportunity cost aggregated through specialties as a result of inappropriate referrals and non-quality care. The second objective function, $R(X)$, minimizes the average costs involved in losing patients for each hospital, as the common objective function for each hospital's manager is to increase its market share.

Operational Constraints

- $\sum_{t=1}^{\tau} \sum_{i,\ j \in F_i} X_{ijh}^{t} \leq B_h^{\tau} \quad \forall h, \tau \in \{1, 2, 3\}$
- $\sum_{i,\ j \in F_i} X_{ijh}^{\tau} + \sum_{t=\tau-3}^{\tau-1} \sum_{i,\ j \in F_i} X_{ijh}^{t} \leq B_h^{\tau} \quad \forall h, \tau \in \{4, 5, ..., |\mathcal{T}|\}$
- $\sum_{h,\ j \in F_i} X_{ijh}^{\tau} = 1 \quad \forall i, \tau$
- $\sum_{i} X_{ijh}^{\tau} \leq m_j \qquad \forall j \in F_i, h, \tau$

The first and second constraints account for bed availability for each hospital at the τ^{th} time block. The third one ensures that each patient should be assigned to only one physician. The last constraint controls the maximum number of patients to be assigned to a physician during each time block, which can be determined based on the physicians' specialty.

4.3.3 Coordinating Decisions Toward System Optimality

Given the differences in the solutions of the system problem and current practice, we utilize cooperative game theory approach and describe a contract that can resolve the misaligned incentives between different physicians and the central referral system. The idea is to intervene the physicians' perceived costs and encourage them to accept requested transfers. The leadership team for the consolidated system pays for this incentive, and in return receives benefits from increased revenue.

To come up with the coordinating contract, we assign the coalitional game $< N, v >$ between the central referral system and individual physicians such that

- N: Set of physicians and the central referral system
- v: The characteristic function v assigns the average number of accepted transfers between physicians and the referral system such that their joint efforts generate revenue.

More precisely, we define $v(S)$, for each $S \subseteq N \setminus \{\emptyset\}$, as the value of

$$v(S) = \frac{|\theta(S)|}{|S_D|} \tag{4.2}$$

where, S_D is the set of patients transfer and $|\theta(S)|$ is the cardinality of the following set

$$\theta(S) = \{l \in S_D | \kappa(\Omega(l)) \subseteq S\} \tag{4.3}$$

and $v(\emptyset) = 0$. $\Omega = [X^{\tau}_{ijh}]_{|N|\times|S_D|}$ is the contract matrix such that $X^{\tau}_{ijh} = 1$ if the requested transfer for patient i is accepted by physician j at time block τ, otherwise $X^{\tau}_{ijh} = 0$. $\kappa()$ represents the support of the corresponding set (each column of the binary matrix Ω).

Note that this game is a proper sub-class of [0, 1]-games. Hence, an equivalent way to calculate the corresponding coalitional game, v, is the sum of unanimity games as follows:

$$v(S) = \sum_{S\subseteq N:S\neq\emptyset} \lambda_S u_S, \tag{4.4}$$

where $\lambda_S = \frac{\bar{\lambda}_S}{|S_D|}$, and $\bar{\lambda}_S$ is the number of occurrences of the coalition S as support in the binary alliance matrix Ω.

We utilize the Shapley value, the most famous solution in the theory of coalitional games, as a possible measure of each physician's contribution to the whole system. This solution can be described in several ways, and we use the following formula:

$$\phi_j(v) = \sum_{S\subseteq N:j\in S} \frac{(|S|-1)!(|N|-|S|)!}{|N|!}[v(S) - v(S\setminus\{j\})], \quad \forall j \tag{4.5}$$

In our model, according to equation 4.4, the computation of the Shapley value for the corresponding game is straightforward. More precisely, it can be written as (Moretti et al., 2007):

$$\phi_j(v) = \frac{1}{|S_D|}\sum_{S\subseteq N:j\in S} \frac{\bar{\lambda}_S}{|S|}, \quad \forall j \tag{4.6}$$

4.3.4 Axiomatic Characteristics of the Shapley Value

Shapley (1953) provided the following axioms and showed that there exists a unique mapping, Shapley value, that satisfies these axioms. Now, we investigate these axioms for the proposed characteristic function:

- Efficiency Axiom: $\sum_{j \in N} \phi_j(v) = v(N)$

  As for the grand coalition, i.e. accepting all transfers by physicians, $v(N) = 1$ (according to equation 4.2). In this case, the Shapley value for each player is equal to $1/|N|$. Therefore, the efficiency axiom holds for the proposed game.

- Symmetry Axiom: if player i and player j are such that $v(S \cup i) = v(S \cup j)$ for every coalition S not containing player i and player j, then $\phi_i(v) = \phi_j(v)$.

  Let $T = S \cup \{i\}$ and $R = N \setminus T$. According to equation 4.4, we can write the game v in terms of unanimity games as below:

  $$v = \lambda_T \cdot u_T + \lambda_R \cdot u_R$$

  By equation 4.6, we have

  $$\phi_i(v) = \frac{1}{|S_D|} \left(\frac{\bar{\lambda}_T}{|T|} \right)$$

Since $\lambda_T = \frac{\bar{\lambda_T}}{|S_D|} = \frac{|\theta(T)|}{|S_D|} = v(T)$, hence $\phi_i(v) = \frac{v(T)}{|T|}$. By defining $U = S \cup \{j\}$ and following the same procedure to obtain $\phi_j(v)$ as well as considering the fact that $v(T) = v(U)$, we can conclude that $\phi_i(v) = \phi_j(v)$.

- Dummy Axiom: if player i is such that $v(S) = v(S \cup i)$ for every coalition S not containing i, then $\phi_i(v) = 0$.

  Let $S = N \setminus \{i\}$ and $T = \{i\}$ such that $v(S) = v(S \cup T) = v(N)$. If $v(N) = 0$, then $\phi_i(v) = 0$ and the property is satisfied. Consider now the case $v(N) > 0$. If the statement is not correct, then $\phi_i(v) > 0$. By condition $v(S) = v(S \cup T) = v(N)$ and equation 4.2, it follows $v(S) = v(S \cup T) = 0 \neq v(N)$ which yields a contradiction. Therefore, the property holds.

Therefore, we can conclude that the Shapley value can be used as a possible measure of the physicians' contribution (power index) to the whole system. The proposed game is also the positive linear combination of unanimity games which guarantees the convexity. It implies that the shapley value is in the core of the game.

4.3.5 Incentive Schemes for Physicians

Comparing the desired contribution of each physician to the whole system, obtained from optimal transfers, to that of obtained from Shapley value provides a framework to design the incentive scheme. The leadership team for the consolidated system assigns the financial or non-financial benefit of G^j to improve physician's perceived cost, where

$$G_j = \begin{cases} \phi_j^*(v) \cdot \hat{I} & \phi_j(v) < \phi_j^*(v) \\ \phi_j(v) \cdot \hat{I} & \phi_j(v) \geq \phi_j^*(v) \end{cases} \tag{4.7}$$

$\phi_j^*(v)$ denotes the optimal shapely value calculated using the system problem's outcomes. The term $\hat{I}$ represents the incentive type to align physicians decisions toward global optimality, which can be either monetary or non-monetary. In case of monetary incentives, it represents the cost-saving obtained from the cooperation of physicians and the central referral system. In other words, the outcome of each physician can be improved relative to their contribution in the cooperative game problem.

The literature is rich regarding different types of incentives to reinforce the support of physicians within consolidated systems. Janus and Brown (2014) conducted an exploratory study of monetary and professional incentives for physicians in three countries including the USA. They provided a detailed overview of all non-monetary incentives employed to the physicians into integrated healthcare systems/organizations. According to their findings, *improved service coordination*, as a non-monetary incentive, is of the essence providing the opportunity to share patient data and jointly work towards a solution.

As for the monetary incentives, integrated healthcare systems are widely utilizing the Pay For Performance (P4P) program. According to Williams and Yanagihara (2009), stakeholders have realized that linking performance to members' cost sharing, and incentives design in combination with quality improvement are required. Hence, the proposed

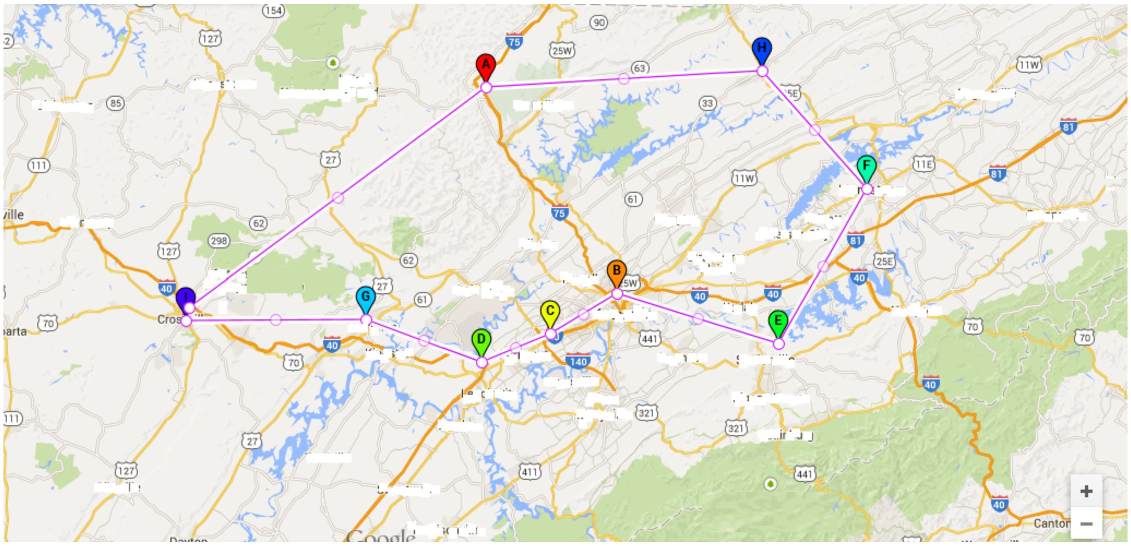


Figure 4.2: Geographical location of hospitals under study

framework in our study facilitates analyzing the contribution of physicians towards system optimality.

4.4 Assessment of Proposed Model via Real Datasets

This section presents a detailed discussion of how our model can be applied in a healthcare setting to facilitate patients transfer considering system optimality. We applied our model to the dataset obtained from an undisclosed healthcare system in Tennessee, including 9 hospitals. Figure 4.2 illustrates the geographical location of the hospitals. Our focus is on incentive schemes for physicians, as their service has the most impact on successful patients transfer. The obtained results are presented in the following sections.

4.4.1 Matching process outcomes

Reviewing some protocols being used in practice regarding patients transfer among hospitals and/or physicians, we dichotomized criteria to define the requirements as presented in Table 4.1. The hospitals' profile based on the aforementioned health attributes, bilateral and critical criteria, and the the corresponding values are given in Table 4.2. It can be observed that the first three hospitals are categorized in the first class providing high technology therapy. Henceforth, we refer to the facilities in this class as the receiving hospitals.

Table 4.2: Hospitals' profile according to the health attributes

Hospital	Class	Bilateral Attributes		Specialty Scope
		Location	Level of Medical care	
H1	H_f	A	VH	Neurosurgery, Cardiology, Hospitalist, Neurology, Urology
H2	H_f	B	VH	Neurosurgery, Cardiology, Hospitalist, Neurology, Urology
H3	H_f	C	H	Neurosurgery, Cardiology, Hospitalist, Neurology, Urology
H4	H_s	D	M	Cardiology, Hospitalist
H5	H_s	E	M	Cardiology, Hospitalist
H6	H_s	F	M	Cardiology, Hospitalist
H7	H_s	G	M	Cardiology, Hospitalist
H8	H_s	H	L	Cardiology
H9	H_s	I	L	Cardiology

Table 4.3: Observed transfer pattern over three months for receiving hospitals

Receiving Hospital (First Class)	**Accepted Transfers**	**Rejected Transfers**	**Total**
H1	345	9 (2.5%)	354
H2	127	2 (1.6%)	129
H3	213	2 (1%)	215

We analyzed a three-month transfer dataset to compare the result of our model and the current practice. The observed transfer pattern, including both accepted and rejected transfers, for the receiving hospitals over three months is summarized in Table 4.3. It can be observed that 5.1% of transfers are not accepted aggregated for all specialties.

To demonstrate the matching process presented in Section 4.3.1, the profile of four patients, including severity of illness, location, and other health attributes, is presented in Table 4.4. Utilizing formula 2.3 to compute the dissimilarity between each pair of hospital

Table 4.4: Sample patients profile according to the health attributes

Patients	Severity of Illness (ρ_i)	Bilateral Attributes		Critical Attributes	
		Location (L_i)	Level of Medical care	Specialty Needed (k)	Established Communication
P_1	2	D	VH	Neurosurgery	No
P_2	0.9	G	M	Hospitalist	No
P_3	1.5	I	H	Cardiology	No
P_4	0.6	F	M	Hospitalist	Yes
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

and patient, the obtained results are summarized in Table 4.5, where $\mathcal{C}$ is a large number. Indeed, lower values indicate a better match for the patients. While we demonstrated the dissimilarities among patients and hospitals in this section, we implemented the proposed matching algorithm among patients and physicians as described earlier. The obtained results will be fed to the optimization model as an input.

Table 4.5: Dissimilarity of patients and hospitals profile

	H1	**H2**	**H3**	**H4**	**H5**	**H6**	**H7**	**H8**	**H9**
P_1	0.95	0.3	0.45	–	$\mathcal{C}$	$\mathcal{C}$	$\mathcal{C}$	$\mathcal{C}$	$\mathcal{C}$
P_2	1.25	1.55	0.75	0.001	1.0006	$\mathcal{C}$	–	$\mathcal{C}$	$\mathcal{C}$
P_3	0.8	0.8	0.2006	0.65	1.25	1.45	0.45	2.2	–
P_4	$\mathcal{C}$	$\mathcal{C}$	1	$\mathcal{C}$	$\mathcal{C}$	–	$\mathcal{C}$	$\mathcal{C}$	$\mathcal{C}$

4.4.2 System problem outcomes

The detailed parameterization of the model was obtained through reviewing exiting documents and several meetings with the referral center's staff. Each day was divided into 2 time blocks; hence, the optimization model is solved and updated at the end of each 12-hour shift. Model sets are assigned the following values:

$\mathcal{T} = \{1, 2, .., 180\}$,

$H_f = \{H1, H2, H3\}$,

$H_s = \{H4, H5, H6, H7, H8, H9\}$,

$K = \{Hospitalist, Cardiology, Neurosurgery\}$,

$J = \{1, 2, ..., 42\}$.

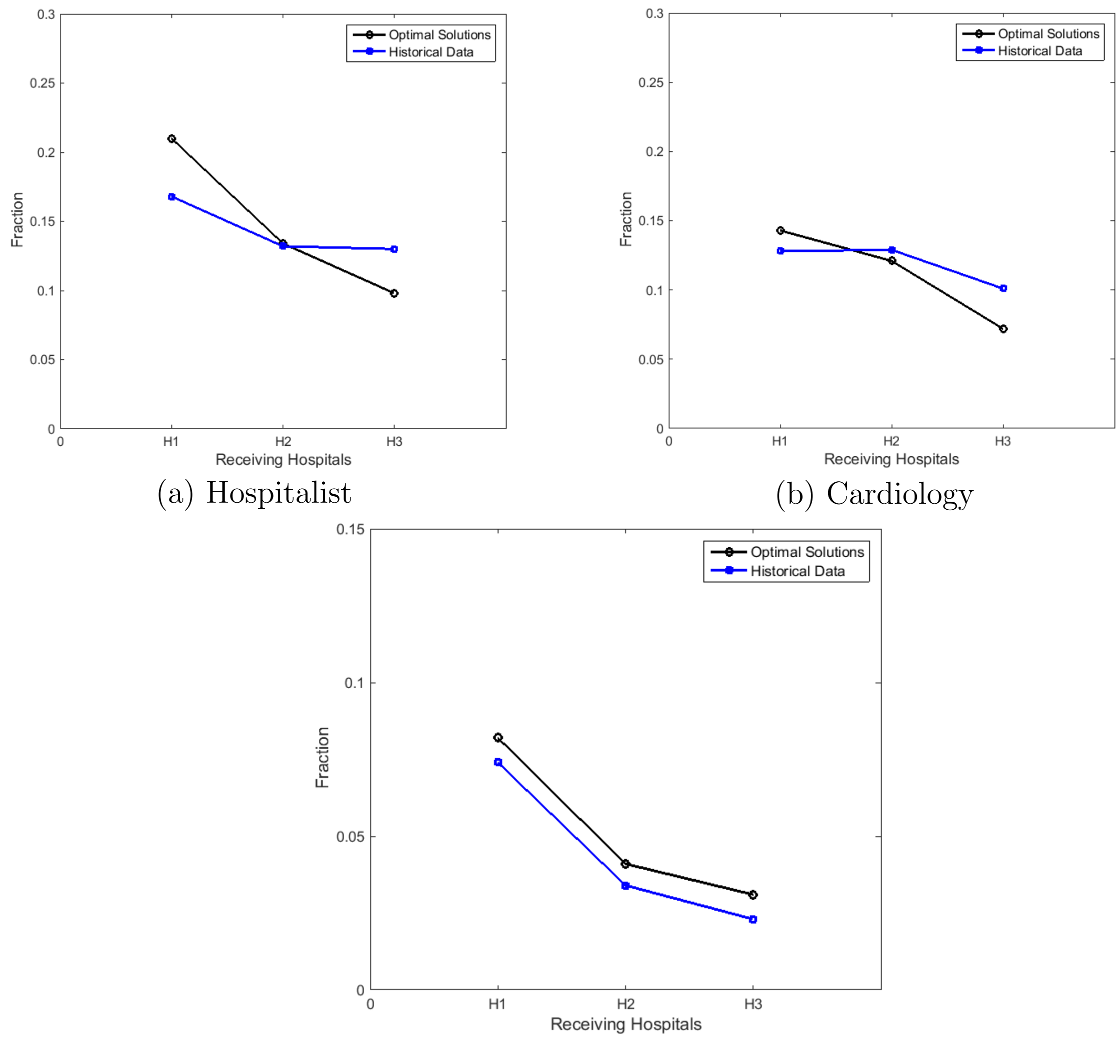
The parameters used in the optimization model are given in Table 4.6. The average cost of losing a potential patient for each specialty is estimated using the cost of medical procedures, to be charged for the service, provided by the Centers for Medicare and Medicaid Services (CMS). We particularly focused on the facility price which is the fee schedule amount when a physician provides this service in a facility setting, such as a hospital or ambulatory surgical center.

Table 4.6: Parameters in the optimization model

Parameter	Value
Severity of illness for cardiology (ρ_{is})	Uniform [0.5, 1.3]
Severity of illness for hospitalist (ρ_{is})	Uniform [0.8, 2.1]
Severity of illness for neurosurgery (ρ_{is})	Uniform [2, 3]
Average cost of losing patient for receiving hospitals (ψ_{hk})	{\$648, \$373, \$2,873}
Average cost of losing patient for referring hospitals (ψ_{hk})	{\$875, \$493, \$3,642}
Average penalty cost (p)	\$1298
Penalty increment ($\triangle\ p$)	2%
α	0.5

Feeding the results of the matching process to the model for each time block, Figure 4.3 compares the solutions of the optimization model to historical data for different specialties over three months. The commercial programming package (CPLEX) is used to solve the model while 200 scenarios are generated for the parameter ρ_{is}. It can be observed that the optimal distribution of patients transfer among hospitals is different from that of currently being practiced. This is mainly due to defining the perceived costs from the perspective of both hospitals' managers and the referral center, considering the quality of care. In addition, as it is shown in Figure 4.3, the fraction of accepted transfers for neurosurgeons is considerably low as compared to the optimal solutions.

The optimal system cost, obtained from the optimization model, is equal to \$158,636.4, while the system cost based on the actual transfers, current practice, over three months is \$321,342.3. This demonstrates the impact of the rejected referrals, lost transfers, and non-optimal assignments on the system cost. As it is discussed earlier, inappropriate referrals can directly influence on the system throughput and increase the length of stay and the number of trips between hospitals, as a result of multiple referrals.



(a) Hospitalist

(b) Cardiology

(c) Neurosurgery

Figure 4.3: Comparison of optimal solutions and historical data for different specialties

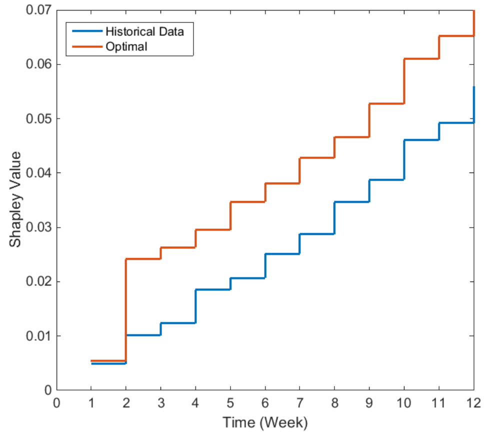
4.4.3 Incentive allocation outcomes

To measure physicians' contribution to the whole system over three months, we computed the Shapley value, according to the rules presented in Section 4.3.3, for a hospitalist at H1, a cardiologist and a neurosurgeon at H2. To demonstrate the Shapley value's computational procedure, consider the following contract matrix for three transfers and four players (three physicians and the referral center). According to equation 4.6, the Shapley value corresponding to this game is equal to $(\frac{5}{18}, \frac{5}{18}, 0, \frac{4}{9})$.

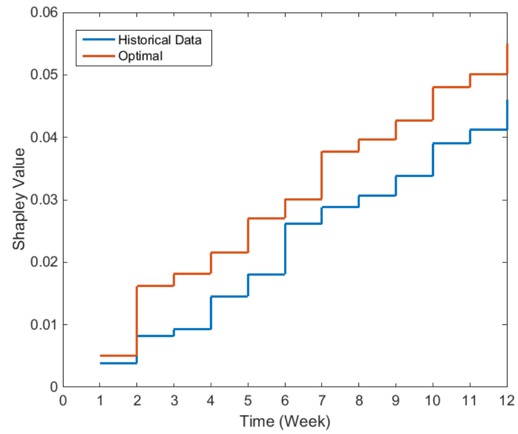
$$\Omega = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix} \tag{4.8}$$

Figure 4.4 compares the cumulative Shapley value of optimal referrals, obtained from the system problem in Section 4.3.2, to that of historical data for the three physicians. It can be observed that the cardiologist's contribution is somehow close to the target obtained by the system problem. A close look at the graph related to the neurosurgeon reveals that there are some cases that the requested transfers has not been processed and the physicians' actual contribution to the whole system is fairly far from the optimal baseline. Due to the potentially high lost opportunity cost in this specialty, it can be indicated that adjusting the neurosurgeon's decision making process can contribute effectively to improve the system optimality.

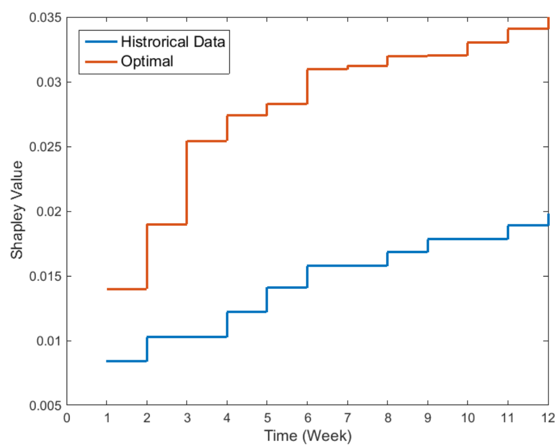
According to the historical data, the first ten physicians with the highest Shapley value over three months are summarized in Table 4.7. The corresponding optimal Shapley value, calculated using the system problem's outcomes, is also given for each physician.



(a) Hospitalist



(b) Cardiologist



(c) Neurosurgeon

Figure 4.4: Comparison of cumulative Shapley value over three months for different specialties

4.5 Conclusions

In this study, we developed an incentive allocation scheme for physicians in a consolidated healthcare system via modeling hospitals coordination within cooperative game framework. Three service categories are proposed to address the potential challenges in such consolidated systems. We first adapted the intelligent matching algorithm to find the most promising healthcare providers for patients based on the defined health attributes. Developing a system

Table 4.7: First ten physicians based on Shapley values

Physician number	Specialty	Shapley value	Optimal Shapley value
J12	Cardiology	0.0566	0.069
J5	Hospitalist	0.0503	0.0524
J8	Hospitalist	0.0464	0.055
J10	Cardiology	0.0421	0.0382
J21	Cardiology	0.0384	0.0352
J11	Hospitalist	0.0301	0.0332
J19	Hospitalist	0.0293	0.0311
J7	Cardiology	0.0261	0.0201
J16	Hospitalist	0.0213	0.0202
J6	Neurosurgery	0.0191	0.035

problem to minimize the perceived cost for the whole system and manage the assignment of patients' transfers, considering the severity of illness, is the second contribution of this study. Indeed, this approach allows for quantifying different collaboration scenarios and synergies among providers. The third contribution is the design of incentive allocation scheme for physicians within cooperative game framework. We also investigated Shapley value axioms and utilized this solution for the proposed game.

To investigate the feasibility of the approach, we examined the model using real world datasets. The obtained results indicated that the optimal distribution of patients transfer among hospitals is significantly different from that of currently being practiced. This transfer pattern alteration can directly influence on the quality of care and lost opportunity costs. To facilitate implementing the optimal strategy for patients' transfer, the model enabled us to measure physicians' contribution towards optimal solutions and provided a quantitative baseline to allocate incentives. It should be noted that different incentive types can be applied depending on the specialty of interest.

Chapter 5

Summary and Future Directions

This work studied collaboration and strategic partnership among members of two complex systems including supply networks and consolidated healthcare system. Considering members' conflict objectives and global performance simultaneously, we presented quantitative models to analyze cooperative relationships. The remainder of this chapter summarizes the findings for the aforementioned applications and points out the direction for future research.

5.1 Summary of Findings

Chapter 1 shed lights on the importance of coordination mechanisms in integrated systems, and introduced our proposed methodology to tackle the potential challenges with application in supply networks and consolidated healthcare systems.

Chapter 2 addressed collaboration among buyers and suppliers in e-supply networks for multi-period procurement processes. We particularly concentrated on the proper definition of data structure for decision making process and longterm relationship among members in the network. The proposed process begins with smart classification of the attributes and the concept of discrepancy between the performances of network's nodes for meeting the buyers needs. A coordination mechanism for long-term agreements is then proposed such that the generated proposals encourage buyers to reveal their demand in advance. Indeed, the mechanism introduces the importance of strategic buyers for suppliers in modeling and decision making process. To validate the approach, we designed an agent-based e-SN to take into account the distributed and dynamic nature of the decision making process. We then investigated two scenarios including normal tendering process and the proposed mechanism. The performance of the both scenarios is measured using total network cost, and average agreed price in terms of buyer's strategic index for 200 simulation rounds. The obtained results indicated that the proposed approach for making long-term partnership outperforms the traditional tendering process. This is mainly due to the intelligent behavior of the proposed approach for making long-term contracts where both the horizontal information sharing among buyers and negotiations among buyers and suppliers have been taken into account.

Chapter 3 extended the proposed model for the supply network through including another layer of collaboration among suppliers to maximize the network capacity utilization, particularly when they are geographically decentralized. Indeed, we modeled suppliers' dynamic coalition formation for multi-period demand via coalitional game theory such that cooperation incurs both cost and benefit. The proposed model relaxed two limiting assumptions in the literature including the formation of the grand coalition, and static or pre-defined coalitional structure due to computational burden. We then derived a fair and practical cooperation algorithm such that the decision to cooperate does not degrade the performance of any of the cooperating members. The proposed algorithm enables suppliers to self-organize into independent disjoint coalitions while the cost structure influences the utility of each possible coalition and reduces computational burden to explore all possible coalitions. To examine the performance of the proposed model, a simulation study and four performance measures were designed. The outcomes are compared for three different fairness criteria including *shared capacity index* which is proposed for the underlying problem. The obtained results demonstrated that the cooperation mechanism provides a significant advantage over the non-cooperative case for all fairness criteria. In addition, the choice of fairness criteria significantly influences on the average individual profit for the large number of suppliers.

Viewing the issue from the same angel, Chapter 4 addressed the coordination of hospitals such that there is a central referral system to facilitate patients transfer. We considered three main players including physicians, hospitals managers, and the referral system. To come up with the incentive scheme for physicians and aligning hospitals activities, we defined a bi-objective mathematical model and obtained optimal transfer pattern. Using optimal solutions as a baseline, a cooperative game between physicians and the central referral system was defined to coordinate decisions toward system optimality. Indeed, this approach allows for intervening physicians' perceived cost function and encourage them to accept requested transfers. The feasibility of the proposed approach was examined via real-world datasets. The obtained results indicated that the optimal distribution of patients transfer among hospitals is significantly different from that of currently being practiced. To facilitate implementing the optimal strategy for patients' transfer, the model enabled us to measure physicians' contribution towards optimal solutions and provided a quantitative baseline to allocate incentives. Depending upon the specialty of interest, different incentive types, monetary or non-monetary, can be applied.

5.2 Future Directions

This work can be extended in several ways. First, in this dissertation, we considered a linear configuration for the supply network. In other words, the value of alliances only depends on its members and the dependency to the structure of other players' collaboration has been ignored. Modeling the behaviors in a partition form can provide insights and practical significance for designing strategic SNs.

In the second place, the process of matching players, buyers and suppliers or patients and physicians, can be improved by modeling their prior experience. Here, we utilized an improved multi-criteria decision making technique to include binary, quantitative, and qualitative attributes for the data structure. Considering the prior experience provides the opportunity to effectively design the psychological part of the selection behaviors.

The third area for future research is to apply the proposed incentive allocation scheme within a consolidated healthcare system for an extensive empirical analysis. While we defined an exponential relationship between the illness severity and the penalty cost to capture the non-linear behavior of the cost structure, it is interesting to elaborate on the cost function and directly include the system throughput, patients' length of stay, and the number of required trips between hospitals. In addition, the type of incentive can vary based on the physicians' specialty. Such incentives are required to be categorized for each specialty and their effectiveness needs to be investigated in practice.

Bibliography

Acerete, B., Stafford, A., Stapleton, P., 2011. Spanish healthcare public private partnerships: The alzira model. Critical Perspectives on Accounting 22 (6), 533–549.

Andersen, P., Christensen, P., 2005. Bridges over troubled water: Suppliers as connective nodes in global supply networks. Journal of Business Research 58 (9), 1261–1273.

Arnold, T., Schwalbe, U., 2002. Dynamic coalition formation and the core. Journal of Economic Behavior and Organization 49 (3), 363–380.

Aveling, E., Martin, G., 2013. Realizing the transformative potential of healthcare partnerships: Insights from divergent literatures and contrasting cases in high- and low-income country contexts. Social Science and Medicine 92, 74–82.

Basar, T., Olsder, G. J. (Eds.), 1999. Dynamic Noncooperative Game Theory (Series in Classics in Applied Mathematics). Philadelphia: PA: SIAM.

Bengtsson, M., Kock, S., 2000. Coopetition in business networks-to cooperate and compete simultaneously. Industrial Marketing Management 29 (5), 411–426.

Boadway, R., Marchand, M., Sato, M., 2004. An optimal contract approach to hospital financing. Journal of Health Economics 23, 85–110.

Cao, M., Luo, X., Luo, X., Dai, X., 2015. Automated negotiation for e-commerce decision making: A goal deliberated agent architecture for multi-strategy selection. Decision Support Systems 73, 1–14.

Charles, S., Hansen, D., 2008. An evaluation of activity-based costing and functional-based costing: a game-theoretic approach. International Journal of Production Economics 113 (1), 282–296.

Chen, Y., Larbani, M., 2005. Simulating the performance of supply chain with various alliances. International Journal of Advanced Manufacturing Technology 25 (7-8), 803810.

Cheng, C., Chan, C., Lin, K., 2006. Intelligent agent for e-marketplace: Negotiation with issue trade-offs by fuzzy inference systems. Decision Support Systems 42 (2), 626–638.

Cho, N., Mahdai, I., Mahdavi-Amiri, N., Mohebbi, S., Zandakbari, M., 2011. e-supply network: Network agents to support information sharing for buyer-buyer-supplier coordination. In: Mahdavi, I., Mohebbi, S., Cho, N. (Eds.), Electronic Supply Network Coordination in Intelligent and Dynamic Environment: Modeling and Implementation. IGI Global, pp. 269–290.

Clayman, M., Makoul, G., Harper, M., Koby, D., Williams, A., 2012. Development of a shared decision making coding system for analysis of patienthealthcare provider encounters. Patient Education and Counseling 88 (3), 367–372.

Custer, W., Moser, J., Musacchio, R., Willke, R., 1990. The production of health care services and changing hospital reimbursement: the role of hospitalmedical staff relationships. Journal of Health Economics 9, 167–192.

Cutler, D., Morton, F., 2013. Hospitals, market share, and consolidation. Clinical Review and Education 310 (18), 1964–1970.

Drechsel, J., Kimms, A., 2010. Computing core allocations in cooperative games with an application to cooperative procurement. International Journal of Production Economics 128 (1), 310–321.

Dubois, A., Fredriksson, P., 2008. Cooperating and competing in supply networks: Making sense of a triadic sourcing strategy. Journal of Purchasing and Supply Management 15 (1), 107–111.

Faratin, P., Sierra, C., Jennings, N., 1998. Negotiation decision functions for autonomous agents. Robotics and Autonomous Systems 24 (3), 159–182.

Fiala, P., 2005. Information sharing in supply chains. Omega 33 (5), 419–423.

Galizzi, M., Miraldo, M., 2011. The effects of hospitals governance on optimal contracts:bargaining vs. contracting. Journal of Health Economics 30 (2), 408–424.

Hadikusumo, B. H. W., Petchpong, S., Charoenngam, C., 2005. Construction material procurement using internet-based agent system. Automation in Construction 14 (6), 736–749.

Harrison, T., 2011. Do mergers really reduce costs? evidence from hospitals. Economic Inquiry 49 (4), 1054–1069.

Hennet, J., Arda, Y., 2008. Supply chain coordination: A game-theory approach. Engineering Applications of Artificial Intelligence 21, 399405.

Hennet, J., Mahjoub, S., 2010. Toward the fair sharing of profit in a supply network formation. International journal of Production Economics 127 (1), 112–120.

Hu, M., Liu, B., 2004. Mining opinion features in customer reviews. In: Proceedings of the nineteenth national conference on artificial intelligence, sixteenth conference on innovative applications of artificial intelligence. pp. 755–760.

Hua, Z., Li, S., 2008. Impacts of demand uncertainty on retailers dominance and manufacturer-retailer supply chain cooperation. Omega 36 (5), 697–714.

Hwang, C., Yoon, K. (Eds.), 1981. Multiple attribute decision making methods and applications. New York: Springer-Verlag.

Jager, W., Janssen, M., De Vries, H., De Greef, J., Vlek, C., 2000. Behavior in commons dilemmas: Homo economicus and homo psychologicus in an ecological-economic model. Ecological Economics 35 (3), 357–379.

Janus, K., Brown, L., 2014. Physician integration revisited-an exploratory study of monetary and professional incentives in three countries. Health Policy 118, 14–23.

Jin, M., Wu, S., 2006. Supplier coalitions in on-line reverse auctions: validity requirements and profit distribution scheme. International Journal of Production Economics 100 (2), 183194.

Kahraman, C., Cevik, S., Ates, N., Gulbay, M., 2007. Fuzzy multi-criteria evaluation of industrial robotic systems. Computers & Industrial Engineering 52, 414–433.

Katz, M., 2013. Provider competition and healthcare quality: More bang for the buck? International Journal of Industrial Organization 31 (5), 612–625.

Kelly, F., 1997. Charging and rate control for elastic traffic. European Transactions on Telecommunications 8 (1), 33–37.

Kutanoglu, E., Wu, S., 2007. Coalitions in coordinated multi-agent production scheduling: A computational study. Journal of Manufacturing Systems 26 (1), 12–21.

La Londe, B., Ginter, J., 2004. The ohio state university 2003 survey of career patterns in logistics. Council of Supply Chain Management Professionals, Available at http://www.clm1.org.

Lattila, L., Hilletofth, P., Lin, B., 2010. Hybrid simulation models when, why, how? Expert Systems with Applications 37 (12), 7969–7975.

Lee, C., Lau, H., Ho, G., Ho, W., 2009. Design and development of agent-based procurement system to enhance business intelligence. Expert Systems with Applications 36 (1), 877–884.

Lee, E. S., Li, R. L., 1998. Comparison of fuzzy numbers based on the probability measure of fuzzy events. Computer and Mathematics with Applications 15 (10), 887–896.

Leng, M., Parlar, M., 2009. Allocation of cost savings in a three-level supply chain with demand information sharing: A cooperative-game approach. Operations Research 57 (1), 200–213.

Li, X., Wang, Q., 2007. Coordination mechanisms of supply chain systems. European Journal of Operational Research 179 (1), 1–16.

Lin, C. C., Chen, S., Chu, Y., 2011. Automatic price negotiation on the web: An agent-based web application using fuzzy expert system. Expert Systems with Applications 38 (5), 5090–5100.

Liu, J., Jing, H., Tang, Y., 2002. Multi-agent oriented constraint satisfaction. Artificial Intelligence 136 (1), 101–144.

Lozano, S., Moreno, P., Adenso-Daz, B., Algaba, E., 2013. Cooperative game theory approach to allocating benefits of horizontal cooperation. European Journal of Operational Research 229 (2), 444–452.

Mahdavi, I., Mohebbi, S., Zandakbari, M., Cho, N., Mahdavi-Amiri, N., 2009. Agent-based web service for the design of a dynamic coordination model in supply networks. Journal of Intelligent Manufacturing 20 (6), 727–749.

Manthou, V., Vlachopoulou, M., Folinas, D., 2004. Virtual e-chain (vec) model for supply chain collaboration. International Journal of Production Economics 87 (3), 241–250.

Millet, I., Saaty, T. L., 2000. On the relativity of relative measures - accommodating both rank preservation and rank reversals in the ahp. European Journal of Operational Research 121, 205–212.

Mohebbi, S., Li, X., 2012. Designing intelligent agents to support long-term partnership in two-echelon e-supply networks. Expert Systems with Applications 39 (18), 13501–13508.

Mohebbi, S., Shafaei, R., 2012. E-supply network coordination: the design of intelligent agents for buyer-supplier dynamic negotiations. Journal of Intelligent Manufacturing 23 (3), 375–391.

Mohebbi, S., Shafaei, R., Cho, N., 2011. Chapter 11: e-supply network: the design of intelligent agents for buyer-supplier-supplier coordination. In: Mahdavi, I., Mohebbi, S., Cho, N. (Eds.), Electronic Supply Network Coordination in Intelligent and Dynamic Environment: Modeling and Implementation. IGI Global, USA, pp. 250–268.

Moreno, E., Giron, F., Vazquez-Polo, F., Negrin, M., 2010. Optimal healthcare decisions: Comparing medical treatments on a cost-effectiveness basis. European Journal of Operational Research 204 (1), 180–187.

Moretti, S., Patrone, F., Bonassi, S., 2007. The class of microarray games and the relevance index for genes. Top 15, 256–280.

Myerson, R. B. (Ed.), 1991. Game Theory, Analysis of Conflict. Cambridge: MA: Harvard Univ. Press.

Nagarajan, M., Sosic, G., 2008. Game-theoretic analysis of cooperation among supply chain agents: Review and extensions. European Journal of Operational Research 187, 719–745.

Osborne, M. J., Rubinstein, A. (Eds.), 1994. A course in game theory. Cambridge MIT Press.

Popescu, A. M., Etzioni, O., 2005. Extracting product features and opinions from reviews. In: Proceedings of human language technology conference and conference on empirical methods in natural language processing, HLT/EMNLP. pp. 339–346.

Renna, P., 2010. Negotiation policies and coalition tools in e-marketplace environment. Computers and Industrial Engineering 59 (4), 619–629.

Renna, P., Argoneto, P., 2011. Capacity sharing in a network of independent factories: A cooperative game theory approach. Robotics and Computer-Integrated Manufacturing 27 (2), 405–417.

Rummery, K., Coleman, A., 2003. Primary health and social care services in the uk: progress towards partnership? Social Science and Medicine 56 (8), 1773–1782.

Saad, W., Han, Z., Debbah, M., Hjorungnes, A., 2009a. A distributed coalition formation framework for fair user cooperation in wireless networks. IEEE Transactions on Wireless Communications 8 (9), 4580–4593.

Saad, W., Han, Z., Debbah, M., Hjorungnes, A., Basar, T., 2009b. Coalitional game theory for communication networks. IEEE Signal Processing Magazine, Special Issue on Game Theory for Signal Processing and Communication 26 (5), 77–97.

Saaty, T. L., 1977. A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology 15, 59–62.

Sadeh, N., Hildum, D., Kjenstad, D., 2003. Agent-based e-supply chain decision support. Journal of Organizational Computing and Electronic Commerce 13 (3-4), 225–241.

Sahina, F., Robinson, E., 2005. Information sharing and coordination in make-to-order supply chains. Journal of Operations Management 23 (6), 579–598.

Seok, H., Nof, S., 2014. Dynamic coalition reformation for adaptive demand and capacity sharing. International Journal of Production Economics 147, 136–146.

Shapley, L., 1953. A value for n-person games. In: H.W., K., A.W., T. (Eds.), Contributions to the theory of games II. Annals of mathematics studies. Princeton University Press, p. 307317.

Smirnov, A.V., S. L. C. N., Cortes, J., 2004. Soft-computing technologies for configuration of cooperative supply chain. Applied Soft Computing 4, 87–107.

Tang, L., Shen, Q., Cheng, E., 2010. A review of studies on publicprivate partnership projects in the construction industry. International Journal of Project Management 28 (7), 683–694.

Wadhwa, S., Mishra, M., Chanb, F., Ducq, Y., 2010. Effects of information transparency and cooperation on supply chain performance: a simulation study. International Journal of Production Research 48 (1), 145–166.

Wang, H., G. M., Efstathion, J., 2004. A game-theoretical cooperative mechanism design for a two-echelon decentralized supply chain. European Journal of Operational Research 157, 372388.

Wang, M., Liu, J.and Wang, H., Cheung, W., Xie, X., 2008. On-demand e-supply chain integration: A multi-agent constraint-based approach. Expert Systems with Applications 34 (4), 2683–2692.

Wang, X., Triantaphyllou, E., 2008. Ranking irregularities when evaluating alternatives by using some electre methods. Omega 36, 45–63.

Warner, J., Burton, D., 2009. The policy and politics of emerging academic-service partnerships. Journal of Professional Nursing 25 (6), 329–334.

Williams, T., Yanagihara, D. (Eds.), 2009. The California Pay For Performance Program. Integrated Healthcare Association.

Wooldridge, M. (Ed.), 2002. An introduction to Multi-Agent Systems. Wiley.

Wu, J., Chen, Y., Greenes, R., 2009. Healthcare technology management competency and its impacts on it-healthcare partnerships development. International journal of medical informatics 78 (2), 71–82.

Wu, Z., Choi, T., Rungtusanatham, M., 2010. Supplier-supplier relationships in buyer-supplier-supplier triads: Implications for supplier performance. Journal of Operations Management 28 (2), 115–123.

Xue, X., Wang, Y., Shen, Q., Yu, X., 2007. Coordination mechanisms for construction supply chain management in the internet environment. International Journal of Project Management 25 (2), 150–157.

Yuh-Wen, C., Larbani, M., Chen-Hao, L., 2010. Simulation of a supply chain game with multiple fuzzy goals. Fuzzy Sets and Systems 161 (11), 1489–1510.

Zhan, J., Loh, H., Liu, Y., 2009. Gather customer concerns from online product reviews a text summarization approach. Expert Systems with Applications 36 (2), 2107–2115.

Zhang, J., Frazier, G., 2011. Strategic alliance via co-opetition: Supply chain partnership with a competitor. Decision Support Systems 51 (4), 853–863.

Zhang, J., Gou, Q., Liang, L., Huang, Z., 2013. Supply chain coordination through cooperative advertising with reference price effect. Omega 41 (2), 345–353.

Vita

Shima Mohebbi was born and grew up in Tehran, Iran. She undertook her earlier graduate studies at K.N. Toosi University of Technology and the University of Tehran. There, she earned the National Outstanding Student award in 2009, and was honored by the president. Since joining the UT community, Shima received the Chancellor's Extraordinary Professional Promise Award in 2013, two Graduate Student Senate travel awards, recognition as the Outstanding Graduate Student in the College of Engineering (2014), and Chad/Ann Blair Holliday Fellowship awarded by the Department of Industrial and Systems Engineering in 2015.

Shima was one of two 2015 nominees by the Institute of Industrial Engineering (IIE) for the "New Faces of Engineering" national program. She was featured in news and DiscoverE's focus, "Engineering New Horizons". She is also on the editorial board of the International Journal of Applied Logistics, IGI-Global, and has served as a reviewer for numerous other journals.