DISTRIBUTED DECISION ALGORITHMS FOR FAIR RESOURCE ALLOCATIONS IN COLLABORATIVE NETWORKS

BY

IBRAHIM YILMAZ

BSc, Gazi University, Turkey, 2010
MSc, Gazi University, Turkey, 2012

DISSERTATION

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Dr. Sang Won Yoon, Committee Chair and Faculty Advisor
Department of Systems Science and Industrial Engineering

Dr. Nagen Nagarur, Committee Member
Department of Systems Science and Industrial Engineering

Dr. Sarah S. Lam, Committee Member
Department of Systems Science and Industrial Engineering

Dr. Chun-An Chou, Committee Member
Department of Mechanical and Industrial Engineering
Northeastern University College of Engineering

Dr. Kyoung-Don Kang, Outsider Examiner
Department of Computer Science

Abstract

This research addresses distributed decisions for to enhance fairness and total profit among collaborative networked enterprises (CNEs). The arbitrary nature of demand and capacity patterns in manufacturing/service enterprises require to form a CNE with other enterprises to overcome such uncertainties. In any CNE, the collaboration process often leads to a dilemma: the need to choose between fairness and total profit. The aim of this research is to investigate a new sharing protocol (SP) to control CNEs and to propose an algorithm that attempts to increase optimal weights of fairness while maintaining total profit. Most CNE research studies have been designed under a centralized SP. However, centralized SPs appear to be unfeasible or inadequate because of enterprises' operating environments and local objectives; therefore, each CNE requires a distributed decision-making mechanism. Furthermore, market globalization and competition necessitate rapid responses to market changes and give rise to two major concerns about CNEs: 1) how can collaborations be rendered re-configurable to dynamically capture and adapt to market patterns; and 2) how can the resources of all CNEs be utilized fairly among enterprises, ensuring mutual benefits? Therefore, Dynamic-Distributed Sharing Protocol (D^2SP), which is inspired by the principles of Collaborative Control Theory and the Contract Net Protocol, is proposed to address these concerns. Under the assumptions used in this research, experimental results and analyses indicate that D^2SP reduces the number of messages and inventory cost of shared amounts by up to 30%, and 9%, respectively and total profit and fairness index are increased by up to 15% and 10%, respectively. The proposed algorithm in which Jain's fairness index and the generalized α-fair concept are utilized, is tested with conceptual heterogeneous and homogeneous CNs (HeCNs and HoCNs, respectively) based on the enterprise capacity. Experimental results indicate that fairness increases up to 28% in HeCN and 32% in HoCN while maintaining the current total profit of a CN. The gap between two CNEs, which are the most benefited and least benefited enterprises in terms of total profit, lost sale cost, and inventory cost, can reduce up to 57%, 54%, and 78%, respectively. Therefore, the proposed algorithm can minimize the deviation between most and least beneficial CNEs in terms of total profit, lost sale cost, and inventory cost.

DEDICATION

To my parents, my wife and my son who are and will be always with me.

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List of Abbreviations

s.t.	Subject To
Col^C	Complete Collaboration Model
Col^N	No Collaboration Model
Col^P	Partial Collaboration Model
CCT	Collaborative Control Theory
CN	Collaborative Network
CNE	Collaborative Network of Enterprises
CNP	Contract Net Protocol
DCSP	Demand and Capacity Sharing Protocol
HoCN	Homogeneous Collaborative Network
HeCN	Heterogeneous Collaborative Network
NM	Negotiation Mechanism
RQ	Research Question
RP	Research Problem
SP	Sharing Protocol
$DCSP$	Dynamic-Centralized Sharing Protocol
D^2SP	Dynamic-Distributed Sharing Protocol
$SCSP$	Static Centralized Sharing Protocol
$SDSP$	Static Distributed Sharing Protocol

List of Nomenclature

c^c_{kt}	Collaboration cost $e_k \in E$ at time t
c^f	Fairness cost
c^l	Lost sale cost per unit
c^{lt}	Lead-time cost
c^h	Holding cost per unit
c^p	Production cost
c^s	Product selling cost in CN
c^u	Collaboration unit cost
e_i	An element of E^+
e_j	An element of E^-
e_k	An element of E
i	Index of CSE in $E^+ = \{e_1, ..., e_i\}$
j	Index of DSE in $E^- = \{e_1, ..., e_j\}$
k	Index of enterprise in $E = \{e_1, ..., e_k\}$
l	Index of aim in the CN, $O = \{obj_1, ..., obj_l\}$
$m(o_{kt})$	Maximum capacity at e_k
$n(o_{kt})$	Amount capacity used in collaboration
obj_l	An element of O
o_{kt}	Costumer order of e_k at time t

p^c	Collaborative unit price
q	Order quantity
$r(o_{jt})$	Requested capacity by e_j for o_{jt}
$s(o_{it})$	Available capacity to share after o_{it}
s^p	Selling price of product in market
t^{lt}	Lead time information
t^d	Order due date
w	Weights of each evaluation criteria in $U_{\omega_{it}}$
A_k	Set of e_k's actions such as a unit of shared demand or capacity
A_k^*	Allocation vector in network based on e_k's actions
E	Set of enterprises in the collaborative network
E^+	Set of capacity sharing enterprises in the collaborative network
E^-	Set of demand sharing enterprises in the collaborative network
IC_k	Inventory cost of e_k
Ji	Jain's fairness index
LC_k	Lost sale cost of e_k
H_{kt}^c	Holding cost in e_k at time t
L_{kt}^c	Lost sale cost in e_k at time t
M_{kt}	Number of messages among CNE
$N(\omega_{jt})$	Negotiation condition for ω_{jt}
O	Set of objectives in the collaborative network

$P(e_k)$	Profit function of each e_k
$P(CN)$	Profit function of CN
$P(\phi)$	Profit function of e_k for $\forall a_l \in A$
$P(\varphi)$	Profit function of e_k for the $a_l \in A$
U_α	α fair utility function
$U_{\omega_{jt}}$	Utility function of ω_j at time t
α	U_α parameter
β	Time-to-money conversion factor
γ	Fairness-to-money conversion factor
δ	Communication cost per message
ϕ	Set of actions between e_i and e_j for $\forall a_l \in A$
φ	Set of actions among e_k for the $a_l \in A$
τ	Collaboration time period
ω_i	Demand sharing proposal of e_i^-
Λ_j	Bid of e_j^+
ζ_{ijl}	An action of e_i with e_j for the l^{th} objective
ρ_{il}	An action of e_i for the l^{th} objective
ϱ_{ij}	An action of e_i with e_j
σ	Select operator
Φ_{kl}	An element of ϕ_k

Ψ_{ij}	An element of φ_k

Chapter 1. Introduction

In parallel with the development of information and communication technologies, market conditions are changing faster than ever. In such a condition, a group of enterprises can form a collaborative network (CN) with intent to survive and achieve mutual benefits by excelling in the individual capacities of each enterprise (Camarinha-Matos et al., 2006, Yoon and Nof, 2011). During the collaboration process, it is also possible that each enterprise of the CN will not be able to utilize the CN to the same degree as other enterprises, even if the CN has sufficient efficiency. This situation creates a dilemma: a choice between fairness and efficiency, which appears to decide the optimal weights during the collaboration process. Therefore, one of the critical problems being faced in CNs is how network resources should be allocated fairly among the networked enterprises while maintaining network efficiency.

The growing complexity and dynamic behavior of modern industries, together with competitive and globalized markets, have gradually transformed traditional centralized systems into distributed networks of enterprises. In this context, enterprises need to work together to enhance their individual capabilities and to rapidly respond to market changes. The use of CNs is accepted as an attractive strategy for enterprises' collaboration. A CN is defined as a set of independent, self-operating enterprises collaborating under certain protocols to reach their local objectives and reap mutual benefits by sharing information, resources, and responsibilities (Nof, 2007). Therefore, an enterprise CN needs a decision-making mechanism without any central control to seek its own local objectives with its own operating environments; therefore, centralized sharing protocols (CSPs) appear to be unfeasible or inadequate. Dynamic-Distributed Sharing Protocol (D^2SP), which is an extension of the demand- and capacity-sharing protocol proposed by Yoon and Nof (2010), is proposed to provide distributed decisions for collaborative network of enterprises (CNEs).

The problem of CSPs can be defined as follows. An authority collects information about all CNEs in order to decide all decisions and processes in CN. In the case of a large network, e.g., one consisting of more than eight enterprises, this situation causes a long decision time, and an exponential increase in the coordination cost (Yilmaz et al., 2017). Therefore, it would be difficult to benefit from a CN that is formed by a large number of enterprises.

Static sharing protocols (SSPs) maintain the operational status for the same conditions occur over a collaboration time period. The crucial disadvantage of a SSP is that a CN cannot have the capability to capture or adapt to dynamic market patterns. D^2SP assumes that no enterprise has central authority over other enterprises or the entire collaborative network, and provides dynamic reformation of partnership subsets to allow fair demand and capacity sharing. In D^2SP, each enterprise can help each other enterprise through a distributed sharing protocol (DSPs) by sharing their excess capacities and demands.

In this research, the Contract Net Protocol (CNP) is used to provide a negotiation mechanism (NM) among CNEs. The CNP is a widely-used and powerful NM in networked systems. However, the performance of NM and fairness of resource allocation can decrease when number of enterprises in a CN increases, because task announcements (i.e., sharing proposals) reach a high frequency. Therefore, the applicability of CN to large-scale networks can be limited. This problem could be solved by extending the CNP with a fairness-based perception of the task announcement strategy.

D^2SP ensures that local objectives can be optimized with respect to global objectives through information sharing. It is possible that excess capacities and demands that are available for sharing in a CN may not be equal or that there may be more than one enterprise willing to make an agreement with a specific enterprise. In this case, the sharing of scarce resources may not be fair, and some enterprises may be unable to benefit from CN to the same degree as others. In literature, various methods were applied to obtain fair resource allocations in a CN. However, the problem of allocating network resources fairly is not always solved due to various obstacles. The first obstacle appears in the definitions of fairness and efficiency; it is often true that each enterprise has a different concept of what is fair and efficient. In other words, an enterprise in the CN may have an approach to fairness or efficiency that does not agree with the other enterprise's point of view. It is therefore difficult to develop a universal and commonly accepted concept of fairness and efficiency (Yilmaz et al., 2017). In the literature, CNs' research has assumed that network resources came from collaborated enterprises' sharing capacities or demand. In this research, fairness and efficiency are considered based on the sharing capacity and demand of an enterprise, which is used in the mathematical formulations (Yilmaz et al., 2016).

D^2SP is implemented based on Collaborative Control Theory (CCT) and a CNP to ensure fairness by means of two strategies: 1) compensating enterprises that are treated unfairly during the previous collaboration time period, such that their losses are somehow addressed in the current allocations, and 2) adjusting the allocations to achieve fairness by reallocating resources among a subset of possible collaborators. The proposed D^2SP is compared with 1) static-centralized sharing protocol ($SCSP$), 2) static-distributed sharing protocol ($SDSP$), and 3) dynamic-centralized sharing protocol ($DCSP$), in terms of the total profit, fairness, communication overhead, and scalability of D^2SP.

Amount of sharing capacity and demand of each distributed enterprise are obtained through based on the sharing protocols. As a result, the amount of sharing capacity and demand of each enterprise is used to input a mathematical formulation of the fairness and efficiency measure based on the α-fairness utility function (U_α), and Jain's fairness index (Ji). Ji is used to determine a fairness measure of the network without considering the efficiency of the network, wherein the efficiency-fairness curve is provided by the U_α. The outcomes of the mathematical formulations answer the following interesting questions: 1) how does one form a CN with maximum efficiency under the specific weight of fairness, and 2) how much should the fairness index be improved by compromising on the specific weight of the efficiency?

In the literature, studies on fairness have indicated that an uneven allocation of throughput is accepted as unfair. According to Jaffe, fair resource allocation is defined as *"each user's throughput is at least as large as that of all other users which have the same bottleneck"* (Jain et al., 1984). Although this statement can be accepted as a general definition of fairness, it may not always be true. In view of the fact that the criterion of fairness may be defined in different ways, the network may not be done by giving everyone equal amounts (Alexander et al., 2014). In other words, an enterprise in the network may have an approach to fairness that does not agree with the other enterprises' point of view. For example, if someone works twice as hard or twice as effectively as another individual, it is expected that these two people should not receive identical salaries. Another example, if a professor assigns a "B" grade to all students regardless of their performance, instead of assigning from "F" to "A", this will provide the correct incentive for learning and will be accepted as unfair by most students (Chiang, 2012). A universal and commonly accepted concept of fairness is very hard to generate. Therefore, the amount of capacity and demand sharing in resource allocation and collection are considered simultaneously in this research.

The fairness measurement is apparent a wide range of existing fields such as economics, network science, game theory, computer science, psychology, philosophy even social network, which include Renyi Entropy, Theil Index, Atkinson Index, α fairness, Shannon Entropy, and Jasso Index (Chiang, 2012). However, the proposed fairness measures are generally proposed for a specific application. Due to this reason, they have undesirable characteristics for general applications. CNs also have their own special specifications and requirements, such as resource allocation, and collection must be considered simultaneously. For example, in computer networks, a resource comes from out of network; in other words, the proposed methods attempt to find a fair allocation of “external resources.” On the other hand, additional resources can be obtained from a networked enterprise in the CNs; in other words, the the proposed methods attempt to find a fair allocation of “internal resources.” In this research, the fairness has been measured in the demand and capacity sharing protocols proposed in Yoon and Nof (2010), such that different perspectives (i.e., demand sharing and capacity sharing) should be considered simultaneously. Therefore, proposed fairness measures in the literature do not cover all CN’s specifications and requirements.

CN may face two situations during the collaboration process: 1) total excess capacity being lower than a total shortage, which results in the CN possibly not having sufficient resources to fulfill all orders of the collaborating network, and 2) total excess capacity being greater than the total shortage, which results in the CN being unable to eliminate the amount of excess capacity. These situations must be utilized in an efficient and fair way; otherwise, a loss of network efficiency and sustainability may occur.

There is limited attention on fairness in CNs. When collaborating enterprises rely on CN resources, enterprises are likely to be distracted from networking in the long term. The level of distraction can be reduced by fair resource allocation in CN. Therefore, a fairness measure that considers the requirements of CNs should be established to achieve network fairness and enhanced network sustainability.

1.1 Problem Description and Research Objectives

The objective of this research is to develop the knowledge on how to collaborate with distributed decision makers and how to coordinate their decisions to improve the fairness of a collaborative network while ensuring mutual benefits of enterprise collaboration. This research addresses a fair collaborative network by information sharing and distributed decision making processes of collaborative members (i.e., enterprises), especially in joint resource allocation control.

Fair resource allocation among distributed or centralized production/service enterprises can be found in many fields such as economics, network science, game theory, computer science even philosophy. As in the other research fields, CN also has specific requirements for fair resource allocation. The fundamental problem in this research is how network resources (i.e., excess capacity and demand) can be allocated fairly among CNE while maintaining CN efficiency in dynamic, heterogeneous, autonomous, and distributed CN.

1.2 Research Problems and Questions

This research address the following research problems (RP) related to the fair resource allocation among CNE.

1. How can fairness index in a collaborative network be maximized while maintaining CN efficiency? Coordination protocols based on demand and capacity sharing decisions cannot handle fairness problems effectively among CNE. Sharing protocols (SPs) (e.g., demand and capacity sharing protocol) have been developed for managing the demand and capacity sharing decisions among CNEs to maximize demand fulfillment rate of customer orders. When a customer order cannot be met by local enterprise capacity, this order can be a potential rejected order. However, the potential rejected order can become acceptable

by sharing their demands and capacities among CNEs during the collaboration time period. The demand sharing enterprise fulfills its own customer request, and the capacity sharing enterprise receives the additional demand, such that mutual benefits can be achieved. However during the collaboration time period, it is also possible that each enterprise of the CN will not be able to utilize the CN to the same degree as other enterprises, even if the CN has sufficient efficiency. Collaboration requires more CN efficiency and causes challenges in resource allocation.

2. What is the impact of different collaborative network characteristics to fairness in resource allocation? CN are mainly divided in two types: 1) heterogeneous CN (HeCN), and 2) homogeneous CN (HoCN). HeCN is formed by different enterprises in terms of enterprise culture, resource transformation, knowledge access, but HoCN is formed by identical enterprises. Also, number of participant enterprises in CN can be accepted as small size, medium size and big size CN. Therefore, the characteristic of CN have impact on the CN fairness. The impact of CN characteristics on resource allocation needs to be evaluated.

3. How should the sharing protocols be designed to handle fairness problems? SPs have been designed to achieve effective control of shared demand and capacity among CNEs to maximize local and global objectives of CNEs. However, such protocols have ability to achieve effective resource allocation and shown good performance, they are limited in their capabilities of handling fairness in CN. SPs need a revision to capture fairness. There is no theory or framework proposed yet for design of SPs deal with fairness problems through distributed decision manner in dynamic, heterogeneous, and autonomous environment.

4. How can determine the degree of fairness when allocating demands and capacities among CNEs? CNEs aim to achieve fair resource allocation while maxi-

mizing local and global objectives simultaneously. The degree of fairness can cause unnecessary or inefficient collaborations, which require network resources and cost in terms of collaboration and transportation cost, can be avoided by a restrictive degree of fairness. Therefore, the degree of fairness must be defined dynamically to avoid current or potential inefficiencies in CN.

1.3 Significance of the Research

Collaborative network (CN) is a good way to be able to cope with changing market conditions and random conditions of demand patterns in terms of total profit, inventory cost, and lost sale cost. However, distribution of CN benefits should be considered as vital elements for CN sustainability. The fairness in CN can be increased by modifying the sharing protocol, and can be proper for the combination of any size of network or can be applied for all types of CN. For small and medium-sized enterprises, it will be more attractive to achieve high fairness index when an enterprise faces extraordinary demand patterns, large forecasting errors, and unreliable production capacity over time. In such conditions, by forming a CN to share their demands and capacities among collaborating members, rapid responsiveness of market changes and efficient production capacity utilization can be achieved while increasing the weight of fairness. Therefore, the degree of fairness in CN is investigated. The customer order acceptance with the consideration of fairness no longer be controlled by static, deterministic decision making of production planning and capacity planning, but rather on dynamic demand and capacity coordination with collaborative enterprises.

The main advantage of the proposed research is to maximize fairness in resource allocation among CNEs by maintaining their global efficiency. Mutual benefits of enterprise collaboration can be achieved, by sharing potentially rejected orders and accepting additional orders from collaborating enterprises. In addition, dramatic demand and capacity transitions can be fulfilled and total profits of collaborative members can be increased fairly. This research will moreover lead to a better understanding of fairness in enterprise collaboration especially in information sharing and distributed decision making processes of CNE in joint resource allocation control.

1.4 Assumptions

The assumptions for this study are summarized as follows.

1. All CNEs are considered to be non-competing.
2. All CNEs are considered to be autonomous and self-operating.
3. All CNEs do not have any authority on other enterprises.
4. Customer orders for each enterprise occur in discrete time periods.
5. Demand parameters are known for each CNE and follow a Normal distribution.
6. Products are non-perishable.
7. Coordination cost are same for all CNEs.
8. All CNEs are wiling to share their excess demand and capacity.
9. All products have same quality and are interchangeable; therefore, excess capacity and demand can be shared among CNEs.

1.5 Overview of the Research

Collaborative network is accepted as an efficient to overcome the changing market conditions and random conditions of demand patterns in terms of total profit, inventory cost, and lost sale cost. However, distribution of collaboration benefits should be considered as vital elements for collaborative network sustainability. Therefore, fair resource allocation among collaborative network of enterprises must be applied to reach a long term collaboration. The overview of research is described as follows. In Chapter 2, related research is reviewed such as collaborative network and applications, coordination in collaborative networks, and fairness in networked systems. The general decision making processes and details of methodology are presented in Section 3. Numerical examples and analyses are presented and discussed in Section 4. In Chapter 5, this dissertation is concluded with the conclusions and future work.

Chapter 2. Literature Review

2.1 Collaborative Network Concept and Applications

2.1.1 Collaborative Network Concept

Collaborative Network (CN) can be described by two basic concepts: "collaboration" and "network." The concept of "collaboration" refers to a process in which entities work jointly by sharing information, resources and responsibilities for joint planning. In addition, collaboration requires the enterprises to implement and evaluate a program of actions based on a communication protocol to obtain mutual benefits. On the other hand, the concept of a "network" is preferred by a variety of fields such as computer science, ecosystems, inventory and production systems, physics, and even education (Camarinha-Matos and Afsarmanesh, 2005). This concept can be described briefly as exchanging information and communication to obtain mutual benefits. A CN is modeled as a multi-agent system in Liu and Min (2008). In that study, a new approach to production planning is proposed to increase the punctuality of delivery of goods and the adaptability of global supply chain. The stability and sustainability of CNs are also commonly pursued topics among CN researchers; i.e., a new decision-making mechanism has been proposed to improve the identification and assessment of CN misalignment (Macedo and Camarinha-Matos, 2013).

2.1.2 Collaborative Enterprise Network

An enterprise is usually an independent organization; however, it cannot be viewed in isolation due to changing market conditions. In this context, a group of enterprises may form a CN when mutual benefits are anticipated. CNs refer to a set of independent enterprises collaborating under certain coordination and collaboration protocols to obtain mutual benefits (Nof, 2007). Therefore, enterprises can improve their stability given changing market conditions under certain protocols when orders of the enterprises cannot be satisfied with their own capacities and when the other enterprises have excess capacity to fulfill said orders (Yoon and Nof, 2010). In this research, the notion of a CN is applied to enterprise collaboration, and the principles of Collaborative Control Theory (CCT) are implemented to support effective CN design. Six principles of CCT have been defined by Nof (2007). These principles have been analyzed, verified and validated through various studies with the intention of enhancing the local and global mutual benefits. CCT is applied in many collaborative, computer-supported and communication-enabled activities performed by distributed groups of humans, robots or autonomous enterprises (Scavarda et al., 2015).

In recent years, CNs have been used effectively to obtain mutual benefits in diverse fields such as capacity and demand sharing, enterprise collaboration, supply chains, health care systems and information technologies (Yoon and Nof, 2010, 2011). When such enterprise collaboration is formed, the success of collaboration must be examined from a local and global economic perspective. The performance of CN depends on the design of well-defined coordination protocols that control information flows among collaborating enterprises and decision-making processes.

The decision-making processes in the design of coordination protocols are essential to the discovery of mutually acceptable and feasible agreements among collaborating members. In this context, collaborative planning in inventory/production distribution systems has been studied for a single organization (Thomas and Griffin, 1996). Also, enterprise collaboration is studied between organizations, which is identified by a non-hierarchical framework in which there is no total control on enterprises. Collaborative enterprises attempt to obtain mutual benefits by exchanging information, negotiation and collaboration. Information sharing and coordination in CNs under the multi-agent system approach is examined in Chan and Chan (2005). Many engineering disciplines have studied and adopted collaboration and coordination principles to improve their system performance (Ireland et al., 2002, Yoon and Nof, 2011).

Previous studies have shown that demand and capacity sharing protocols (DCSPs) are efficient in enhancing the CN profit, specifically when the random demand appears. DCSPs trigger the collaborating enterprises whenever excess capacity or shortages appear in CN; thus, each enterprise interacts cooperatively to obtain mutual benefits. Moreover, partner selection becomes more challenging due to the increased competition in the industry. Partner selection is based on various criteria, such as cost, efficiency, and consistency; more importantly, it should guarantee that the requirements of the collaborated enterprises are met (Khader et al., 2016). Therefore, best matching protocol (BMP) has been proposed to attain the best match among collaborating enterprises (Chiam and Nof, 2004). A multi-enterprise inventory model has been considered as an attractive collaboration model for study (Yoon and Nof, 2010, 2011). Moreover, BMP has been applied in different areas to ensure proper collaboration, i.e., supplier and partner selection, matching assembly parts, and matching distributed components and suppliers (Velásquez and Nof, 2008).

2.1.3 Homogeneous and Heterogeneous Collaborative Networks

In literature, HoCN and HeCN are two types of CN. HoCNs formed by identical enterprises. On the other hand, HeCNs are formed by different enterprises. The network heterogeneity is widely studied in different aspects such as enterprise culture, resource transformation, knowledge access (Ahuja, 2000). In particular, heterogeneity could be assumed as different enterprises in terms of inventory levels, product price and cost structures in addition different customer demand patterns (Galeotti et al., 2006). In this research, network heterogeneity bases on the enterprises' capacities and demand distribution also based on enterprises' capacities.

The objective of forming a CN is usually to maximize both network (global) and enterprise (local) profit or to minimize the effects of changing market conditions. Enterprises achieve mutual goals only through well-designed protocols which imply that decision-making processes in CN. However, during collaboration process, each enterprises often encounter a dilemma concerning fairness and efficiency: the apparent need to choose between fairness and efficiency.

2.2 Coordination in Collaborative Networks

Information sharing play a vital role in CNEs coordination and enhancing the collaboration among the enterprises (Cruz Di Palma and Scavarda Basaldúa, 2009). The success of any CN is the degree of cooperation function among the integrated sub-systems especially for complex, highly distributed and collaborative sub-systems. In addition, integration and cooperation become more necessary (Anussornnitisarn et al., 2005). Coordination among CNEs is supported by coordination protocols such as demand and capacity sharing protocol (DCSP) is proposed in Yoon and Nof (2010), best matching protocol (BMP) is proposed in Velásquez and Nof (2008), task allocation protocol (TAP) is proposed in Ko and Nof (2010). Such protocols have been designed to achieve effective control among CNEs and to reach local objectives of each enterprises and global objectives (mutual benefits) in CN (Ko and Nof, 2010). Coordination protocols could be divided to four subsets which are 1) Static-centralized, 2) Static-distributed, 3) Dynamic-centralized, and 4) Dynamic-distributed protocol. Enterprise collaboration investigated in literature from variety of sharing protocols as shown in Table 2.1.

Table 2.1: Coordination protocols in CN

	Centralized	Distributed
Static	Adida et al. (2011) Lopez et al. (2016) Schleich et al. (2017)	Yoon and Nof (2010) Yoon and Nof (2011) Seok and Nof (2014a) Jahanpour et al. (2016)
Dynamic	Nof and Chen (2003) Mahdavi (2010) Neapolitan and Naimipour (2010) Zhong et al. (2013) Dommel et al. (2015)	Ko and Nof (2012) Seok and Nof (2014b) Zhang et al. (2015)

2.2.1 Centralized Coordination in Collaborative Networks

In terms of the centralized decision-making, the proposed CNs need complete information from all participants of CN i.e., each CNEs send their current invontery level information to central decision maker. It is possible that if CN has complete information, it is highly possible that decision making can provide more effective management to CN, such as reallocating excess inventory and demand among CNEs, and high performance in reducing local and global costs (Adida et al., 2011, Schleich et al., 2017). However, CNEs need to give their response without any centralized control due to their autonomous business process. Therefore, a centralized decision making among autonomous and self-operating enterprises seems unrealistic.

2.2.2 Distributed Coordination in Collaborative Networks

During recent years business environments have been transform from only one organization to a network distributed organizations (Ko and Nof, 2010). In such distributed environments, the success of collaboration depends on effective coordination to solve sharing problems in a collaboration manner. In this context, there have been numerous studies in distributed problem solving by multiple agents to show a good performance in terms of computational efficiency, stability, utilization of resources, robustness, and flexibility, compared to the centralized decision-making (Bozdag, 2008, Scavarda et al., 2015).

In the context of a highly distributed, network environment, enterprises must act autonomously, interact with other enterprises for a local or global objective by sharing information (Ko and Nof, 2010). CNEs have ability of self-operating without any direct intervention of other enterprises or authority and have control on their internal operation state and external actions with other enterprises.

2.2.3 Static Coordination in Collaborative Networks

In CN research, coordination protocols are designed as static over time period (Yoon and Nof, 2010, Seok and Nof, 2014a, Jahanpour et al., 2016). Static CNs assume that all conditions in a CN remain stable over collaboration time period. CN could not respond to dynamic changes in market conditions by changing network topology or collaboration partners over collaboration time period. For example, if a same specific condition occurs at $t = t_1$ and $t = t_2$, then the collaboration decisions remain stable CNE in both time periods, because previous collaborations at time $t = t_1$ recorded as achieving mutual benefits based on the static coordination mechanism. Therefore, static network could not evaluates collaboration partners dynamically over collaboration time period.

2.2.4 Dynamic Coordination in Collaborative Networks

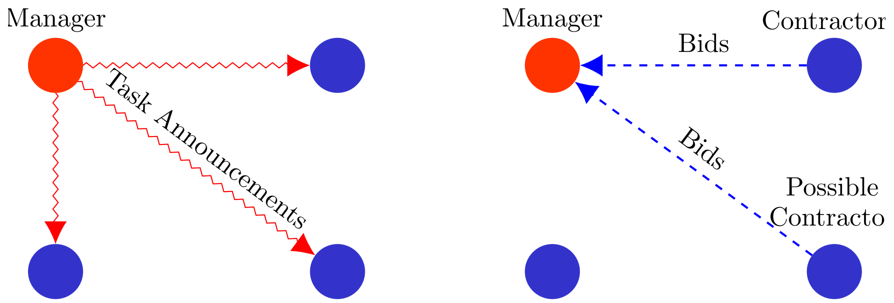
The dynamic nature of market demand pattern, uncertain condition and requirements, and unexpected production problems require to be able to response the changing environments. This situation needs for dynamic in terms of re-configurable collaborations, and distributed in terms of decision making mechanism coordination protocols. Therefore, CNEs can perceive their environments and react to the dynamic environmental changes rapidly and be able to learn from their experience and capable of adapting to the changes in the environment to improve themselves (Huang and Nof, 2002). Due to the such properties, CNs are used in variety areas, including manufacturing and service systems, supply chain management, multi-robot systems, assembly line balancing, smart-grid applications, etc.

CNEs have exclusive information to pursue its local objectives and try to obtain required information by communicating with other enterprises to make a contribution to reach global objectives. Although all of information available in a CN, CNEs, which have enough information, did not know to share it with other CNEs which needs the information. In addition, a CNEs which need the information do not know whom to ask for the information (Schwemmer and Havrilla, 2011). That is the reason why distribution of information in a CN is a crucial problem. In this study, it is suggested that a way of knowing which enterprise needs what capacity and which enterprise access to excess capacity.

2.2.5 Contract Net Protocol

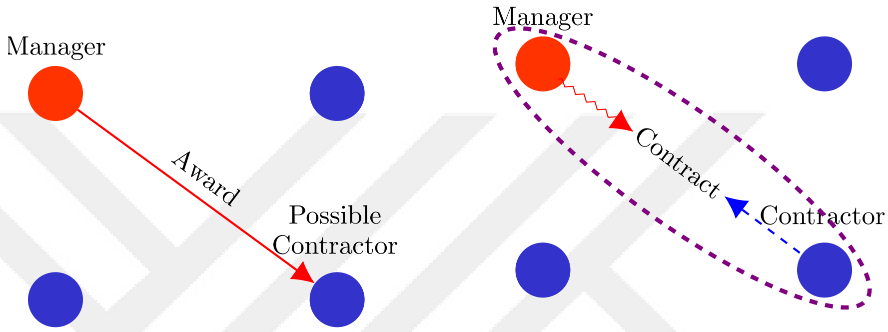
Contract Net Protocol (CNP) which is one the well-known coordination protocol in distributed scheme. In CNP, there is no central decision maker i.e., there is no central authority in total control of other enterprises (Smith and Davis, 1981). Also, each enterprise has limited information to solve global problem. In general, CNP assign responsibilities such as managers which have tasks to complete and contractors which are candidates for acquiring task, to each nodes (enterprises) in a network.

The situation of nodes as managers or contractors are not assigned a priori role. Each node can take on either role dynamically during collaboration time period (Bozdag, 2008). The negotiation process in CNP, which is market place approach, begins by managers' task announcements and contractors examine the task and sub-



(a) Sending a task announcement

(b) Bidding



(c) Bid evaluation and awarding

(d) Making contract

Figure 2.1: Steps of Contract Net Protocol

mit reasonable bids to the manager. After the manager receive all bids, the manager evaluates the bids and select the most appropriate bid. At the end of negotiation, manager select its contractor and award contract which is established by the mutual selection based on a two-way negation. CNP has four main steps: 1) task announcement, 2) bidding process, 3) evaluation of bid and awarding, and 4) making contract as shown in Figure 2.1.

2.3 Fairness in Networked Systems

2.3.1 Types of Fairness Measures in Networked Systems

Fairness measures are taking more attention than ever before. In the field of networking, various fairness measurement techniques have been proposed. These techniques are apparent a wide range from simple measures, such as, the min-max ratio between the biggest and smallest entries (Marsan and Gerla, 1982), to complicated functions, such as, *Ji* (Jain et al., 1984) and entropy function (Shannon, 1948).

The min-max ratio is calculated by ratio between resource allocations of any two entries. A feasible allocation in min-max fairness is every entity could only be allocated a certain amount of resource. The min-max ratio is defined as a feasible allocation in which each entity cannot increase its resource without decreasing another entity's resource allocation. Fairness ratio should be 1, if the ratio is lower than 1, then the network accepts as unfair. Min-max fairness is also know as bottleneck optimality, and has been widely used in computer science applications such as radio channel accessing, flow control, bandwidth sharing (Jain et al., 1984, Radunović and Boudec, 2007). Similar to min-max fairness, max-min fairness is proposed in Radunović and Boudec (2007). Max-min fairness is reached if the resource allocation is feasible. In addition, max-min fairness aims to maximize the resource allocation of any entries necessarily results in a minimize the allocation of other entries with a same or small allocation (Le Boudec, 2005).

Ji was proposed in Jain et al. (1984), and computes a normalized square mean to find the system fairness. Four properties of *Ji* were defined as 1) The index should be independent of population size; 2) The index should be finite and the ratio could be between 0 and 1, where 0 implies the most unfairness point and 1 implies the most fair point; 3) The index should be continuous on resource allocations among involved entities and should have ability to measure different resource allocations; 4) The index should not be depended on scale and metric, which implies that the index is not effected by any changing with measures and metrics (Jain et al., 1984). *Ji* is a well-known fairness measures and widely studied to get insight into the overall network fairness. However, *Ji* does not consider unfairly treated entities in the network. Complete information of the resource allocation is required to compute the fairness index. In addition, *Ji* could be modified to compute multiple resource allocation fairness by weighting the resources in network. Therefore, Ji could be applied in different research fields, and shows that the resource allocation in network tends to be fairer when Ji is closer to 1 (Shi et al., 2014).

Shannon Entropy calculates the expected value (average) of the amount contained in each entity. Shannon Entropy focuses on uncertainty of the resource allocation, and measure of unpredictability of the state. However, Shannon Entropy is widely studied, especially in information sciences, the quality of measuring the fairness has doubts because the sensitivity of function is not clear. There is no boundedness for fairness measurement. For example, Ji is a ratio between 0 and 1. In Shannon Entropy, the unfair and fair points are not clear to define whether the network is fair or not. Shannon Entropy states that if the entropy is larger then resource allocation in network is fair, but this statement is clear as comparing different networks. Also, the unfairness is not located in Shannon Entropy. Similar to Ji, Shannon Entropy requires complete information of resource allocations among entities (Lin, 1991).

The simple measures and its various weighted versions are used to allocate throughput to research optimal service. Some fairness measures imply that a large value indicates greater fairness. Some other measures work in between 0 and 1, where the minimum point of fairness is 0, the maximum point of fairness is 1 (Lan et al., 2010).

Beside these proposed measures, a theoretic concept of α fairness is gaining the networking research community attention. The new concept try to optimize the α fairness and network efficiency simultaneously. A maximizer of the U_α try to maximize the α fairness under a given set of feasible allocations. The generalized α fairness function cover two well-known utility function are as follows: 1) log utility function ($\alpha = 1$), and 2) max-min fair utility function ($\alpha \rightarrow \infty$). Once more, varied measures are being derived from U_α (Uchida and Kurose, 2011).

Fairness is considered in various fields with different axioms, such as information theory, where the Renyi entropy generalized form of the Shannon entropy, which quantifies the diversity, uncertainty, or randomness of a system. The Renyi entropy is important in ecology and statistics as an index of diversity (Renyi, 1961). The Renyi entropy contains the following set of five axioms: 1) Symmetry, 2) Additivity, 3) Mean-value property, 4) Continuity, and 5) Normalization. On the other hand, the Lorenz Curve has been used mainly in economics in terms of the characterization of relative income differences and the social welfare distributions. An axiomatic characterization of Lorenz-curve derived from four axioms: 1) Transitive and complete, 2) Dominance, 3) Continuity, and 4) Independence (Aaberge, 2001). In the economic study of groups, the Shapley value is another well-known fairness concept (Shapley, 1953). Shapley value has also its specific axioms which are: 1) Pareto Optimality, 2) Dummy, 3) Symmetry, and 4) Additivity.

2.3.2 Characteristic of Fairness Measurements

Each fairness measurement has different characteristics and requirements. The basic requirements of a fairness measure are defined in (Shi et al., 2014). A quantitative fairness measure ($F(A_k)$) must be:

R1: Continuous,

R2: Independent of network size,

R3: Range of fairness index should be easily mapped on to $\{0, 1\}$,

R4: Easily extendable to multi-resources case,

R5: Easy to implement,

R6: Sensitive to the variation of A_k (Shi et al., 2014).

A variety of metrics are applied to quantify fairness measures, e.g., Ji (Jain et al., 1984), which is used in this research to show whether enterprises are receiving a fair share of network resources. The U_α controls the balance between fairness and efficiency. On the other hand, the efficiency of the network is measured by (Watts and Strogatz, 1998, Latora and Marchiori, 2001). In their research, the authors proposed how efficiently networked entries exchanges information and the concept of efficiency can be applied at both the local and global scale in a network.

Each fairness measure has some advantages and disadvantages. For example, some measures need complete information on the other hand some of them do not need. Comparison of fairness measures is summarized in Table 2.2.

Table 2.2: Comparison of fairness measures (revised from (Shi et al., 2014)).

Models	Jain's Index	Entropy	Max-min	Proportional	Tian Lan's
Definition	Yes	No	Yes	Yes	Yes
Measurability	Yes	Yes	No	No	Yes
Locating Unfairness	No	No	No	No	No
Weight	Yes	No	Yes	Yes	No
Utility	No	No	No	Yes	No
Data	Full	Full	Either	Full	Full
Requirements	R1-R6	R1,R2,R5, R6	No	No	R1,R2,R3,R6
Algorithm	Simple	Simple	Simple	Medium	Complex

In Table 2.2, definition refers to whether definition of fairness is placed or not. Measurability defines how to compute the fairness in a network. Locating unfairness implies what happens in case of the unfairness. Weight defines priorities in resource allocation. Utility considers the reflection of tradeoff between efficiency and fairness. Data defines whether the measure needs all network data or not. The complexity of the algorithm defined as simple, medium, and complex (Shi et al., 2014).

2.3.3 Fairness in Collaborative Networks

Overall CN fairness emphasizes the overall fairness among CNEs in CN. On the other hand, individual fairness address whether a specific enterprise is benefited fairly by the CN. For example, in case of the six-enterprise CN assumed that five enterprise

Table 2.3: Review of some existing models.

Literature	Decision Criteria	Fairness	Methodology
Liu and Min (2008)	On-time delivery	No	N/A
Chen et al. (2008)	Capacity sharing	No	N/A
Abreu and Camarinha-Matos (2008)	Profit Distribution	Yes	Shapley value
Yoon and Nof (2010)	Capacity sharing	No	N/A
Adida et al. (2011)	Minimize cost	No	N/A
Yoon and Nof (2011)	Capacity sharing	No	N/A
Renna and Argoneto (2011)	Capacity sharing	No	N/A
Scavarda Basaldua (2012)	Task Allocation	No	N/A
Ko and Nof (2012)	Task Allocation	No	N/A
Macedo and Camarinha-Matos (2013)	Network stability	No	N/A
Seok and Nof (2014b)	Cost/Profit Allocation	Yes	Variance
Zhong et al. (2013)	Time-cycle minimization	No	N/A
Moghaddam and Nof (2014)	Profit distribution	No	N/A
Zhang et al. (2015)	Task Allocation	No	N/A
Dommel et al. (2015)	Network efficiency	No	N/A
Scavarda et al. (2015)	On-time delivery	No	N/A
Bertsimas and Gupta (2016)	Distribution of Delays	Yes	Optimization
Jahanpour et al. (2016)	Network sustainability	No	N/A
Lopez et al. (2016)	Resource utilization	No	N/A
Schleich et al. (2017)	Cost/Profit Allocation	Yes	Variance
Yilmaz et al. (2017)	Total profit	Yes	α-utility

ask capacity from one enterprise which has enough capacity for the five enterprises. If overall CN fairness can be defined as equal allocation of network resources i.e., each enterprise which needs capacity gets 20% and then the CN reaches the fairness. However, an enterprise can reach individual fairness without considering other enterprises. Also, if an enterprise needs only 10% of resources and the enterprise accept the CN is fair when it gets the 10% of network resources. When a CN reaches overall fairness, all enterprises should reach the individual fairness (Shi et al., 2014).

A fair resource allocation in CNs has not been taken as the same attraction of researchers as computer networks. The brief summary of existing research on CN and the consideration of fairness on the literature are shown in Table 2.3.

In this study, demand fulfillment rate of each CNEs is chosen to measure overall collaborative network fairness, and amount of shared capacity and demand is chosen as fairness criteria to measure local fairness. The aim of measuring local fairness, during negation process each CNEs gives priority based on its historical report to other enterprises, which are possible collaborators in collaboration time period.

2.4 Summary and Open Research Questions

Most of research in collaborative network has focused on enterprise collaboration within a supply network, and it is assumed that existence of an independent decision-maker who has a global view and authority for entire supply chain. Thus, only centralized models are emphasized under allowance of clear and complete information sharing. Centralized models have usually emphasized coordination under allowance of clear and complete information sharing among members, which is impractical to apply in any given distributed manufacturing and supply systems. A set of enterprises forms a CN, and each member of the CN has decentralized, distributed decision criteria to maximize individual objectives. The fairness in demand and capacity sharing coordination is the main focus of this research and it is based on information sharing and distributed decision-making protocols. In this research, it is assumed that a set of independent enterprises collaborate with others, such that a limited amount of information sharing has been considered. Fairness measurements and assumptions are extended from computer science research.

Chapter 3. Methodology

3.1 A Framework and Algorithm for Fair Demand and Capacity Sharing in Collaborative Network

3.1.1 Introduction

In the literature, computer science or business management researchers have given a lot of importance to fair resource attraction in computer networks. The resources in computer networks originate from out of the network; in other words, the proposed papers attempt to find a fair allocation of "external resources." On the other hand, CNs' resources originate from networked enterprises; in other words, this research attempts to find a fair allocation of "internal resources." A fair resource allocation in CNs has not been taken as the same attraction of researchers as computer networks. In this study, the distributed decision protocol was developed for collaborative enterprises with a well-balanced collaboration via a fair redistribution of mutual benefits. The brief summary of existing research on CN and the consideration of fairness on the literature are shown in Table 2.3. This results in two subsets in CNEs: a subset of capacity-sharing enterprises and a subset of demand-sharing enterprises. Both subsets must be considered simultaneously when measuring fairness in CNs.

3.1.2 Collaborative Network

This research examines fair resource allocation and collection in HeCN and HoCN network models that consider Ji and U_α, with the details of the CN models which are presented as follows: A CN is given a quadruple notion, which is a pair of triples of the network properties and network value $(< E, O, \zeta_{kl} >, P(CN))$, where $E = \{e_1, \ldots e_i, e_j, \ldots e_k\}$ and $O = \{obj_1, \ldots, obj_l\}$ are sets of enterprises and objectives in CN, respectively. Each enterprise has an associated finite set of value-related actions, ζ_{ijl}, corresponding to the relationships between each e_i and e_j to obtain the l^{th} mutual objective. $P(CN)$ is a profit function of a CN, which is a sum of value-related actions.

Definition 1. *Every enterprise has a unique protocol-driven action set. The action set of* e_k*,* $A_k = \{\zeta_{kl} | k = 1, 2, \ldots, K; l = 1, 2, \ldots, L\}$*, is a collection of actions between enterprises for different 'L' objectives. The actions are in one-to-one correspondence with an enterprise's individual relationship in the CN such as demand and capacity sharing.*

Definition 2. *Every enterprise has a value function* $P(e_k)$*, that is derived from interactions of enterprises as they attempt to achieve a mutual objective.*

To explain how the value function is derived, the n-tuple concept is used and $P(e_k)$ is explained in two different ways, as follows:

1) As a unique extension of the n-tuples of 'L' objectives with a specific enterprise. This extension is represented by $\phi_k = \{\rho_{k1}, \rho_{k2}, ..., \rho_{kl}\}$, where $\rho_{kl} = \sum_{l=1}^{L} \zeta_{kl}$. In this way, $P(e_k)$ is calculated via the sum of actions used to achieve mutual objectives.

2) As a unique extension of the n-tuples of 'K' entities for a specific objective. This extension is represented by $\varphi_k = \{\varrho_{k1}, \varrho_{k2}, ..., \varrho_{kj}\}$, where $\varrho_{ij} = \sum_{i=1}^{I} \zeta_{ijl}$. Thus, $P(e_k)$ is computed based on actions with other entities to achieve a specific objective.

If the elements of ϕ_k substitute with $\rho_{kl} = \sum_{l=1}^{L} \zeta_{ijl}$, then the set of ϕ_k becomes $\phi_k = \{\sum_{l=1}^{L} \zeta_{i1l}, \sum_{l=1}^{L} \zeta_{i2l}, ..., \sum_{l=1}^{L} \zeta_{ijl}\}$, where the opened version of such a set is determined as

$$\phi_{kl} = \begin{bmatrix} \zeta_{i11}, & \zeta_{i12}, & \cdots & , \zeta_{i1l}, \\ \zeta_{i21}, & \zeta_{i22}, & \cdots & , \zeta_{i2l}, \\ \vdots & \vdots & \ddots & \vdots \\ \zeta_{ij1}, & \zeta_{ij2}, & \cdots & , \zeta_{ijl} \end{bmatrix}. \tag{3.1}$$

The substitution again is applied to elements of φ_k with $\varrho_{ij} = \sum_{j=1}^{n} \zeta_{ijl}$; then, the set of φ_k becomes $\varphi_k = \{\sum_{j=1}^{n} \zeta_{ij1}, \sum_{j=1}^{n} \zeta_{ij2}, ..., \sum_{j=1}^{n} \zeta_{inm}\}$, where the opened version of such a set is determined as

$$\varphi_k = \begin{bmatrix} \zeta_{i11}, & \zeta_{i21}, & \cdots & , \zeta_{ij1}, \\ \zeta_{i12}, & \zeta_{i22}, & ..., & \zeta_{ij2}, \\ \vdots & \vdots & \ddots & \vdots \\ \zeta_{i1l}, & \zeta_{i2l}, & ..., & \zeta_{ijl} \end{bmatrix}. \tag{3.2}$$

Then, it will be obvious from a comparison of Eqs. (3.1) and (3.2) that these two sets are the same; therefore, the sum of the set elements will be equal to each other, $P(\phi_k) = P(\varphi_k)$, which is determined as in Eqs. (3.3a) and (3.3b):

$$P(\phi_k) = \sum_{j=1}^{J} \rho_{ij} = \sum_{j=1}^{J} \sum_{l=1}^{L} \zeta_{ijl} \tag{3.3a}$$

or

$$P(\varphi_k) = \sum_{l=1}^{L} \varrho_{il} = \sum_{l=1}^{L} \sum_{j=1}^{J} \zeta_{ijl} \tag{3.3b}$$

$P(\phi_k) = P(\varphi_k)$ can be used to determine the value function of e_k, $P(\phi_k) = P(\varphi_k) = P(e_k)$. The value function of the CN is a collection of all the value functions of the entities, which is determined as

$$P(CN) = \sum_{k=1}^{K} P(e_k), \tag{3.4}$$

where $P(e_k)$ represents the value function of e_k and $P(CN)$ is calculated through the sum of all actions in the CN, which is determined as

$$P(CN) = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} \zeta_{ijl}, \tag{3.5}$$

where ζ_{ijl} represents the action of e_i with e_j for the l^{th} objective.

To simplify some of the equations, additional notations are given as follows: $(\phi_k; \Phi_{kl'})$ stand for $(\rho_{k1}, ..., \Phi_{kl'}, ..., \rho_{kl})$, where $\phi_k = (\rho_{k1}, \rho_{k2}, ..., \rho_{kl})$, and $(\varphi_k; \Psi_{kj'})$ stand for $(\varrho_{k1}, ..., \Psi_{kj'}, ..., \varrho_{kj})$, where $\varphi_k = (\varrho_{k1}, \varrho_{k2}, ..., \varrho_{kj})$, in which ϕ_k and φ_k are introduced as an n-tuple of the action sets of e_k and $\Phi_{kl'}$ and $\Psi_{kj'}$ denote a specific action.

e_k wants to maximize its value if and only if the actions of all entities are based on the determined protocol. Therefore, each enterprise's actions are appropriate to those of the other enterprises. Each enterprise attempts to obtain the maximum value from every objective and every relationship between other enterprises. The objective of e_k is determined as

$$P(\phi_k) = \max \forall_{kl'} [v(\phi_k; \Phi_{kl'})] \tag{3.6a}$$

or

$$P(\varphi_k) = \max \forall_{kj'} \left[v(\varphi_k; \Psi_{kj'})\right]. \tag{3.6b}$$

In addition, the CN attempts to obtain the maximum value as follows

$$P(CN) = \max \forall_{kl} \left[\sum_{l=1}^{L} v(\phi_l; \Phi_{kl'}), \sum_{j=1}^{J} v(\varphi_i; \Psi_{kj'}) \right]. \tag{3.7}$$

The main purpose of forming a CN is to create value and obtain mutual benefits. The created value is considered not only by an enterprise but also by the CN. The enterprise considers and analyzes benefits of the network. If e_k produces a better value than its individual actions, then e_k decides to affiliate itself with the CN. The decision of e_k is based on the following necessary and sufficient condition:

$$\sigma_{P(e_k)\geq 0}(E, O, P(CN)), \tag{3.8}$$

where σ represents the select operation and applied to select a subset of the n-tuples which satisfies a selection requirement: $P(e_k) \geq 0$.

Figure 3.1 represents a sample of a four-enterprise CN, where $E = \{e_1, \dots e_4\}$, $L = 2$, $\zeta_{ijl} = 7$ and $P(CN) = 20$ ($i = 1, ..., 4$, $j = 1, ..., 4$ and $l = 1, 2$). The lines among collaborative enterprises represent Objective-1 (demand sharing) and Objective-2 (capacity sharing), respectively. If an arrow goes from e_i to e_j, which refers to the value of e_i comes from e_j.

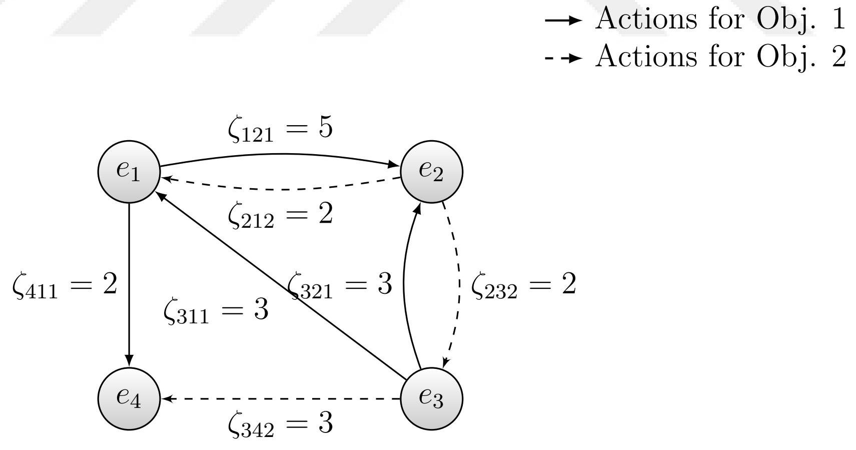


Figure 3.1: A sample collaborative network ($< 4, 2, 7 >, 20$)

.

Suppose that a CN is formed by K enterprises and that each enterprise satisfies its own customer orders, o_{kt}, with the quantity at each time period. In the case of collaboration, the demand sharing enterprise that receives the products from CN will be responsible for the cost of the collaboration, which must be less than the shortage/lost sale cost, L^c. However, the demand sharing enterprise will receive the products at reduced price, which is the aggregated price in the CN, p^c. On the other hand, the capacity sharing enterprise will suffer a coordination cost, which must be less than the inventory cost, I^c. However, it will receive a reward from sharing these products with CN at a price, p^c.

3.1.3 Demand and Capacity Sharing Protocols

In this research, a special case of external collaboration is applied as in Yoon and Nof (2011), Seok and Nof (2014a,b). This special case can be defined as demand and capacity sharing among independent, self-operative and geographically distributed enterprises. Although CNEs produce similar types of products, it is assumed that they are not competitors with each other. These enterprises meet their own customer demands from different markets or regions, and they focus on their own profits. These types of enterprises attempt to enhance their sustainability through minimizing outdated inventory by reducing idle capacity and to increase market responsiveness by minimizing lost sales. During the collaboration process, enterprises with extra capacity help enterprises that do not have sufficient capacity to meet their demands.

A CN consists of a set of collaborative networked enterprises, $E = \{e_1, \ldots, e_k\}$, in which each e_k seeks to maximize its local objectives by satisfying its customer orders, $o_{kt} = \{q_{kt}, t^d\}$, where q_{kt} is the order quantity and t^d is the order due date. Each e_k evaluates its o_{kt} with respect to its capacity, $m(o_{kt})$. If an e_k has $q_{kt} > m(o_{kt})$ at time t, then it becomes a capacity-sharing enterprise, e_i; if $m(o_{it}) > q_{it}$, then the e_k becomes a demand-sharing enterprise, e_j. Therefore, E is a union of two disjoint sets: $E^+ = \{e_1, \ldots, e_i\}$ and $E^- = \{e_1, \ldots, e_j\}$.

During a collaboration time period, τ, there is no a priori role assigned to any e_k, such as being an e_i or e_j; i.e., an e_k could be either an e_i or e_j based on o_{kt} and $m(o_{kt})$. Thus, $\forall e_k \in E$ achieves mutual benefits by dynamically forming a CN; an e_j

requests capacities, $r(o_{jt})$, from $\forall e_i \in E^+$ to fulfill o_{jt}.

$$r(o_{jt}) = \max\left(0,\ q_{jt} - m(o_{jt})\right) \tag{3.9}$$

The requested capacity, $r(o_{jt})$, is defined in Eq. (3.9). An e_j prepares a demand-sharing proposal, ω_j, to announce its requests, such as $r(o_{jt})$, and due date information, t^d, to complete o_{jt}. ω_j can be defined as

$$\omega_{jt} = (r(o_{jt}),\ t^d). \tag{3.10}$$

Meanwhile, over τ, a self-interested e_i collaborates with an e_j to maximize its local objectives by sharing its excess capacities, $s(o_{it})$, which is defined as

$$s(o_{it}) = \max(0,\ m(o_{it}) - q_{it}). \tag{3.11}$$

e_i send its $s(o_{it})$ by announcing a capacity sharing proposal, Γ_{it} with lead time information, t^{lt}. Γ_{it} is defined as

$$\Gamma_{it} = (s(o_{it}), t^{lt}). \tag{3.12}$$

If CNEs are aggregated with a collaboration, the shared amount of capacity, $n(o_{kt})$, is determined as

$$n(o_{kt}) = \min(r(o_{kt}), s(o_{kt})). \tag{3.13}$$

The pseudocode of this collaboration is presented in *DCSP* Pseudocode. *DCSP* helps CNEs to fulfill their demands, o_{kt}, when mutual benefits can be obtained among the collaborative enterprises. e_j fulfills its own demands by taking a capacity form e_i, and e_i receives the additional demand from e_j (Yoon and Nof, 2011).

```
$DCSP$ Pseudocode
Step 1.  Calculate $r(o_{jt})$ and $s(o_{it})$ $\forall e_k \in E$ starting with
         $e_k$ which has the highest demand at time $t$
Step 2.  Analyze $r(o_{jt}) > 0$ and $s(o_{it}) > 0$
    2.a.  If $r(o_{jt}) > 0$, then send $\omega_{jt}$
    2.b.  If $s(o_{it}) > 0$, then send $\Gamma_{it}$
          Otherwise, go to Step 7
Step 3.  Analyze $\omega_{jt}$ and $\Gamma_{it}$ $(i \in E^{-}, j \in E^{+}, t \in \tau)$.
    3.a.  Check if $r(o_{jt}) > 0$ and $s(o_{it}) > 0$, then go to Step 4.
          Otherwise, go to Step 7
    3.b.  Check if $s(o_{it}) > 0$ and $r(o_{jt}) > 0$, then go to Step 5.
          Otherwise, go to Step 7
Step 4.  Request $s(o_{it})$ from $e_i$ and go to Step 6.
Step 5.  Request $r(o_{jt})$ from $e_j$.
Step 6.  Update $I_{kt}$, $H_{it}$ and $L_{jt}$. Go to Step 1.
Step 7.  Terminate algorithm.
```

3.1.4 α-Utility Function (U_α)

Two concepts are applied in this research to discover a balance between fairness and efficiency in sharing protocols: generalized U_α and Ji. The other fairness indexes or utility functions, e.g., the Atkinson's Index and the Shannon entropy, are not appropriate for calculating the CN fairness index since they are based on computer networks and require more notifications to use in the CN. In computer networks, the resources come from out of network; in other words, they attempt to find a fair allocations of "external resources." In CNs, the resources come from networked enterprises; in other words, they attempt to find a fair allocations of "internal resources." This produces two subsets in CNs: the capacity sharing subset and the demand sharing subset. Therefore, other fairness indexes or utility functions must be greatly modified to be applied in CNs; even if the U_α and Ji require modification, their application is more appropriate. Preserving Pareto optimality for the U_α is shown in Lan et al. (2010). The U_α is described as follows:

$$U_\alpha\left(\sum_{k=1}^{K} A_k^*\right) = \begin{cases} \dfrac{\sum\limits_{k=1}^{K}\left(A_k^*\right)^{1-\alpha}}{1-\alpha}, & \text{if } 0 \leq \alpha < 1 \\ \log\left(\sum\limits_{k=1}^{K} A_k^*\right), & \alpha = 1. \end{cases} \tag{3.14}$$

U_α contains two components: 1) fairness, and 2) efficiency. It implies that U_α corresponding to fairness measure and efficiency, simultaneously. Then, it can be demonstrated that the factorization of U_α for a fixed α shows a specific point on the optimal tradeoff curve between fairness and efficiency (Lan et al., 2010). In this research, α is not used bigger than 1, because U_α does not provide statistically significance results in these experiments. Rearrangement of Eq. (3.14) defined as

$$\begin{aligned} U_\alpha(A_k^*) &= \frac{1}{1-\alpha}|f_\alpha(A_k^*)|^\alpha \left(\sum_{k=1}^{K} A_k^*\right)^{1-\alpha} \\ &= |f_\alpha(A_k^*)|^\alpha U_\alpha\left(\sum_{k=1}^{K} A_k^*\right), \end{aligned} \tag{3.15}$$

where $U_\alpha\left(\sum_{k=1}^{K} A_k^*\right)$ is a univariate version of the α-fair utility function with $\alpha \in [0, \infty)$ (Lan et al., 2010). $f_\alpha(A_k^*)$ refers to fairness function and captures proportional fairness at $\alpha = 1$ and max-min fairness at $\alpha \to \infty$. A fairness and efficiency measures are captured in Eq. (3.15) ($f_\alpha(A_k^*)$ and $U_\alpha\left(\sum_{k=1}^{K} A_k^*\right)$, respectively). The fairness measure bases on the normalized distribution of resources. On the other hand, efficiency measure consider only the sum resources. The factorization of α-fair utility function is illustrated in Table 3.1. The efficiency component skews the optimizer away from an equal allocation. On the other hand, fairness component increase the fairness. For this to happen, the resource allocation vector should be feasible over all allocation allocations the relative importance of fairness and efficiency. In this study, importance of fairness and efficiency are considered as equal.

Table 3.1: Illustration of α-fair utility function factorization (from Tian et al., 2008)

Allocation	A_k^*	
Factorize	$\frac{A_k^*}{\sum_{k=1}^{K} A_k^*}$	$\sum_{k=1}^{K} A_k^*$
Measure	$f_\alpha\left(\frac{A_k^*}{\sum_{k=1}^{K} A_k^*}\right)$	$U_\alpha\left(\sum_{k=1}^{K} A_k^*\right)$
Combine	$U_\alpha\left(A_k^*\right)$	

3.1.5 Jain's Fairness Index

Ji is used to calculate the overall fairness measure in the CN. Fairness became an important consideration in various societies of life such as teams, groups or networks. Especially in distributed systems, where a group of users shares a set of resource, fair resource allocation is important to the collaboration in long-term aspect. Ji has four properties: 1) Population size independence, 2) Scale and metric independence, 3) Boundedness and 4) Continuity (Jain et al., 1984). Ji could be applied in different research fields, and shows that the resource allocation in network tends to be fairer when Ji is closer to 1. In this research, Ji is applied for demand sharing enterprises and capacity sharing enterprises simultaneously to calculate CN fairness measure. Ji is computed as

$$Ji = \frac{\left(\sum_{k=1}^{K} \overline{\lambda}_{kt}\right)^2}{K \cdot \sum_{k=1}^{K} \left(\overline{\lambda}_{kt}^2\right)}, \tag{3.16}$$

where the demand fulfillment rate λ_{jt} for $r(o_{jt})$, which is defined as

$$\lambda_{jt} = \frac{n(o_{jt})}{r(o_{jt})} \tag{3.17}$$

or the capacity utilization rate λ_{it}

$$\lambda_{it} = \frac{n(o_{it})}{s(o_{it})}. \tag{3.18}$$

3.1.6 Demand and Capacity Sharing Protocol with U_α

If interpretation of fairness is accepted as sharing network resources equally among the enterprises, then all collaborating enterprises achieve the same amount. For example, CN resources are allocated among two enterprises equally with the rate of 0.5, as shown in Figure 3.2. This allocation of rates may cause an unsatisfied demand or overstock among the networked enterprises. For example, if e_1 needs less rate than 0.5, then it will face an overstock at the end of period. On the other hand, if e_2 needs more rate than 0.5, then it will face an unsatisfied demand at the end of period. Therefore, this interpretation of fairness will reduce network efficiency (Daniel and Narayanan, 2013). Because this will ensure that a given volume of capacity is transferred sooner than in the case of equal sharing, this allocation is better for the network.

A basic requirement of any efficient resource-sharing principle has to satisfy Pareto efficiency. Pareto efficiency is described as an allocation of resources in a system if no other allocation can make some user better off and simultaneously none of the other users worse off. In other words, if any enterprise's resource allocation cannot be improved without making other enterprise's resource allocation smaller. A resource allocation vector in CN, A_k^*, if Pareto dominated by A_k^* then $A_k^* \leq A_k$ for all e_k and $A_k < A_k^*$ for at least one k. If a resource allocation is not Pareto dominated by any other feasible allocation, then the allocation is accepted as Pareto optimal.

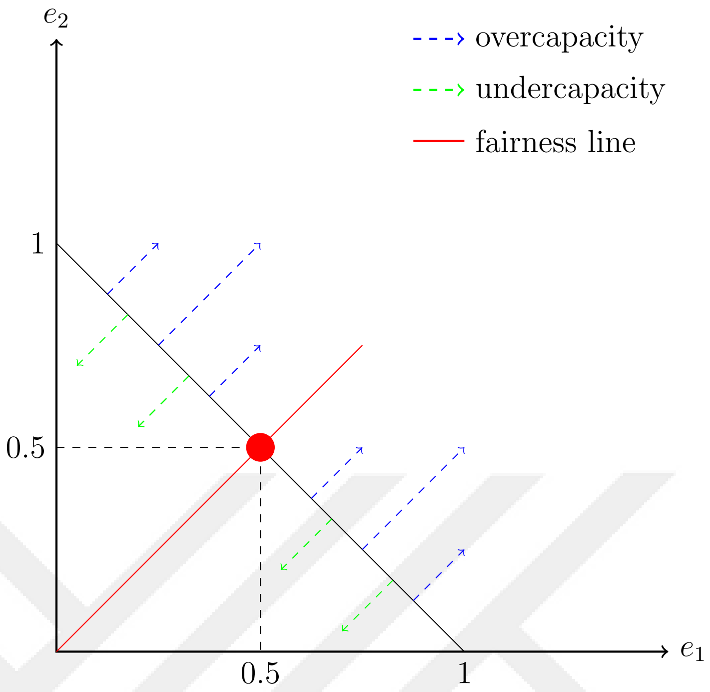


Figure 3.2: Fairness-Efficiency tradeoff curve

When the U_α is implemented in DCSP, demand and capacity sharing in the CN will be restricted. In this context, an enterprise cannot take all resources if another enterprise has unsatisfied demand at the same time. The pseudocode of this collaboration is shown in DCSP with U_α.

3.1.7 Mathematical Model

Profit Function

$$\sum_{t=1}^{T} P(e_k)_t = \sum_{t=1}^{T} \left[s^p(x_{kt} + n(o_{kt})) + c^p(n(o_{kt})) - c^l L_{kt} - c^h H_{kt} - c^p m(o_{kt}) \right] \tag{3.19}$$

An enterprise profit function is shown in Eq.(3.19). The $P(e_k)$ represents difference between the sum of profits for the collaborating enterprise and the total cost of

```
      DCSP with $U_\alpha$ Pseudocode
Step 1.  Calculate $r(o_{jt})$ and $s(o_{it})$ $\forall e_k \in E$ and $U_\alpha$ utility function
         value starting with $e_i$ who has the highest demand at time $t$.
         Eqs. (3.9, 3.11, and 3.14)
Step 2.  Analyze $r(o_{jt})$ and $s(o_{it})$ $(i \in I,\ j \in J,\ t \in \tau)$.
    2.a. Check If $r(o_{jt}) > 0$, then send $\omega_{jt}$.
    2.b. Check If $s(o_{it}) > 0$, then send $\Gamma_{it}$. Otherwise, go to Step 9
Step 3.  Analyze $\omega_{jt}$ and $\Gamma_{it}$ $(i \in I,\ j \in J,\ t \in \tau)$.
    3.a. Check if $r(o_{jt}) \geq s(o_{it})$, then go to Step 4.
         Otherwise, go to Step 9.
    3.b. Check if $s(o_{it}) \geq r(o_{jt})$, then go to Step 6.
         Otherwise, go to Step 9.
Step 4.  Request $r(o_{jt})$ from $e_i$.
Step 5.  Check if $r(o_{jt})$ violates $U_\alpha$, then revise resource allocation and
         go to Step 8. Otherwise, go to Step 9.
         Eq.(3.22)
Step 6.  Request $s(o_{it})$ from $e_j$.
Step 7.  Check if $s(o_{it})$ violates $U_\alpha$, then revise resource allocation and
         go to Step 8. Otherwise, go to Step 9.
         Eq.(3.23)
Step 8.  Update $I_{kt}$, $H_{it}$ and $L_{jt}$.. Go to Step 1.
         Eqs.(3.24 - 3.26)
Step 9.  Terminate algorithm.
```

production, lost sale and inventory holding.

$$P(CN)_t = \sum_{k=1}^{K} P(e_k)_t \tag{3.20}$$

The CN profit function is shown in Eq.(3.20). $P(CN)_t$ represents the sum of profits for the collaborating enterprises. In the collaboration process, the enterprise that receives capacity from CN, will be rewarded by meeting its demand from both its own inventory and the received quantity from the CN. On the other hand, the enterprise that shares demand to CN will be rewarded by fulfilling its own demand and by sharing items to CN.

$$\sum_{t=1}^{T} P(e_k)_t = \sum_{t=1}^{T} \left[P(x_{kt}) - c^l L_{kt} - c^h H_{kt} - c^p m(o_{kt}) \right] \tag{3.21}$$

If no collaboration exists among these enterprises, the profit function is calculated as shown in Eq.(3.21).

Model Formulation

$$\begin{aligned}
& r(o_{jt}) \leq U_\alpha && j \in E^-, t \in \tau && (U_\alpha \text{ const. for } r(o_{jt})) && (3.22)\\
& s(o_{it}) \leq U_\alpha && i \in E^+, t \in \tau && (U_\alpha \text{ const. for } s(o_{it})) && (3.23)\\
& \quad I_{kt} = I_{k(t-1)} + P_{kt} && k \in E, t \in \tau && (\text{Inventory level}) && (3.24)\\
& \qquad + r(o_{jt}) - s(o_{it}) - x_{it} && j \in E^-, i \in E^+ && && \\
& \quad H_{kt} = I_{kt} - x_{kt} - S^-_{kt} && k \in E, t \in \tau && (\text{Holding inventory}) && (3.25)\\
& \quad L_{kt} = d_{kt} - I_{kt} - S^+_{it} && k \in E, t \in \tau && (\text{Unsatisfied order}) && (3.26)\\
& \quad x_{kt} \leq d_{kt} && k \in E, t \in \tau && (\text{Supply constraint}) && (3.27)\\
& \quad H_{kt} \leq m(o_{kt}) && k \in E, t \in \tau && (\text{Capacity const.}) && (3.28)\\
& \qquad \text{Eqs } (3.9,\ 3.11) && && && \\
& \quad I_{kt}, H_{kt}, L_{kt}, r(o_{jt}), s(o_{it}), x_{kt} \geq 0 && k \in E, t \in \tau && (\text{Feasibility}) && (3.29)\\
& && j \in E^-, i \in E^+ && &&
\end{aligned}$$

A demand and capacity sharing CN is shown in Eqs.(3.22 - 3.29). The demand-sharing quantity comes from the capacity sharing enterprise and represents the unsatisfied demand of e_i at time t before collaboration, as shown in Eq.(3.9). On the other hand, the capacity-sharing quantity is calculated based on the remaining items of e_i at time t before collaboration and after e_i fulfills its own demand, as shown in Eq.(3.11). Eqs.(3.22 - 3.23) put restrictions on demand- and capacity-sharing quantity. The inventory level of e_i at period t is defined by the sum of the remaining inventory from period $t-1$, produced quantity at time t, received products from network $r(o_{jt})$, and products shared to the network $s(o_{it})$, as shown in Eq.(3.24). During the collaboration process, it is possible that e_i may only receive or share products or not be involved in any possible collaboration. A holding inventory appears after the demand of e_i at time t is fulfilled, and shared products are produced in the CN if e_i is involved in any collaboration, which is calculated using Eq.(3.25). The unsatisfied demand quantity is counted after fulfilling the demand from the inventory and received products from the CN if e_i is involved in any collaboration, as shown in Eq.(3.26). The amount of product supplied by any e_i that is less than or equal to the demand at any time t is ensured by Eq.(3.27). The holding products at any e_i have a capacity of less than or equal to the inventory capacity; therefore, Eq.(3.28) prevents capacity limit violations for each enterprise. Eq.(3.29) guarantees the feasibility of the decision variables. In case of no collaboration, $r(o_{jt})$ and $s(o_{it})$ are removed from the calculations shown by Eqs.(3.24 - 3.29) and the profit functions of the enterprise and network Eqs.(3.19 - 3.21).

At time t, each enterprise in the CN evaluates its extra capacity after fulfilling its demand or its shortage capacity if there is unsatisfied demand. On the other hand, in case the available inventory exactly meets the demand, no collaboration occurs for this specific enterprise. In case the available inventory does not exactly match the demand, then e_i will prepare capacity-sharing proposals, and e_j will prepare demand-sharing proposals.

In the CN, enterprises are facing the dilemma of a choice between fairness and efficiency, which appears during the collaboration process. Balancing efficiency and fairness are prevalent in many aspects of life. Different societies and countries make different choices regarding these balances. This research provides a framework for the evaluation and presentation of such a balance in the context of CNs.

3.1.8 Summary and Open Research Questions

A new demand and capacity sharing protocol (DCSP) has been developed. The α utility function (U_α) has been implemented in traditional DCSP. Fairness in collaborative network is guided with U_α that computes maximum amount of shared network resources (i.e., excess capacity and inventory) among CNEs. The proposed protocol is not violated the network efficiency in terms of total profit, lost sale cost, and inventory cost. Mathematical model is developed to explain a CNE and to study the effects of different α on system efficiency and fairness.

3.2 Dynamic Reformation of Partnership Subsets for Fair Demand and Capacity Sharing Collaborative Network

3.2.1 Dynamic Negatiation Mechanism

In this paper, a new dynamic negotiation mechanism (DNM) is proposed as an extension of CNP, which was presented by Smith (1980). CNP has a set of rules to govern CNE's interactions and communication to achieve mutual benefits, as shown in Figure 2.1. An e_j is accepted as the manager agent and an e_i as the contractor agent of CNP. After ω_{jt} is announced by e_j, e_i evaluates ω_{jt} to decide whether to submit $\Lambda_{i\omega_{jt}}$. A contract between e_j and e_i is established by a two-way negotiation (Yilmaz and Yoon, 2017) that begins with following condition, $N(\omega_{jt})$:

$$N(\omega_{jt}) = \begin{cases} 1, & s(o_{it}) \neq 0, \\ 0, & \text{otherwise}, \end{cases} \tag{3.30}$$

where 1 means that negotiation start and 0 means that do not start negotiation. The negotiation process is conducted by submitting ω_{jt} and $\Lambda_{i\omega_{jt}}$. If $N(\omega_{jt}) = 0$, $r(o_{jt})$ cannot be accepted by any e_i and the e_j needs to ask for capacity from other $e_i \in E^+$.

	Dynamic Negotiation Mechanism Algorithm
Step 1.	ω_{jt} announcement
	Eq. (3.10)
Step 2.	Evaluation of ω_{jt} and submission of $\Lambda_{i\omega_{jt}}$
	Eqs. (3.30, 3.31)
Step 3.	Selection of the best $\Lambda_{i\omega_{jt}}$ and awarding of proposals
Step 4.	Collaboration execution and record collaborated e_i

If $N(\omega_{jt}) = 1$, then ω_{jt} can be accepted by the e_i. e_i evaluates ω_{jt}, including factors such as fairness, cost, due date, and quantity. If the evaluation of ω_{jt} results that ω_{jt} is acceptable, then the e_i prepares a bid for a ω_{jt}, $\Lambda_{i\omega_{jt}}$, which includes $s(o_{jt})$, lead time information, t^{lt}, and collaborative unit price, c^u. $\Lambda_{i\omega_{jt}}$ is defined as

$$\Lambda_{i\omega_{jt}} = (s(o_{it}),\ t^{lt},\ c^u). \tag{3.31}$$

where c^u, is defined as

$$c^u = \frac{c^c_{kt}}{n(o_{kt})} \tag{3.32}$$

where $n(o_{kt})$, the shared amount of capacity, is defined as

$$n(o_{kt}) = \min(r(o_{kt}), s(o_{kt})). \tag{3.33}$$

Coordination cost of e_k at time t, c^c_{kt}, is due to the cost of purchasing from CN, c^s_{kt}, the cost of lead time, c^{lt}, the cost of fairness, c^f, and the cost of coordination. c^c_{kt} is defined as

$$c^c_{kt} = c^s_{kt} + c^{lt}_{kt} + c^f_{kt} + c^m_{kt}. \tag{3.34}$$

c^s_{kt}, the cost of selling a product in CN, is defined as

$$c^s_{kt} = p^c \cdot n(o_{kt}), \tag{3.35}$$

where p^c is the initial collaborative unit price in the CN. The lead-time information refers to the time at which the e_i can fulfill $n(o_{jt})$. If the e_j requires $\omega(o_{jt})$ within a short time, the e_i can ask a high price, and the e_j can either accept the high price or consider another e_i. The lead time of $n(o_{jt})$ affects c^u according to the gap between t^d and t^{lt}. c^{lt} is defined as

$$c^{lt}_{kt} = \beta \cdot \max(0,\ (t^d - t^{lt})), \tag{3.36}$$

where β is a time-to-money conversion factor. c^f is defined as

$$c^{f}_{kt} = \gamma \cdot \max(0,\ (Ji_t - Ji_{t-1})), \tag{3.37}$$

where γ is a fairness-to-money conversion factor, which penalizes unfair resource allocation among e_k, and Ji_t is the fairness index at time t, which was proposed by Jain et al. (1984). In this proposed DNM, each e_k is responsible for its own resource allocation over τ; therefore, if an e_k insists on abandoning fair resource allocation over τ, it is penalized based on its historical collaboration record in terms of the demand fulfillment rate, λ_{jt} for $r(o_{jt})$, which is defined as

$$\lambda_{jt} = \frac{r(o_{jt})}{n(o_{jt})}. \tag{3.38}$$

Ji is defined as for e_k

$$Ji = \frac{\left(\sum\limits_{k=1}^{K} \overline{\lambda}_{kt}\right)^2}{K \cdot \sum\limits_{k=1}^{K} \left(\overline{\lambda}^2_{kt}\right)}, \tag{3.39}$$

where $\overline{\lambda}_{jt} = \frac{\sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{it}}{t}$ denotes the moving average of λ_{jt}. If Λ_{it} offers $c^u_{jt} > s^p_j$, then collaboration between the e_j and e_i is impossible; therefore, c^u must be between c^p_j and s^p_j to be accepted by the e_j.

Proposition 1. *Collaboration can exist in a CN if* $0 \leq c^{lt}_{kt} \leq (s^{p}_{kt} - p^{c}_{kt}) \cdot n(o_{kt})$.

Proof. In Eq. (3.36), β and γ are assumed to be 0. Eq. (3.34) can be written as

$$c^{c}_{kt} = c^{s}_{kt} + c^{lt}_{kt} + 0 + 0. \tag{3.40}$$

c^{u}_{kt} is defined in Eq. (3.32) and can be rewritten as

$$c^{u}_{kt} = \frac{c^{c}_{kt}}{n(o_{kt})} = \frac{c^{s}_{kt} + c^{lt}_{kt}}{n(o_{kt})} = \frac{(p^{c} \cdot n(o_{kt})) + \left(c^{lt}_{kt}\right)}{n(o_{kt})} = (p^{c}) + \frac{\left(c^{lt}_{kt}\right)}{n(o_{kt})}$$

and c^{lt}_{kt} can be defined as

$$c^{lt}_{kt} = (c^{u}_{kt} - p^{c}) \cdot n(o_{kt}). \tag{3.41}$$

$c^{u}_{kt} \geq s^{p}_{kt}$ is be applied to Eq. (3.41), yielding

$$c^{lt}_{kt} \leq (s^{p}_{kt} - p^{c}) \cdot n(o_{kt}). \tag{3.42}$$

It is known that $lt \geq t$. Hence, $(t^{d} - lt) \geq 0$, and thus, c^{lt}_{kt} can be bounded as

$$0 \leq c^{lt}_{kt} \leq (s^{p}_{kt} - p^{c}) \cdot n(o_{kt}).$$

□

Proposition 2. *Collaboration can exist in a CN if* $0 \leq c^{f}_{kt} \leq (s^{p}_{kt} - p^{c}) \cdot n(o_{kt})$.

Proof. In Eq. (3.37), β and γ are assumed to be 0. Eq. (3.34) can be written as

$$c^{c}_{kt} = c^{s}_{kt} + 0 + c^{f}_{kt} + 0. \tag{3.43}$$

Eq. (3.32) can be rewritten under the condition $c^{u}_{kt} \geq s^{p}_{k}$:

$$c^{u}_{kt} = \frac{c^{c}_{kt}}{n(o_{kt})} = \frac{c^{s} + c^{f}_{kt}}{n(o_{kt})} = \frac{(p^{c} \cdot n(o_{kt})) + \left(c^{lt}_{kt}\right)}{n(o_{kt})} = (p^{c}) + \frac{\left(c^{f}_{kt}\right)}{n(o_{kt})},$$

and c^f_{kt} can be redefined as

$$c^f_{kt} = (c^u_{kt} - p^c) \cdot n(o_{kt}). \tag{3.44}$$

Eq. (3.37) implies that $c^f_{kt} \geq 0$; therefore, c^f_{kt} can be bounded as

$$0 \leq c^f_{kt} \leq (s^p_{kt} - p^c) \cdot n(o_{kt}). \qquad \square$$

Theorem 1. *Collaboration among e_k requires $p^c_{kt} \leq c^u_{kt} \leq s^p_{kt}$. The objectives of e_k and CN can be affected by cost of lead time, fairness, and communication.*

Proof. Proposition 1 and Proposition 2 imply that collaboration can be affected by the cost of delivery time, fairness, and communication for $r(o_{jt})$. Such violations result in unfeasible collaboration conditions. Hence, collaboration conditions must be satisfied to gain maximum mutual benefits from a CN. $\square$

Therefore, if $c^u_{jt} \leq s^p_{kt}$, then an e_j can build a utility function, U, to evaluate Λ_{it} with the weights of the evaluation criteria, w. U can be defined as

$$U_{\omega_{jt}}\left(n(o_{kt}),\, c^u_{kt},\, lt(s(o_{it}))\right) = \begin{cases} w^q \cdot \frac{(r(o_{kt}) - n(o_{kt})}{r(o_{kt})} + w^c \cdot \frac{(s^p_{kt} - c^u_{kt})}{s^p_{kt}} \\ + w^{t^d} \cdot \frac{\left(t^d(o_{jt}) - lt(s(o_{it}))\right)}{t^d(o_{jt})}, \end{cases} \tag{3.45}$$

where w^q, w^c, and w^{t^d} denote the weights of the offered q, c^u, and t^d, respectively. Each criterion can have a different $w_{j'}$ over τ based on the demand patterns of e_j. $w_{j'}$ exhibit the properties 1) $w_{j'} \in [0, 1]$, and 2) $\sum_{j'=1}^{3} w_{j'} = 1$.

$$U^*_{\omega_{jt}} = \max U_{\omega_{jt}}(n(o_{kt}),\, c^u_{jt},\, lt(s(o_{it}))) \tag{3.46}$$

$$\text{s.t.} \quad c^u_{jt} \leq s^p_j \qquad \forall j \in E^-\,,\ \forall t \in \tau \tag{3.47}$$

$$t^d(r(o_{jt})) \leq lt(s(o_{it})) \qquad \forall j \in E^-\ \forall i \in E^+\,,\ \forall t \in \tau \tag{3.48}$$

$$\text{Eqs. } (3.31,\ 3.32)$$

$$c^u_{jt},\ t^d \geq 0 \qquad \forall j \in E^-\,,\ \forall t \in \tau. \tag{3.49}$$

DNM proceeds between e_j and e_i based on the dynamic conditions of $n(o_{kt})$, c^u, lt. e_j aims to find $U^*_{\omega_{jt}}$ to select the best Λ_{it}, as shown in Eq. (3.46). Eq. (3.47) enforces that e_i cannot offer a higher c^u than s^p_{jt}. Eq. (3.48) ensures that delivery cannot occur earlier than the collaboration time. The feasibility of variables is shown by Eq. (3.49). After e_j selects the best Λ_{it}, it is rewarded by its $n(o_{jt})$ being fulfilled to the extent that e_i can supply. The reward of e_j, A_{jt}, is defined as

$$A_{jt} = \left(s^p - c^u_{jt}\right) \cdot n(o_{jt}) + r(o_{jt}) \cdot l^c_{jt}. \tag{3.50}$$

where l^c_{it} is the lost sale cost for e_j at time t. Meanwhile, the e_i is rewarded by the e_j in terms of reducing inventory cost. The reward of e_i, A_{it} is defined as

$$A_{it} = c^u_{it} \cdot n(o_{it}) + (s(o_{it}) - n(o_{it})) \cdot h^c_{it}, \tag{3.51}$$

where h^c_{it} is the holding cost of the e_i at time t. At the end of DNM, e_i records e_j that accept Λ_{it} for future negotiations. Over τ, each e_k wishes to optimize its own benefits. In this research, the benefit to e_k is considered as profits, and the profit function for an e_k, $P(e_k)$, is defined as

$$P(e_k) = \begin{cases} \sum_{t=1}^{\tau} (s^p_{kt} \cdot (n(o_{kt}) + m(o_{kt})) - c^u \cdot n(o_{kt}) - c^p \cdot m(o_{kt}) & \\ \qquad -c^l_{jt} \left(q_{kt} - (n(o_{kt}) + m(o_{kt}))\right), & \text{if } q_{kt} > m(o_{kt}), \\ \sum_{t=1}^{\tau} (s^p_{kt} \cdot q_{kt}) + c^u \cdot n(o_{kt}) - c^p \cdot m(o_{kt}) & \\ \qquad -h^c \cdot (m(o_{kt}) - n(o_{kt}) + q_{kt})), & \text{if } q_{kt} \le m(o_{kt}). \end{cases} \tag{3.52}$$

In addition, the profit function of a CN, $P(CN)$, is defined as

$$P(CN) = \sum_{k=1}^{K} P(e_k). \tag{3.53}$$

A coordination mechanism among e_k needs to be designed to coordinate ω_{jt} and Λ_{it}. For this purpose, D^2SP is proposed as follows.

3.2.2 Dynamic-Distributed Sharing Protocol

D^2SP is intended to enhance the fairness and efficiency in a CN by inspiring the principles of CCT and CNP. The second principle of CCT, which is called collaborative e-work parallelism (CEP), is adopted in D^2SP. The features of CEP are defined as: 1) resource-sharing decomposition and formulation among e_k, 2) management of interactions of e_k under an SP, 3) synchronization of e_k so that they act accurately in the decision-making process, 4) support of e_j in coordination with other e_i, and 5) development of a conflict resolution and recovery strategies (Scavarda et al., 2015). In D^2SP, coordination among CNEs is supported by the CNP principles, as illustrated in Figure 2.1. The dynamic nature of D^2SP originates from the DNM, as presented in Section 3.1. The DNM allows an e_j to dynamically select its collaboration partner over τ, as shown in Figure 3.3a. A more detailed illustration of D^2SP is provided in the D^2SP pseudocode describing the steps applied from when the e_j announces

```
$D^2SP$ Pseudocode
Step 1. Define $\tau$, and each $e_k$ receives its $o_{kt}$
Step 2. Calculate $r(o_{jt})$ and $s(o_{it})$, and define $e_j$ and $e_i$
        Eqs. (3.9, 3.11)
Step 3. Initiate negotiation by announcing $\omega_{jt}$ at time $t$
        Eq. (3.10)
Step 4. Check whether $s(o_{kt}) \neq 0$; then, calculate $n(o_{kt})$, $c^u_{kt}$, $c^{lt}_{kt}$, and $c^f_{kt}$
        and send $\Lambda_{it}$; otherwise, go to Step 8
        Eqs. (3.31 - 3.37)
Step 5. Collect all $\Lambda_{it}$ and select the best $U_{\omega_{jt}}$
        Eqs. (3.46 - 3.49)
Step 6. Assign $\omega_{jt}$s to $e_i$ and record $\lambda_{it}$ for each $e_i$
        Eq. (3.38)
Step 7. Check whether $r(o_{jt}) \quad \forall e_j \in E^-$; then, go to Step 1
Step 8. Terminate algorithm
```

ω_{jt}, and collaboration continues over τ until $s(o_{it}) > 0 \; \forall e_i \in E^+$. The aim of all $e_i \in E$ is to obtain maximum mutual benefits by solving the best-matching problem between ω_{jt} and Λ_{it}. This problem can be treated as an order fulfillment problem or as an extension of the stable marriage problem. Dynamically accounting for c^u_{kt} implies a nested set of bid submission decisions. The analysis of ω_{jt} and Λ_{it} requires $\mathcal{O}(K^2)$ time, where K is the number of enterprises in CN. A trade-off between achieving the optimal collaboration decision and the shortest solution time can be found in (Bhargava et al., 2016). Therefore, a solution algorithm is proposed as shown in the following *D²SP* pseudocode for the demand and capacity allocation decisions. Various SPs are proposed, as described in the following sections.

3.2.3 Static-Distributed Sharing Protocol

SDSP assumes that all conditions in a CN remain stable over τ. In *SDSP*, all of e_k have the ability to make decisions based on their collaboration requirements.

```
$SDSP$ Pseudocode
Step 1. Define $\tau$, and each $e_k$ receives its $o_{kt}$
Step 2. Calculate $r(o_{jt})$ and $s(o_{it})$, and define $e_j$ and $e_i$
        Eqs. (3.9, 3.11)
Step 3. Send $\omega_{jt}$ and $\Lambda_{it}$ to $e_i$ and $e_j$, respectively
        Eqs. (3.10, 3.31)
Step 4. Select the best $\Lambda_{it}$ and assign $\omega_{jt}$ to $e_i$ and record $\lambda_{jt}$ for each $e_i$
Step 5. Check whether $r(o_{jt}) > 0 \;\; \forall e_j \in E^-$; then, go to Step 1
Step 6. Terminate algorithm
```

However, the decision-making mechanism does not provide the ability to change decisions in response to changing conditions, as shown in Figure 3.3b. Therefore, $SDSP$ will produce the same sharing decisions under the same conditions for e_k. Partial information, which is sufficient to form a collaboration, is required for $SDSP$. The proposed $SDSP$ is inspired by Yoon and Nof (2010) and Jahanpour et al. (2016). Solution algorithm is shown in $SDSP$ Pseudocode.

3.2.4 Dynamic-Centralized Sharing Protocol

$DCSP$ assumes that a CN can respond to dynamic changes in market conditions by changing network topology or collaboration partners over τ. CN can change the decisions under specific conditions. For example, if a same specific condition occurs at $t = t_1$ and $t = t_1 + \Delta$, then the collaborations may vary among e_k in both time periods, as shown in Figure 3.3c, because previous collaborations at time $t = t_1$ may not achieve mutual benefits at time $t = t_1 + \Delta$. Therefore, $DCSP$ evaluates collaboration partners dynamically over τ.

All ω_{jt} and Λ_{it} are collected by $DCSP$. Therefore, $DCSP$ is only authority responsible for a successful CN. The difference between $SCSP$ and $DCSP$ rests on which DNM is used to determine c^u over τ. In this study, $DCSP$ is defined as the combination of the models proposed by Mosqueira Rey et al. (2009) and Schleich

```
$DCSP$ Pseudocode
Step 1.  Define $\tau$, and each $e_k$ receives its $o_{kt}$
Step 2.  Calculate $r(o_{jt})$ and $s(o_{it})$, and define $e_j$ and $e_i$
         Eqs. (3.9, 3.11)
Step 3.  Initiate negotiation by announcing $\omega_{jt}$ at time $t$ and collect $\Lambda_{it}$
         Eqs. (3.10, 3.31)
Step 4.  Check whether $r(o_{jt}) \neq 0$ and then calculate $n(o_{kt})$; $c^{u}_{kt}$, and $c^{lt}_{kt}$
         otherwise, go to Step 9
         Eqs. (3.32 - 3.37)
Step 5.  Select the best $\Lambda_{it}$ for each $\omega_{jt}$ with the aim of $P(CN)$
Step 6.  Assign $\omega_{jt}$ to $e_i$ and record $\lambda_{jt}$ for each $e_i$
Step 7.  Check whether $r(o_{jt}) \quad \forall e_j \in E^{-}$, and then go to Step 1
Step 8.  Terminate algorithm
```

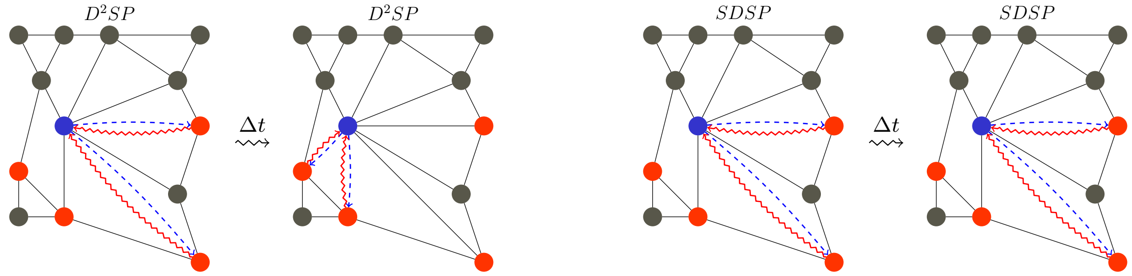
et al. (2017). The solution algorithm is shown in $DCSP$ pseudocode.

3.2.5 Static-Centralized Sharing Protocol

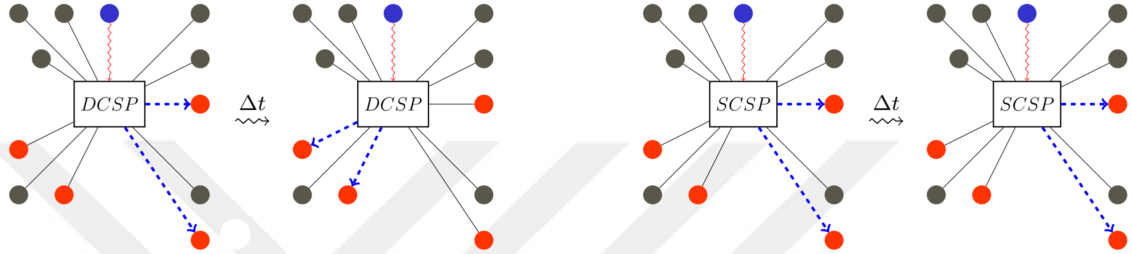
$SCSP$ assumes that a CN cannot have any dynamic conditions such as that the network topology is maintained for ever or the collaboration partners are always the same over τ. Each e_k knows what it will do under the same conditions.

```
$SCSP$ Pseudocode
Step 1.  Define $\tau$, and each $e_k$ receives $o_{kt}$
Step 2.  Calculate $r(o_{jk})$ and $s(o_{ik})$, and define $e_j$ and $e_i$
         Eqs. (3.9, 3.11)
Step 3.  Collect all $\omega_{jt}$ and $\Lambda_{it}$
         Eqs. (3.10, 3.31)
Step 4.  Select the best $\Lambda_{it}$ for each $\omega_{jt}$ and assign $\omega_{jt}$ to $e_i$
Step 5.  Check whether $r(o_{jk}) \quad \forall e_j \in E^{-}$, and then go to Step 1
Step 6.  Terminate algorithm
```

For example, if the same condition occurs at time $t = t_1$ and $t = t_2$, then the same collaborations will be formed by the same e_k, as shown in Figure 3.3d. All ω_{jt} and Λ_{it}



(a) D^2SP (b) $SDSP$



(c) $DCSP$ (d) $SCSP$

Figure 3.3: Sharing protocols

are collected by $SCSP$, and all e_k are informed by $SCSP$ to form a collaboration. The $SCSP$ considered in this study is an extension of that in Adida et al. (2011), Lopez et al. (2016), and Schleich et al. (2017). The solution algorithm for $SCSP$ is summarized in the $SCSP$ pseudocode.

3.2.6 Summary and Open Research Questions

This research addresses distributed decisions for dynamic partnership reformation to enhance fairness and efficiency among collaborative networked enterprises (CNEs). The aim of this research is to investigate a new sharing protocol (SP) to control CNEs. Most CNE studies have been designed under a centralized SP. However, centralized SPs appear to be unfeasible or inadequate because of enterprises' operating environments and local objectives; therefore, each CNE requires a distributed decision-making mechanism. Furthermore, market globalization and competition necessitate rapid responses to market changes and give rise to two major concerns about CNEs: 1) how can collaborations be rendered re-configurable to dynamically capture and adapt to market patterns? and 2) how can the resources of all CNEs be utilized fairly among enterprises, ensuring mutual benefits? Therefore, Dynamic-Distributed Sharing Protocol (D^2SP), which is inspired by the principles of Collaborative Control Theory and the Contract Net Protocol, is proposed to address these concerns. The performance of D^2SP is evaluated by comparing it with three SPs: 1) a static-centralized SP, 2) a static-distributed SP, and 3) a dynamic-centralized SP. The experimental results show that D^2SP performs at least equally or better than centralized and static SPs in terms of total profit, fairness, scalability, and communication overhead.

Chapter 4. Experimental Results and Analysis

4.1 A Framework and Algorithm for Fair Demand and Capacity Sharing in Collaborative Network

4.1.1 Experimental Design and Scenarios

This research was motivated by problems of resource allocation in CNs based on sharing protocols. HeCN and HoCN based on enterprise capacity are used to illustrate a balance fairness between efficiency in CN resource allocation. Four, six and eight enterprises are simulated as a CN. In addition, three different types of collaboration model are applied: 1) No collaboration (Col^N) model, 2) partial collaboration (Col^P) model, and 3) complete collaboration (Col^C) model. Based on these three main types of models, 21 different scenarios are applied for HeCN and HoCN in the experiments, which are summarized in Table 4.1.

Table 4.1: Scenarios for HeCN and HoCN

Network size	[4, 6, 8]
Collaboration modes	$\left[Col^N, Col^P, Col^C\right]$
α	$\forall\alpha \in \{0.2y \,\vert\, y \in [0,5],\, y \in Z^+\}$

In the Col^N model, each enterprise attempts to satisfy its own costumer demands with its own capacities. Consequently, there is no interaction among enterprises or capacity and demand sharing in this model. The Col^N model is used to evaluate collaboration strategies.

The Col^P model is defined as U_α places a limitation on the amount of shared demand and capacity in one iteration, which is evaluated dynamically based on the workflow of DCSP with the U_α, which is shown in DCSP with U_α algorithm. Therefore, DCSP with the U_α algorithm aims to increase network fairness while maintaining current efficiency. In Col^P model, the interactions among enterprises are organized by U_α. The experiment scenarios with U_α and $y \neq 0$ are used as a model.

In the Col^C model, there are no limitations on the amount of shared demands and capacities among collaborating enterprises. If an enterprise has excess capacity, then the enterprise shares all excess capacity to CN if collaborating enterprises need this excess capacity. In preference to shortage, when an enterprise faces a shortage during the collaboration process, the enterprise can take all network resources without considering the other enterprises in the CN. The shortage and excess capacity appear due to the random nature of customers' demand. The experiment scenarios with U_α and $y = 0$ present Col^C.

Demand distribution of enterprises is accepted as a normal distribution ($\mathcal{N}(\mu, \sigma^2)$) for all experiment scenarios, where μ equals production capacity of the enterprise, and σ^2 is constant ($\sigma^2 = 20$ for all enterprises) and details of the simulation parameter settings are summarized in Table 4.7.

Three performance criteria are defined to validate the performance of proposed CNs: total profit (TP), lost sale cost (LC), and inventory cost (IC). CN models have been examined under an assumption that is all CN resources shared among collaborating enterprises with different demand and various α values from 0 to 1. In other words, if an enterprise has an available demand or capacity to share, then the enterprise tries to share all excess demand or capacity with a set of collaborating enterprises who need demand or capacity. Individual enterprises were not considered in the experiments, but rather the results based on all network activities. Simulation model that is used in experiments has been performed using Matlab with the given

Table 4.2: Summary of parameter settings

Parameter	Value
Number of collaborative enterprises	$K = (4,\ 6,\ 8)$
Unit selling price in CN at e_i,	$s^p = 10$
Production cost per unit	$c^p = 5$
Collaborative price per unit	$p^c = 8$
Lost sale cost per unit	$c^l = 3$
Inventory cost per unit	$c^h = 2$
Number of $\alpha-$utility functions	$\forall \alpha \in \{0.2y \,\vert\, y \in [0,5],\ y \in Z\}$
Replication	100
Production Capacity in HoCN	m_k=120 $\forall k \in K$
Production Capacity in HeCN	$m_k = \left\{120\frac{k}{K/2} \vert\ \forall k \in K\right\}$

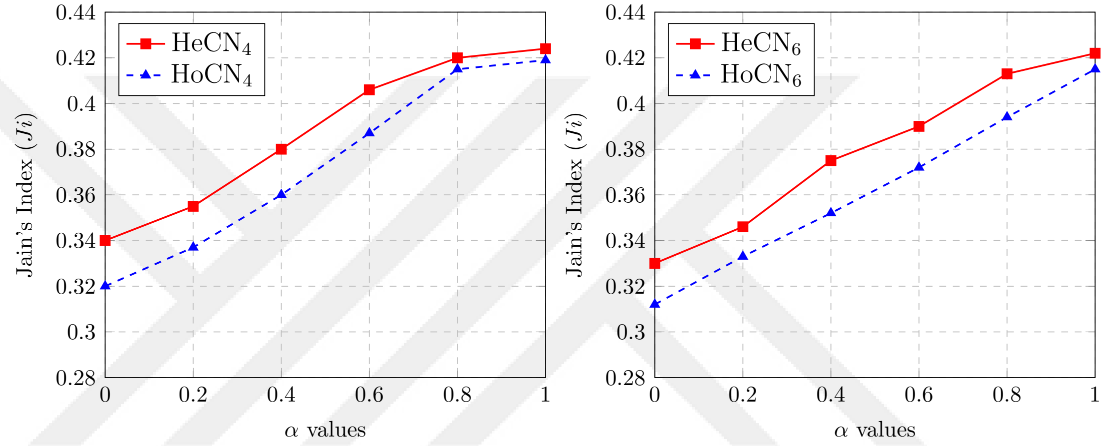
parameter settings. The experimental results are shown as follows;

4.1.2 Analysis of Fairness at HeCN and HoCN:

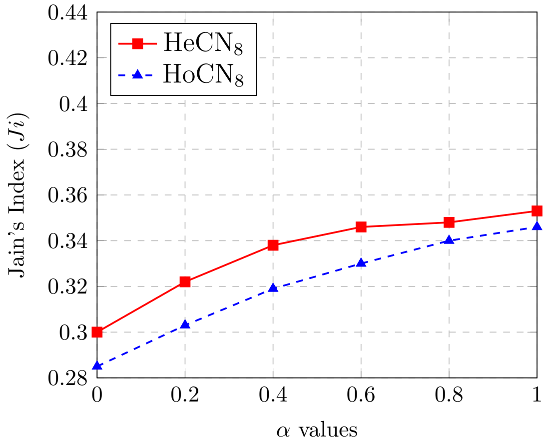
HeCN and HoCN are analyzed under the same demand distribution of a customer order and the same size network ($K = 4, 6, 8$). Figure 4.1(a) compares Ji of HeCN$_4$ and HoCN$_4$ for various α values from 0 to 1. Overall, Ji index increased when α increased to 1 from 0 for HeCN$_4$ and HoCN$_4$. This result indicates that a large α value results in a larger Ji, therefore a fair network could be designed under large α values. In addition, when α is approximately 0, which refers to Col^C model, Ji of HeCN$_4$ and HoCN$_4$ are 0.340 and 0.320, respectively and when $\alpha \approx 1$, Ji of HeCN$_4$ and HoCN$_4$ are 0.424 and 0.419, respectively. The gap between Ji of HeCN and HoCN is reduced 75% when α is increased to 1. In addition, Col^P model provides fairer resource allocation than Col^C model.

Figure 4.1(b) illustrates Ji of HeCN$_6$ and HoCN$_6$ for values of α from 0 to 1. It is evident that Ji of HeCN$_6$ and HoCN$_6$ increase with increasing α. Although Ji of HoCN$_6$ increased more so than did the Ji of HeCN$_6$ (33% and 28%, respectively), Ji of HeCN$_6$ is always larger than HoCN$_6$.

Similar results are shown in Figure 4.1(c), which illustrate Ji of HeCN_8 and HoCN_8. The total increases in Ji of HeCN_8 and HoCN_8 (16% and 20%) are not as high as when $K = 4, 6$. It implies that U_α could not provide fair resource allocation in the CN when network size was increased. However, large α values still produce large Ji. The gap between Ji of HeCN and HoCN was reduced by 50% when α was approximately 1.



(a) $K = 4$ (b) $K = 6$



(c) $K = 8$

Figure 4.1: Jain's index at HeCN and HoCN for $K = (4, 6, 8)$ with various values of α

Figures 4.1(a)-(c) indicate that HeCN always has a larger Ji than does HoCN. It states that HeCN is fairer than HoCN under the same demand distribution. However, large α values produced fair networks in HeCN and HoCN, and the difference between Ji of HeCN and HoCN was reduced by more than 80% when α increased from 0 to 1. Even if α increased, HeCN still obtained a large Ji. Therefore, HeCN collaboration model provides fair results than does HoCN. It implies that different types of enterprises should collaborate to reach a fair network model.

A paired t-test is used for pairwise comparisons between the results of the experiments in terms of Ji. A number of statistical methods are performed in the literature to determine test samples are significantly different from each other. Some methods, such as Duncan's Multiple Range Test, are used for comparing all pairs of mean values in multiple ranges. Some other methods, such as ANOVA, are applied to compare the mean values for more than two treatments. In this research, the means of the differences between Jain's Index (Ji) of HeCN and HoCN for various network sizes are tested. Therefore, the Pairwise t-test is sufficient to analyze the hypothesis of the two populations, and is commonly used for comparisons by CN researchers (Yoon and Nof, 2010, Seok and Nof, 2014b, Moghaddam and Nof, 2014, 2016). The pairwise t-test compares mean value of Ji in the two experiments with the following hypotheses: 1) $H_0 : (\overline{HeCN_4} = \overline{HoCN_4})$ and $H_1 : (\overline{HeCN_4} \neq \overline{HoCN_4})$, as shown in the first row of Table 4.3; 2) $H_0 : (\overline{HeCN_6} = \overline{HoCN_6})$ and $H_1 : (\overline{HeCN_6} \neq \overline{HoCN_6})$, as shown in the second row of Table 4.3; and 3) $H_0 : (\overline{HeCN_8} = \overline{HoCN_8})$ and $H_1 : (\overline{HeCN_8} \neq \overline{HoCN_8})$, as shown in the third row of Table 4.3.

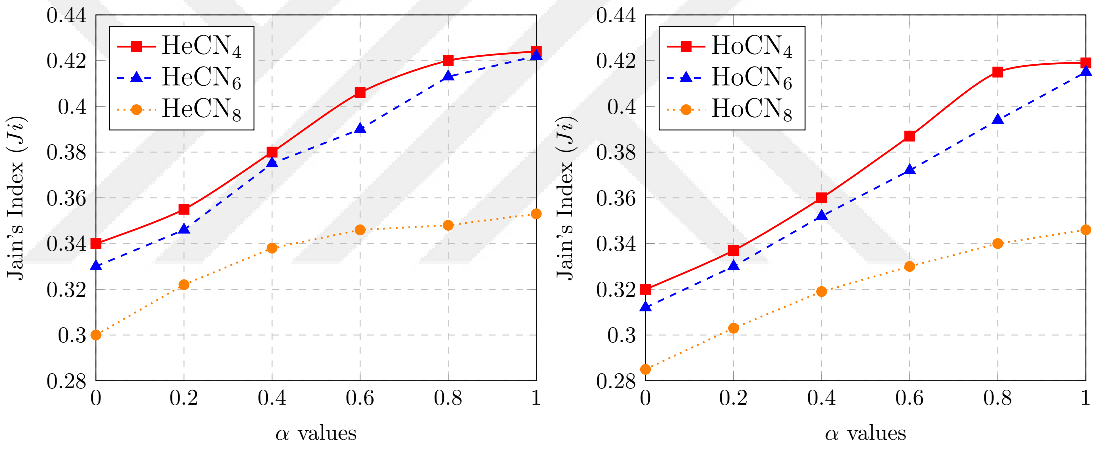
Table 4.3: Pairwise t-tests: Jain's Index (Ji) of HeCN and HoCN for various network sizes

	HeCN_4	HeCN_6	HeCN_8
HoCN_4	0.002	-	-
HoCN_6	-	0.002	-
HoCN_8	-	-	0.001

There is no evidence to suggest that means of Ji in HoCN under the U_α is higher than the means of Ji in HeCN under U_α. There is evidence to suggest that HeCNs obtain a larger Ji than do HoCNs based on network types. In other words, HeCN significantly outperforms HoCN in terms of CN fairness.

4.1.3 Analysis of Fairness for Variable Network Sizes:

HeCN and HoCN are analyzed under the same demand distribution for customer orders and variable network sizes ($K = 4$, 6 and 8). Figure 4.2(a) presents a comparison of Ji under various α values for HeCN. Overall, it is shown that Ji is increased when $\alpha \approx 1$ and when network size is small.



(a) Jain's index at HeCNs (b) Jain's index at HoCNs

Figure 4.2: Jain's index for $K = (4, 6, 8)$ at HeCN and HoCN with various values of α

Even if Ji increases when α is large at all network sizes, the gap between Ji of different network sizes is not always reduced. The reason for not reducing the gap is that U_α does not provide fair resource allocation in terms of the increasing Ji when CN size is increased. For example, when α values are 0.2, 0.4, and 0.6, the Ji of HeCN_4 and HeCN_6 are almost equal, but when α is 0.6, the gap between Ji appears again. However, a similar situation appears in the comparisons of HeCN_6 and HeCN_8 and of HeCN_4 and HeCN_8 when α goes from 0 to 1. Ji of HeCNs in different network sizes ($K = 4, 6, 8$) are increased by 27%, 28%, and 18%, respectively.

Figure 4.2(b) presents the comparison of Ji under various α from 0 to 1 in HoCN. By far, the highest Ji in this figure appears at a network size of four and α of 1. All network sizes follow an increasing trend with increasing α. For example, HoCN_4, HoCN_6 and HoCN_8 increased by 33%, 33%, and 21%, respectively. In this experiment, when α is increasing, the gaps between the Ji of HoCN_4, HoCN_6 and HoCN_8 are not always reduced. However, it is obvious that the gap is generally reduced when α is increasing.

Figures 4.2(a)-(b) present the summary of the analysis results and indicate that the U_α provides a fair resource allocation under all network sizes. However, the U_α function does not provide effective results with higher K. Due to this situation, the differences in the Ji as a function of K follow an increasing trend with increasing K. Therefore, a large network size causes unfair resource allocation. In the CN, an equal number of buyers and vendors is not always possible, and sometimes, one vendor provides all network needs. On the other hand, the opposite situation is also possible: one enterprise, being the only vendor in the CN, could satisfy the demands of 1 to $K - 1$ buyers in the network. A large K causes a low Ji in the CN. Therefore, small size network is suggested to achieve a fair network model.

Table 4.4: Pairwise t-tests: Jain's Index (Ji) for $K = (4, 6, 8)$ at HeCN and HoCN

(a) Pairwise t-tests for HeCNs

	HeCN_6	HeCN_8
HeCN_4	0.023	0.011
HeCN_6	-	0.010

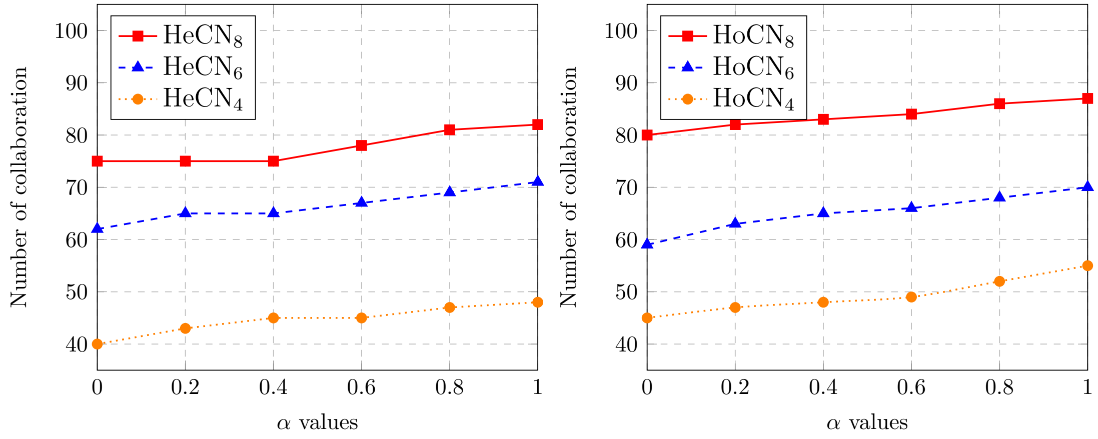
(b) Pairwise t-tests for HoCNs

	HoCN_6	HoCN_8
HoCN_4	0.017	0.005
HoCN_6	-	0.013

The pairwise t-test is also applied from the CN size point of view for pairwise comparison between the results of experiments in terms of Ji. The pairwise t-tests of these experiments are summarized in Tables 4.4(a) and (b). The t-test results indicate that there is no evidence to suggest that the mean of Ji for small network sizes under U_α is higher than the mean of Ji for large network sizes under U_α. There is evidence to support that large network sizes obtain a lower Ji than do small networks based on network sizes. In other words, small networks significantly outperform large networks in terms of network fairness.

4.1.4 Analysis of the Number of Collaborations:

For analysis of number of collaborations at HeCNs and HoCNs, Figure 4.3, shows that total number of collaborations increases among collaborating enterprises when α increases. It is obvious that if there is a collaboration/coordination cost per collaboration, then this cost decreases the total network profit. For this reason, a network may loss its efficiency in terms of total profit.



(a) HeCNs (b) HoCNs

Figure 4.3: Number of collaborations at HeCNs and HoCNs for $K = (4, 6, 8)$ with various values of α

The number of collaborations is increased under all network sizes when α is increased. For instance, Figure 4.3(a) illustrates that the number of collaborations is increased by 20%, 14%, and 10% at HeCN$_4$, HeCN$_6$, and HeCN$_8$, respectively. Even if the large network sizes are not increased as much as small network sizes, they always achieve large numbers of collaborations under the same values of α.

In Figure 4.3b, the number of collaborations always increases with increasing α under all network sizes. The large network size dominates the small network size in terms of the number of collaborations. HoCN$_8$ always obtains a higher number of collaborations than HoCN$_6$ and HoCN$_4$. HoCN$_6$ also always obtains a higher number of collaborations than HoCN$_4$. The number of collaborations is increased at HoCN$_4$, HoCN$_6$ and HoCN$_8$ by 22%, 18%, and 10%, respectively. Experimental results indicates that the number of collaborations increases more so under small network sizes. In summary, U_α increases the number of collaborations under small network sizes faster than under large network sizes due to its constraint on resource allocation. Thus, a large CN size could loss its efficiency faster than small CN sizes in terms of total profit if there is a collaboration/coordination cost.

4.1.5 Analysis of Collaboration Models:

In this research, HeCN and HoCN are used to illustrate a balance between fairness and efficiency in CN resource allocation. Four, six and eight enterprises are simulated as CN. In addition, three types of collaboration models are applied: Col^N, Col^P, and Col^C models. Based on these three models, different scenarios were applied, as summarized in Table 4.1. Additional explanations about the collaboration models are given in Section 5. The Col^N model is used to compare values of the Col^P and Col^C models under the same U_α values. Table 4.5 and 4.6 show analysis of collaboration models under three performance criteria: TP, IC, and LC.

The comparison of Table 4.5 and 4.6 implies that collaboration among network enterprises is a good way be able to cope with changing market conditions and random conditions of demand patterns in terms of TP, IC, and LC. TP is increased at

Table 4.5: Summary of enterprise performance without collaboration

Network Type	Performance Criteria	Col^N Min	Col^N Average	Col^N Max	Col^C Min	Col^C Average	Col^C Max
$HeCN_4$	TP	1,336	1,533	3,148	1,398	2,754	3,750
	IC	224	268	348	92	121	166
	LC	296	440	580	48	134	536
$HeCN_6$	TP	1,740	3,751	5,273	2,258	4,207	4,494
	IC	153	212	368	85	152	249
	LC	142	192	251	62	114	186
$HeCN_8$	TP	2,258	2,921	3,751	3,754	4,385	4,548
	IC	220	352	475	68	170	268
	LC	146	193	278	52	134	220
$HoCN_4$	TP	207	721	1017	1,285	1,387	1,433
	IC	141	192	263	132	149	170
	LC	208	304	476	99	247	747
$HoCN_6$	TP	1,211	2,610	2,007	1,964	2,243	2,468
	IC	78	215	193	20	87	170
	LC	120	321	242	72	136	188
$HoCN_8$	TP	2,882	3,256	3,566	4,068	4,484	4,670
	IC	186	229	282	28	60	122
	LC	255	373	504	24	160	228

$HoCN_4$, $HoCN_6$, $HoCN_8$, $HeCN_4$, $HeCN_6$ and $HeCN_8$ (92%, 85%, 37%, 79%, 21%, and 50%, respectively). On the other hand, IC is reduced at $HoCN_4$, $HoCN_6$, $HoCN_8$, $HeCN_4$, $HeCN_6$, and $HeCN_8$ (28%, 47%, 52%, 21%, 39%, and 17%, respectively). In addition, LC is reduced at $HoCN_4$, $HoCN_6$, $HoCN_8$, $HeCN_4$, $HeCN_6$, and $HeCN_8$ (23%, 36%, 33%, 28%, 68%, and 44%, respectively).

The experimental results illustrate that when α is increased, the variances of TP, IC, and LC in CN are reduced. The maximum values of these criteria become much smaller and minimum values get bigger. On the other hand, the average values of

Table 4.6: Summary of network performance with Col^P in HeCN, HoCN for $K = (4, 6, 8)$

Network	Performance		$\alpha = 0.2$		$\alpha = 0.4$		$\alpha = 0.6$		$\alpha = 0.8$		$\alpha = 1$	
Type	Criteria	Avg.	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
HeCN_4	TP	2,754	1,440	3,708	1,480	3,668	1,480	3,668	1,498	3,650	1,571	3,631
	IC	121	100	158	106	146	112	138	112	136	114	134
	LC	134	62	496	78	474	82	450	90	400	90	372
HeCN_6	TP	4,207	2,300	4,452	2,312	4,440	2,348	4,404	2,348	4,404	2,348	4,404
	IC	152	90	244	98	236	106	220	106	220	122	204
	LC	114	72	166	81	156	87	147	87	147	90	141
HeCN_8	TP	4,385	3,800	4,502	3,857	4,485	3,935	4,467	4,090	4,402	4,170	4,402
	IC	170	80	256	92	248	112	230	136	220	140	220
	LC	192	150	261	159	249	165	230	171	222	171	222
HoCN_4	TP	1,387	1,289	1,439	1,292	1,436	1,300	1,428	1,300	1,428	1,302	1,426
	IC	149	132	170	134	168	140	162	142	160	142	160
	LC	247	120	724	120	724	120	724	126	718	135	709
HoCN_6	TP	2,243	1,964	2,468	2,000	2,432	2,012	2,420	2,030	2,402	2,030	2,402
	IC	86	28	162	28	162	40	150	46	144	52	138
	LC	135	72	188	84	176	84	176	99	161	105	155
HoCN_8	TP	4,484	4,077	4,460	4,122	4,416	4,132	4,406	4,150	4,388	4,150	4,388
	IC	60	34	116	48	102	56	94	56	94	66	84
	LC	160	48	204	63	189	63	189	75	177	81	171

these criteria do not change. When these improvements appear on such criteria, the total amounts of each criteria do not change because the U_α is divided into two components which are fairness and efficiency. It means that, a certain level of α seems to be as a specific point on the tradeoff curve of optimal fairness and efficiency (Lan et al., 2010). In addition, maximum value of fairness is reached at this specific point while maintaining feasibility of A_k^* under a given constraint set of the resource allocation in terms of demand and capacity sharing.

4.1.6 Summary

The balance between fairness and efficiency in resource allocation in the CN of enterprises is studied in this research. Two concepts are utilized to distinguish a balance between fairness and efficiency in sharing protocols: 1) the generalized U_α to find a fair resource allocation and 2) Ji to calculate the degree of fairness in a CN. Furthermore, this research proposed to find the optimal weights of fairness while maintaining current efficiency. The experimental results indicate that the total amounts of each evaluation criteria do not change while U_α becomes large, because U_α incorporates both fairness and efficiency simultaneously. The efficiency component of U_α skews the optimizer while gaining in efficiency over all feasible allocations.

Experimental results indicate that 1) HeCN is fairer than HoCN, 2) Col^P provides fairer CN than Col^C, and 3) a small network size obtains a higher Ji than a large network size. When $\alpha \approx 1$, the CN becomes fairer than small α value. For instance, Ji of HeCN_4, HeCN_6, and HeCN_8, are increased by 27%, 28%, and 18%, respectively. On the other hand, Ji of HoCN_4, HoCN_6, and HoCN_8 increased by 33%, 33%, and 21%, respectively, when α goes to 1 from 0. As bigger α supports a fair network, it reduces the variance of resource allocation among the collaborating enterprises even if the average of performance criteria is not changed. The experimental results illustrate that the gap between the two enterprises, which are the most benefited and least benefited enterprises in CN, becomes smaller, when α value is increased. In addition, the number of collaborations in CN is also effected by U_α. Therefore, the number of collaborations is increased when $\alpha \approx 1$. It is also shown that collaboration strategy is one of the best effective ways to increase survivability in changing market conditions. The results also show that enterprises may increase their total profit and decrease their lost sale cost and holding cost simultaneously. It implies that a fair CN could be formed by heterogeneous enterprises, in terms of the enterprise capacity, with small network sizes under partial collaboration model. The outcomes of this research demonstrate that incorporating a certain level of efficiency results in a fair network resource allocation.

4.2 Dynamic Reformation of Partnership Subsets for Fair Demand and Capacity Sharing Collaborative Network

4.2.1 Experimental Design and Scenarios

Numerical experiments are conducted using case studies to analyze the proposed D^2SP in terms of total profit, fairness, scalability, and communication overhead. This research is motivated by the problems of resource allocation in a CN that is simulated as consisting of eight enterprises ($K = 8$). It is difficult to benefit from a CN when $K = 2 \rightarrow \infty$, because the coordination cost increases exponentially. Therefore, a large-scale CN seems unrealistic, and most CN research assumes that ($2 \leq K \leq 8$) (Ko and Nof, 2010, Yoon and Nof, 2010, Seok and Nof, 2014b, Yilmaz et al., 2017). The demand distribution for e_k is assumed to be a normal distribution for all experimental scenarios. The details of the simulation parameter settings are summarized in Table 4.7. The proposed SPs are examined under the following assumptions: 1) All CNEs are non-competing and autonomous, 2) No CNE has authority over other en-

Table 4.7: Summary of parameter settings

Parameter	Value
Number of collaborative enterprises	$K = (8)$
Production capacity of e_k	$m(o_{kt}) = \{120 + 5y \| y \in [1, 8],\, y \in Z\}$
Demand distribution of customer orders	$q_{kt} = \mathcal{N}(m(o_{kt}), 30)$
Time distribution of customer orders	$t^d = \mathcal{N}(1, 3)$
Unit selling price in the CN for e_k	$s^p = 10$
Production cost per unit [\$/unit]	$c^p = 5$
Coordination cost per message [\$/mess.]	$\delta = 0.005$
Lost sale cost per unit [\$/unit]	$l^c = 3$
Holding cost per unit [\$/unit]	$h^c = 2$
Values of β [\$/time]	$\forall \beta \in \{y \,\|\, y \in [0, 10],\, y \in Z\}$
Values of γ [\$/fairness]	$\forall \gamma \in \{y \,\|\, y \in [0, 100],\, y \in Z\}$
Replications	1000

terprises, 3) o_{kt} apply through discrete time periods, 4) Products are non-perishable, and interchangeable. 5) All CNEs are willing to share their excess demand and capacity. The simulation model is implemented using MATLAB and statistical analyses are performed using Minitab with given parameter settings. The results are presented as follows.

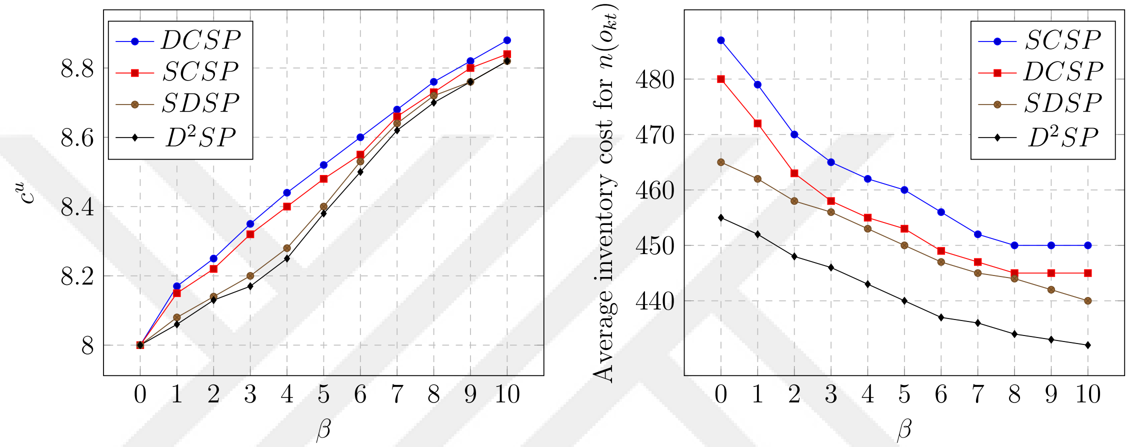
4.2.2 Analysis of Sharing Protocols Under a Variable Time-to-money Conversion Factor (β)

D^2SP was compared with $SCSP$, $SDSP$, and $DCSP$ under the same demand patterns of o_{kt} when $0 \leq \beta \leq 10$. The fairness-to-money conversion factor, γ, was assumed to be zero in this section to show the effect of α on SPs.

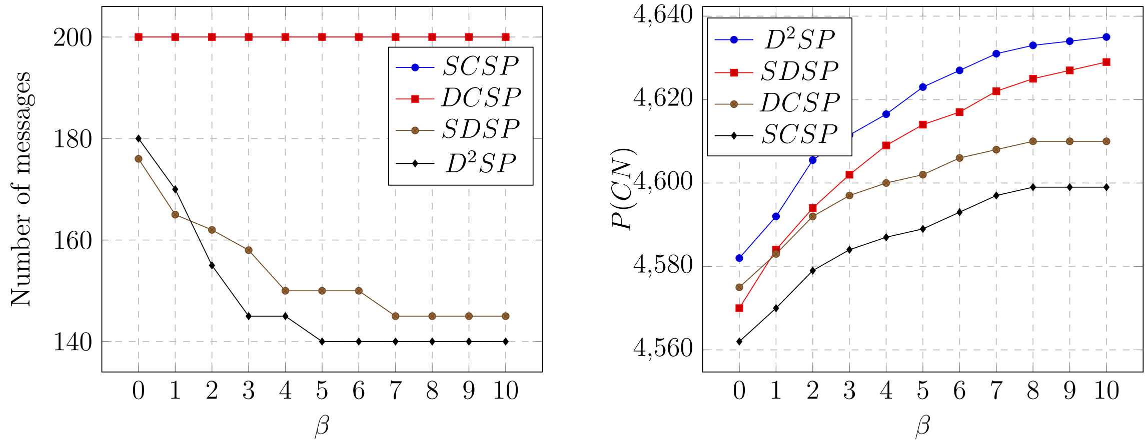
Figure 4.4 shows the performance of D^2SP, $SCSP$, $SDSP$, and $DCSP$ when $\beta \rightarrow 10$ in terms of c^u_{kt}, average inventory cost for $n(o_{kt})$, average inventory time for $n(o_{kt})$, total profit, $P(CN)$, and number of messages. The performance rates of the four SPs showed a steady trend until reaching their upper or lower bounds.

As shown in Figure 4.4a, c^u_{kt} gradually increases by more than 10% over τ as $\beta \rightarrow 10$. Interestingly, c^u_{kt} in CSPs responds more quickly to changes in α, while distributed sharing protocols (DSPs) experience slower responses to changes. However, the gap between c^u_{kt} in CSP and DSP is reduced by up to 75% when $\beta \rightarrow 10$. Table 4.8 presents an analysis of variance (ANOVA) to determine whether the means of c^u_{kt} are different for all SPs. The means of c^u_{kt} are compared with the following hypotheses: 1) H_0: $\mu_{SDSP} = \mu_{DCSP} = \mu_{SCSP} = \mu_{D^2SP}$ and 2) H_1: not all $\mu_{.}$ are equal. Table 4.8 shows that H_0 cannot be rejected because p-value is 0.949, which is greater than significance level of 0.05. Therefore, there is sufficient evidence to conclude that c^u has statistically same means in all SPs.

Figure 4.4b shows information about the average inventory cost after collaboration occurs because of the differences between t^d and t^{lt} when $\beta \rightarrow 10$. The average inventory cost for $n(o_{kt})$ is decreased by up to 9%, 6%, 5%, and 4% in $SCSP$, $SDSP$, D^2SP, and $DCSP$, respectively. These results were tested by ANOVA, as shown in Table 4.8, which implies that the p-value is 0.754, which is higher than the significance level of 0.05. Therefore, SPs have statistically same efficiency when $\beta \to 10$ in terms of reducing average inventory cost for $n(o_{kt})$.



(a) c^u when $0 \leq \beta \leq 10$ (b) Inventory cost of $n(o_{kt})$ when $0 \leq \beta \leq 10$



(c) Number of messages when $0 \leq \beta \leq 10$ (d) $P(CN)$ when $0 \leq \beta \leq 10$

Figure 4.4: Analysis of D^2SP, $SDSP$, $DCSP$, and $SCSP$ when $0 \leq \beta \leq 10$

Figure 4.4c represents the number of messages that are sent over τ to form a collaboration when $\beta \to 10$. It can be seen that the CSPs collect all information about the CN even if the information is not used to form a collaboration. Thus, the number of messages is steady when $\beta \to 10$; however, the number of messages in DSPs is decreased by up to 25%. CSPs and DSPs are statistically different, as shown in Table 4.8. This situation affects $P(CN)$ in a CN. Figure 4.4d illustrates that $P(CN)$ over τ is stable in CSPs; however, $P(CN)$ is increased in DSPs by up to 12% and 10% in D^2SP and SDSP, respectively.

Table 4.8: ANOVA test results when $\beta \rightarrow 10$

	c^u	Inventory cost for $n(o_{kt})$	Inventory time for $n(o_{kt})$	$P(CN)$	Number of messages
p-value	0.949	0.989	0.889	0.001	0.001

Table 4.9: Tukey test results for μ_{SDSP}, μ_{DCSP}, μ_{SCSP}, and μ_{D^2SP}

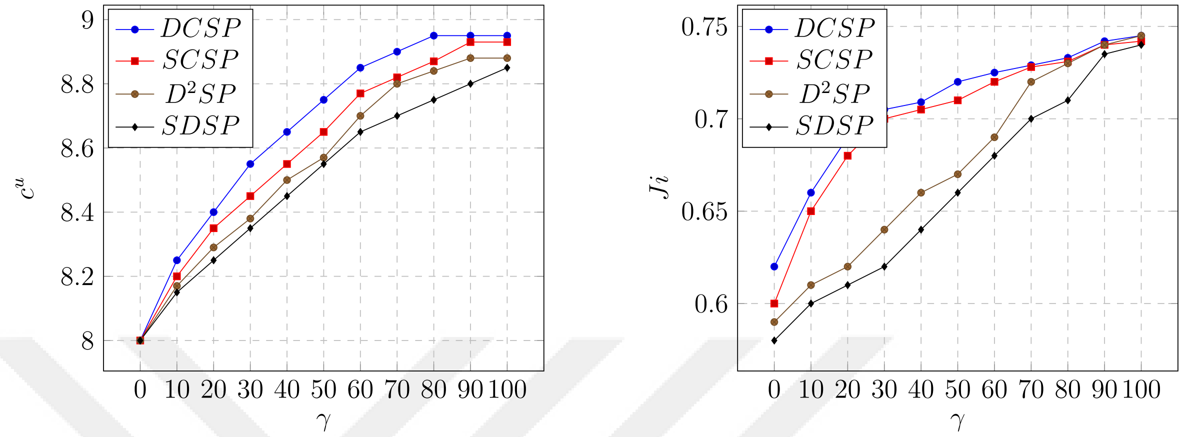
Number of Messages					$P(CN)$				
Factor	N	Mean	Grouping		Factor	N	Mean	Grouping	
D^2SP	11	148.6	A		D^2SP	11	4617.3	A	
$SDSP$	11	153.7	A		$SDSP$	11	4608.4	A	
$SCSP$	11	200		B	$SCSP$	11	4599.3		B
$DCSP$	11	200		B	$DCSP$	11	4587.1		B

In addition, DSPs have higher μ for $P(CN)$ than CSPs. The results of ANOVA is presented in Table 4.8, show that the means of $P(CN)$ are not same for all SPs. Tukey test was applied to find groups of SPs that are significantly different from each other. Tukey test results imply that CSPs and DSPs are grouped into two different groups, as shown in Table 4.9.

4.2.3 Analysis of Sharing Protocols Under a Variable Fairness-to-money Conversion Factor (γ)

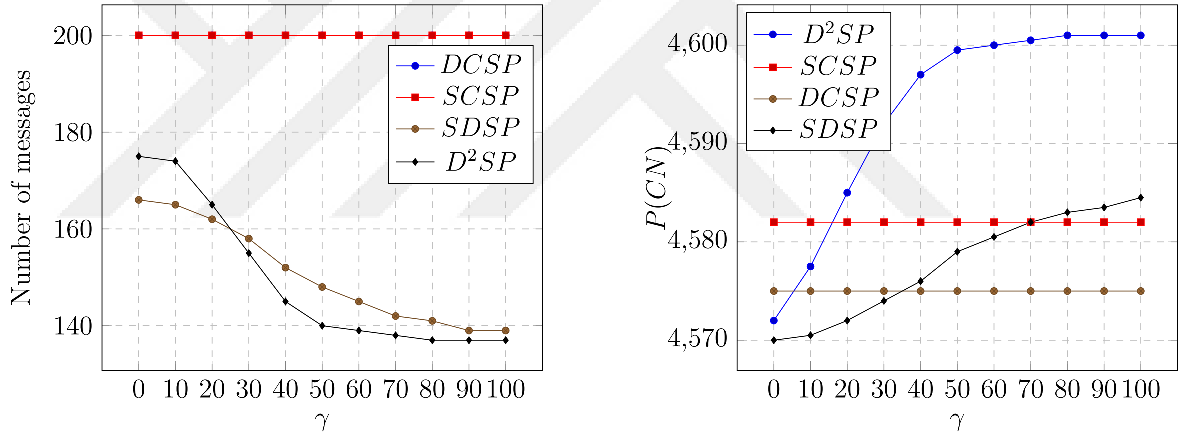
Figure 4.5 illustrates the performance of SPs when $\gamma \rightarrow 100$. In this analysis, β is assumed to be zero. Figure 4.5a illustrates that c^u_{kt} is increased steadily when $\gamma \rightarrow 100$ in all SPs because fair resource allocation violations increase c^u_{kt} up to 15% in SPs. As seen in Table 4.10, μ_{SDSP}, μ_{DCSP}, μ_{SCSP}, and μ_{D^2SP} are significantly same, because

p-value is higher than significance value (0.05). Therefore, all SPs have a significantly identical performance in response to changes in γ.



(a) c^u when $0 \leq \gamma \leq 100$

(b) Ji when $0 \leq \gamma \leq 100$



(c) Number of messages when $0 \leq \gamma \leq 100$

(d) $P(CN)$ when $0 \leq \gamma \leq 100$

Figure 4.5: Analysis of D^2SP, $SDSP$, $DCSP$, and $SCSP$ when $0 \leq \gamma \leq 100$

Figure 4.5b depicts the changing in Ji as $\gamma \rightarrow 100$. CSPs react quickly to any small changes in γ; however, after γ passes 60, the gap between CSP and DSP becomes narrower. All SPs show a similar performance for Ji when $90 < \gamma < 100$. Thus, CSPs seem more sensitive than DSPs to changes in γ.

Figure 4.5c shows the number of messages in SPs when $\gamma \rightarrow 100$. Similarly to Figure 4.4, Figure 4.5c also implies that CSPs require all information in the CN over τ. Therefore, the number of messages in CSPs is stable over τ. However, DSPs require fewer messages to choose a collaboration partner from $e_k \in E$ by assigning priorities with U. Therefore, DSPs could require up to 30% less information to form a collaboration than CSPs, while ensuring $P(CN)$.

Table 4.10: ANOVA test results when $\gamma \to 100$

	c^u	JI	$P(CN)$	Number of messages
p-value	0.899	0.912	0.001	0.002

Table 4.11: Tukey test results for μ_{SDSP} μ_{DCSP} μ_{SCSP} and μ_{D^2SP}

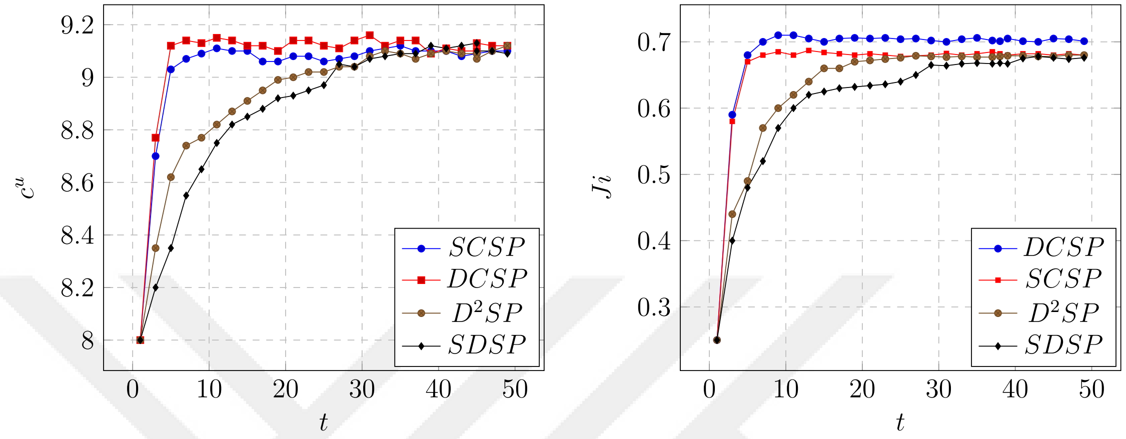
Number of Messages					$P(CN)$				
Factor	N	Mean	Grouping		Factor	N	Mean	Grouping	
D^2SP	11	148	A		D^2SP	11	4608	A	
$SDSP$	11	153	A		$SDSP$	11	4602	A	
$SCSP$	11	200		B	$SCSP$	11	4582		B
$DCSP$	11	200		B	$DCSP$	11	4575		B

The smaller number of messages causes an increase in $P(CN)$ up to 5% in a CN that is managed by a DSP, as shown in Figure 4.5d. CSPs and DSPs are separated at the required number of messages and $P(CN)$. The values in Table 4.10 imply that the SPs have not significantly identical μ and Table 4.11 shows CSPs and DSPs are grouped significantly into two different groups. Therefore, DSPs can perform at least equally as well as or better than centralized and static SPs with limited information.

4.2.4 Analysis of Sharing Protocols Over the Collaboration Period (τ)

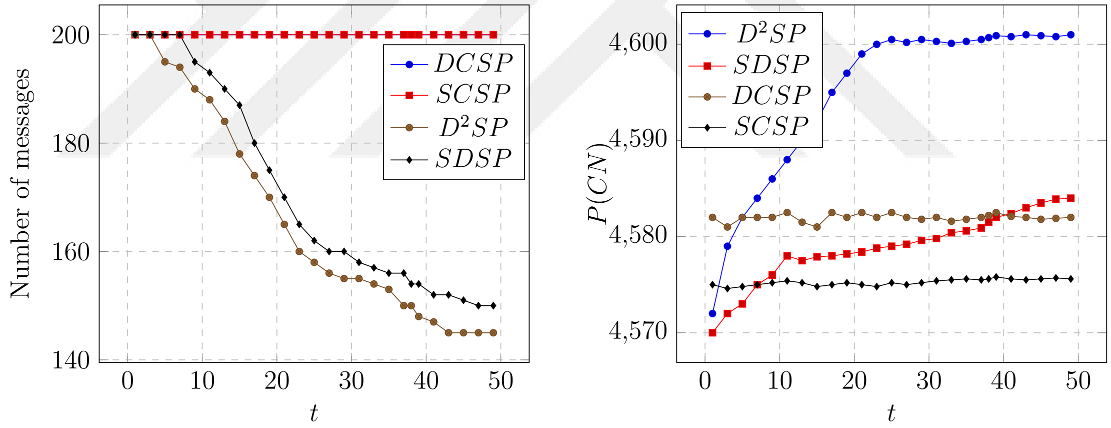
Figure 4.6 illustrates the changes in c^u_{kt}, Ji, number of messages, and $P(CN)$ over τ ($0 < t < 50$). In this analysis, the values of α and γ are assumed to be 5 and 50, respectively. Figure 4.6a shows that CSPs require less time to reach the upper bounds of c^u_{kt} than DSPs. After a certain time period, all SPs show the same performance. The certain time period is defined as the time required to assign priorities for e_k.

Figure 4.6b shows Ji's trends over τ. CSPs can penalize unfair resource allocations in a short time. However, DSPs should wait until all e_k attend a collaboration. After each e_k attends a collaboration, U starts to assign priorities and provide effective collaboration decisions to allocate resources fairly.



(a) c^u over τ

(b) Ji over τ



(c) Number of messages over τ

(d) $P(CN)$ over τ

Figure 4.6: Analysis of D^2SP, $SDSP$, $DCSP$, and $SCSP$ over τ

Figure 4.6c shows that the number of messages required to form a collaboration in CSPs is the same over τ. Even if DSPs require the same number of messages as CSPs at the beginning of τ, after a certain time period, the number of required messages can be reduced by up to 30%. In parallel with the number of required messages, $P(CN)$ is affected. As shown in Figure 4.6d, the average $P(CN)$ per collaboration can increase in DSPs because of the lower coordination cost. Conversely, $P(CN)$ in in CSPs shows fluctuations over τ because of the effects of c_{kt}^{lt} and random o_{kt}.

4.2.5 Scalability Analysis of Sharing Protocols

An important aspect of analyzing the performance of SPs is its evaluation in terms of how it varies with the network size, K. In the literature, the value of K is typically assumed to be less than eight because of the exponentially increased c_{kt}^{c} (Scavarda et al., 2015, Yoon and Nof, 2010, Seok and Nof, 2014b, Yilmaz et al., 2017). c_{kt}^{c} is related to the number of messages between $E^{-} = \{e_1 \ldots e_j\}$ and $E^{+} = \{e_1 \ldots e_i\}$. The maximum number of connections, M, among "K" entities in a generic network was calculated by Kim and Glass (2015) as follows:

$$M = \frac{K \cdot (K-1)}{2}. \tag{4.1}$$

Each element of one subset (E^{+} or E^{-}) can form a connection with an element of the other subset and cannot form a connection with another element within the same subset. Therefore, the maximum number of connections in a CN can be found by modifying the product rule proposed by Lefebvre (2007):

$$\begin{aligned} z = \quad & \max(I \cdot J) && (4.2)\\ \text{s.t.} \quad & I + J = K && (4.3)\\ & I,\ J \geq 0, && (4.4) \end{aligned}$$

where $I = |E^{+}|$ and $J = |E^{-}|$. The optimal solution of the number of connections in a CN can be found when $I = J$. However, this situation might not be appropriate for DSPs, which do not require all the information about all the connections. Thus, the maximum number of connections in a DSP is defined as

$$z = \max((I-a)\cdot(J-b)) \tag{4.5}$$

$$\text{s.t.} \quad I + J - (a+b) \leq K \tag{4.6}$$

$$b \leq J \tag{4.7}$$

$$a \leq I \tag{4.8}$$

$$a,\ b,\ K \geq 0 \tag{4.9}$$

where $I = |E^+|$, $J = |E^-|$, and a and b is the number of elements that are not included in any collaboration. It is also assumed that each awarded collaboration requires five messages and that each failed collaboration requires two messages.

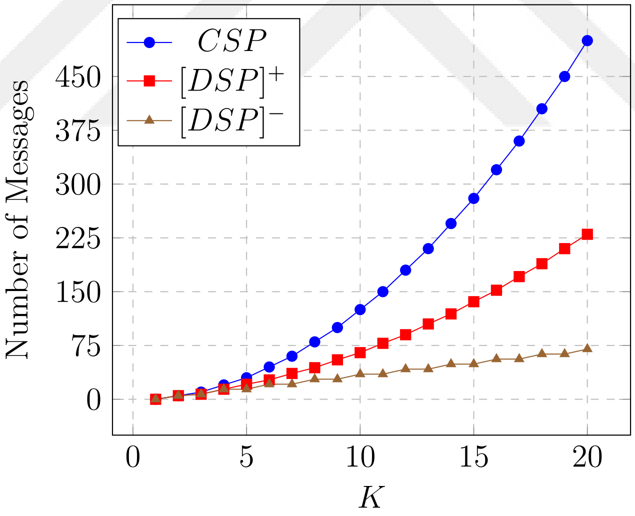


Figure 4.7: Scalability analysis of sharing protocols in terms of the number of messages

Figure 4.7 shows that as K increases, the number of required messages increases exponentially in CSPs. This causes an increase in c^c_{kt} and reduces $P(CN)$. However, DSPs require between approximately 60% and 80% fewer messages as $K \rightarrow 20$. It is clear that the gap between the number of required messages for CSPs and DSPs can grow as K continues to increase.

4.2.6 Summary

This research addressed a new sharing protocol, D^2SP, which is inspired by the principles of CCT and CNP. Beneficial collaboration conditions were defined. An optimization model was adapted to CNP in the bid evaluation step to select the best bid from capacity sharing enterprises. In this context, a DNM is proposed to achieve the maximum mutual benefits of CNEs. This research aims to analyze the effectiveness of distributed decision making in CNs.

The experimental results indicate that D^2SP enables a collaboration among distributed e_k by reducing the coordination cost and number of messages and increasing the fairness in resource allocation in a CN. D^2SP assigns priority to an e_k based on lead time and fairness violations in resource allocation. e_i sends a bid to e_j that has the highest priority and might not send messages to e_j that has a lower priority than other elements of E^-. Therefore, the number of messages is reduced by up to 30% in D^2SP. The inventory of $n(o_{kt})$ is reduced by up to 9% by penalizing early deliveries. It is also shown that a collaboration could be benefited under specific conditions. In this context, the limits of the collaboration unit price were analyzed in terms of c^f_{kt} and c^{lt}_{kt}. The experimental results imply that there are no statistical differences among the SPs in terms of the network profit. CSPs have a power similar to that of distributed protocols to control fairness in resource allocation when $\gamma \neq 0$ and the fairness index can increase by up to 10%. Even if the number of messages in CSPs is higher by 30% than that in distributed protocols, the performance of all the SPs is identical in terms of fair resource allocation. In comparison with CSPs, DSPs are scalable in terms of the number of messages. The number of messages causes more computing time and coordination cost. Therefore, it was shown in this paper that the fairness and total profit in a CN could increase simultaneously by reducing the number of which are messages required to form a collaboration.

Chapter 5. Conclusions and Future Work

5.1 A Framework and Algorithm for Fair Demand and Capacity Sharing in Collaborative Network

The balance between fairness and efficiency in resource allocation in the CN of enterprises is studied in this research. It is shown that fairness in collaborative network can be increased by implementing the α-utility function to a traditional demand and capacity sharing protocol. A framework and algorithm is proposed to find the optimal weights of fairness while maintaining current efficiency. The generalized U_α and Ji are utilized to find the balance between fairness and efficiency in sharing protocols. The generalized U_α is applied to find a fair resource allocation. Ji is applied to calculate the degree of fairness in a CN.

The experimental results indicate that

1. HeCN is fairer than HoCN,
2. Col^P provides fairer CN than Col^C,
3. A small network size obtains a higher Ji than a large network size.

When $\alpha \approx 1$,

1. Ji of HeCN_4, HeCN_6 and HeCN_8, are increased by 27%, 28%, and 18%, respectively.
2. Ji of HoCN_4, HoCN_6 and HoCN_8 increased by 33%, 33%, and 21%, respectively,

3. The experimental results illustrate that the gap between the two enterprises, which are the most benefited and least benefited enterprises in CN, becomes smaller, when α value is increased.
4. The number of collaborations in CN is also affected by U_α.

The results also show that enterprises may increase their total profit and decrease their lost sale cost and holding cost simultaneously. It implies that a fair CN could be formed by heterogeneous enterprises, in terms of the enterprise capacity, with small network sizes under partial collaboration model. The outcomes of this research demonstrate that incorporating a certain level of efficiency results in a fair network resource allocation.

5.2 Dynamic Reformation of Partnership Subsets for Fair Demand and Capacity Sharing in Collaborative Network

The proposed protocol in literature requires complete information of demand- and capacity-sharing proposals. Therefore, a new demand and capacity sharing protocol with limited information sharing is introduced. In this context, distributed decision protocol have to be introduced to coordinate all members of a collaborative network. Collaborative network of enterprises are autonomous decision makers and more than one decision maker is involved in accordance with an overall profit function or in line with some equilibrium conditions while maximizing their mutual benefits.

Dynamism has to be implemented to the protocol which accounts for time-dependent changes in the state of the collaborative network. The dynamism can be provided by a negotiation mechanism which is inspired by contract net protocol (CNP) (Smith, 1980). The CNP can be improved by adding dynamically changing priority to collaborative networked enterprises.

Fairness in a collaborative network must be tested, analyzed and compared to algorithms without and with complete information sharing; in addition, static and dynamic nature of coordination protocols.

The experimental results indicate that

1. D^2SP enables a collaboration among distributed e_k by reducing the coordination cost and number of messages and increasing the fairness in resource allocation in a CN.
2. D^2SP assigns priority to an e_k based on lead time and fairness violations in resource allocation.
3. Number of messages is reduced by up to 30% in D^2SP.
4. The inventory cost of $n(o_{kt})$ is reduced by up to 9% by penalizing early deliveries.
5. The limits of the collaboration unit price were analyzed in terms of c_{kt}^{f} and c_{kt}^{lt}.
6. The fairness index can increase by up to 10%.
7. Even if the number of messages in CSPs is higher by 30% than that in DSP, the performance of all the SPs is identical in terms of fair resource allocation.
8. In comparison with CSPs, DSPs are scalable in terms of the number of messages.

Therefore, it was shown in this paper that the fairness and total profit in a CN could increase simultaneously by reducing the number of messages required to form a collaboration.

5.3 Future Work

The conclusions of collaborative network of enterprises in demand and capacity sharing and in control of entire network actions addressed in this research. However, the contributions from this research, the open issues in several areas for future research are summarized as follows.

5.3.1 Fairness Responsibility

The responsibility of fairness have to be distributed to all members of collaborative networked enterprises. Distributed decision making mechanism must be implemented to coordination protocol of collaborative network. In addition, the effects of network fairness on individual enterprises have to be considered, because such methods do not consider the influence of the fair resource allocation on individual enterprise. However, while getting a fair network, an individual enterprise may get less profit than before, even if the total profit of the collaborative network does not change (Husam et al., 2017). This situation leaves open the question of whether or not this affects the long-term sustainability of collaborative network.

5.3.2 Perishable and Multi-product Network

In many collaborative network research, it is assumed that the products in the network are non-perishable. The effect of perishable inventory on collaboration, and proposes a strategy to manage the tradeoff between shortage and waste. A collaboration strategy is proposed to find efficient decisions that minimize waste, shortage, and holding costs in the network, while maximizing the demand fulfillment rate. In addition, the collaboration strategy could help to find how excess demand at any location is satisfied from outside sources. Therefore, upper and lower bounds for the expected out-dating products are obtained for the case of general demand distribution. Incorporating inventory lead times and analyzing collaborative network performance are another future research issues.

5.3.3 Subset Networks in a Collaborative Network

It is assumed in most collaborative network research that the collaborative network of enterprises are willing to collaborate to achieve mutual benefits. Collaborative network of enterprises are group-oriented, seeking a set of mutual benefits while ensuring their individual objectives. In some cases such as extraordinary situations, force majeure, the individuals could show self-oriented behaviors and their individual objectives may contradict the mutual benefits of the collaborative network. This situation cause to unfair resource allocation that could be acceptable by some collaborative network of enterprises. Therefore, the effect of unfair resource allocations in subset of collaborative network of enterprise on collaborative network sustainability will be analyzed in future research.

5.3.4 Limits of Collaborations in a Collaborative Network

Limits of collaborations such as rate of collaboration, profitability ratio, sustainability will be addressed under more complicated cases with real life assumptions, i.e., various demand pattern, market prices, production/service costs and coordination costs among manufacturers or service providers. Also, by comparing/combining the short-term and long-term partnership in network, the differentiated information sharing strategies during collaboration time period will be discussed.

5.3.5 Appearance of Coo-petition

Despite benefits of collaboration, competition is also another inevitable fact in distributed systems. The conditions of competition will be proposed to enhance the network profitability. The notion of collaboration of competitors is commonly studied by game theory researchers. The limits of competition among collaborative enterprises will also be analyzed and theoretical findings will be proposed.

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