A COOPERATIVE SHIPMENT CONSOLIDATION GAME WITH EMISSION CONSIDERATIONS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

HALIT KEVEN

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
INDUSTRIAL ENGINEERING

JANUARY 2020

Approval of the thesis:

A COOPERATIVE SHIPMENT CONSOLIDATION GAME WITH EMISSION CONSIDERATIONS

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ABSTRACT

A COOPERATIVE SHIPMENT CONSOLIDATION GAME WITH EMISSION CONSIDERATIONS

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January 2020, 76 pages

Logistic operations constitute one of the most significant cost components for many companies. Furthermore, these activities have turned out to be one of the main causes of carbon emissions in the world. The carbon emission issue has been under the spotlight in many countries due to the rising concerns about global warming which brought about new regulations. Large majority of these regulations tend to increase the total costs of logistic operations by a variable factor directly related to carbon emission amounts, so that companies have to consider costs related to carbon emissions resulting from their logistic operations as well as direct costs like fuel consumption. To compensate the increase in the cost amounts new approaches need to be developed. One way to achieve increased operational efficiencies under such a problem environment might be collaboration with other companies which also involves a competition on a smaller scale. In our study, we consider a market characterized by uncertain shipment requests where shippers are willing to collaborate for their shipment activities. They also compete for truck space within this collaboration process. We assume that the companies aim to maximize the profit from their shipments. We assume the shippers form a coalition and make dispatch decisions jointly. To ensure a fair and stable allocation of the savings we develop allocation schemes that require a low computational effort. We evaluate and compare the schemes based on several criteria.

Keywords: Allocation Scheme, Carbon Emission Allocation, Cooperative Game Theory, Inventory Management, Markov Decision Process, Optimization, Profit Allocation

ÖZ

Nakliyede İşbirliğinin Taşıma Maliyeti ve Karbon Salınımı Üzerine Etkileri

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Lojistik faaliyetleri birçok işletme için en önemli maliyet kalemlerinden birisini oluşturduğu gibi aynı zamanda dünyadaki karbon salınımlarının da temel nedenlerindendir. Küresel ısınmayla ilgili artan farkındalık ve endişeler dolayısıyla karbon salınımlarının azaltılması çabaları birçok ülkede ön plana çıkmaktadır. Tedbir olarak ortaya konulan yasal düzenlemelerin çoğunluğu belli bir faaliyet sonucu ortaya çıkan karbon salınımını faaliyetten sorumlu işletmelere sebep oldukları karbon salınımı miktarıyla doğru orantılı olacak şekilde bir maliyet olarak yansıtmayı hedefler. Bu durum ilgili işletmeler için lojistik aktivitelerinin maliyetlerini önemli ölçüde artırır. Sonuç olarak işletmeler lojistik faaliyetleriyle ilgili olarak yakıt tüketimi gibi direkt maliyetlerin yanı sıra karbon salınımı maliyetlerini de dikkate almak durumundadırlar. Bu koşullar altında farklı organizasyonların işbirliği yapması verimliliklerin artmasını, maliyetlerin azalmasını sağlayabilir. Böyle bir işbirliği bir rekabeti de beraberinde getirecektir. Bu çalışmada nakliye gönderimi yapmak isteyen oyuncuların belirsiz sevkiyat taleplerinin bulunduğu durumlarda işbirliği ve rekabet koşullarının değerlendirilmesi amaçlanmıştır. Oyuncular gönderilerini ortak bir araç ile yapmanın avantajlarından faydalanmak ister ve maksimum fayda elde etmeyi amaçlayan bu oyuncular aynı zamanda ortak kullanılan araçta yer alabilmek için birbirleriyle rekabet ederler. Oyuncuların temel amacının nakliye ve bekleme maliyetleri ile karbon salınımını en aza indirirken elde edilen geliri en üst seviyeye çıkarmak olduğu bu oyunda göndericiler bu kazançları elde edebilmek için bir koalisyon oluşturur ve gönderi ve bekleme kararlarını ortak olarak alırlar. Koalisyon girişiminden elde edilen tasarrufların oyuncular arasında adil ve dengeli bir şekilde dağıtılmasını sağlamak için düşük hesaplama çabası gerektiren fayda tahsis kuralları geliştirilip, bunlar çeşitli kriterler altında değerlendirilmiş ve karşılaştırılmıştır.

Anahtar Kelimeler: Fayda Tahsis Kuralı, Karbon Emisyon Tahsisi, Kooperatif Oyun Teorisi, Envanter Yönetimi, Markov Karar Süreci, Optimizasyon,

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CHAPTER 1

INTRODUCTION

Logistic operations are one of the major cost items for many companies. Furthermore, these activities have turned out to be one of the main causes of carbon emissions in the world. According to USA Environmental Protection Agency, in USA transportation sector was responsible for the 29% of total greenhouse gas (GHG) emissions in 2017 followed by electricity consumption which caused 28% of all GHG emissions (United States Environmental Protection Agency, 2018).

The carbon emission issue has been under the spotlight in many countries due to the rising concerns about global warming. United Nations (UN) aims to achieve a 25% to 55% decrease in GHG emissions by the year 2030 compared to 2017 realizations to limit the global warming from 2^{o}C to 1^{o}C. According to the UN Emission Gap Report, transportation is one of the 6 key sectors with emissions reduction potential which is expected to account for approximately the 15% of targeted reduction in GHG emissions (Olhoff, 2018).

Efforts to decrease GHG emission amounts bring about new regulations. Large majority of these regulations tend to increase the total costs of logistic operations as a result of penalty costs related to environmental effects, so that companies have to consider costs related to carbon emissions resulting from their logistic operations as well as direct costs like fuel consumption. To compensate the increase in cost, new approaches need to be developed. One way to achieve increased operational efficiencies under such an issue might be collaboration. Collaboration has been proven to be an effective way to achieve large scale benefits. These benefits involve both economic and environmental cost improvements as a result of increased capacity utilization and shared fixed costs.

Vast amount of work has been done discussing potential areas of collaboration and its potential gains in many practical situations. As Shenle et al. (2019) discussed in their survey study, there are two main types of collaboration in logistics. In vertical collaboration the members of a single supply chain collaborate through vertical relationships. On the other hand, the horizontal collaboration implies the cooperation of different companies to perform supply chain activities jointly. In the same study the horizontal collaborative transport is defined to be all types of cooperation in freight operations, which may involve members from shippers, carriers, logistics service provides or receivers, carried out at any level of separate supply chains. They analyze the horizontal collaborative transport in six categories based on previous work, which include, shipper collaboration, carrier collaboration, transport marketplace, flow-controlling entities collaboration, logistics pooling, and physical internet.

Guajardo and Ronnqvist (2016) classifies the studied horizontal collaboration problems into 5 main categories. These are transportation planning, travelling salesman, vehicle routing, joint distribution and inventory problems. In transportation planning problems considered, the collaboration of different agents for delivering desired goods to demand points on a specific network is considered. In the collaborative travelling salesmand problem, the issue of distributing costs of a tour to the cities visited is considered. In the collaborative vehicle routing problem, the goal is to find common routes for satisfiying the demand of the customers on these routes. Most of the collaborative vehicle routing problem studies reviewed also deals with the allocation of costs to the cities visited. Joint distribution problems studied involve the cases where two or more sperate organizations make joint decisions to distribute their goods on a shared network. Inventory problems discussed in this review study involve the cost allocation issues in inventory problems where pooling of resources is considered.

There are many successfully applied projects in the area of collaborative logistics. One of them is the EU FP7 funded “Collaborative Concepts for Co-Modality (CO^3) Project”. The fact that almost 25% of the freight vehicles in Europe were running empty while for the rest the utilization level was below 60% (World Economic Forum, 2009), was one of the major drivers for the CO^3 Project. The goal of the project was to encourage the companies in Europe for horizontal collaboration in their freight activities (CO3|Collaboration Concepts for Co-modality, 2014). The study involve 4 applied case studies involving different companies. The Nestle and PepsiCo project involves the collaboration of the two companies through joint distribution of their goods. Within the scope of this project, the cost savings are around 10-15%, with the similar percentage of reduction amounts of GHG emissions. Tupperware and P&G have similar transportation lanes. That is, they both have plants and need to define DC's in Belgium and they both ship their products to Greece. The trucks of Tupperware were full in volume but, load capacities were underutilized. For the P&G, the condition was the opposite, so that there was a big chance for the collaboration of transportation activities. In Tupperware and P&G project, 150.000 truck-km are eliminated while 200 metric tons of GHG emissions are avoided by consolidation. The JSP and HF-Czechforge project also involves collaborative transportation. The lightweight shipments of JSP (plastic bags) and heavy load shipments of Czechforge (automotive brake disks) are organized to be within the same trucks from Czech Republic to Germany. Significant amounts of cost savings, increased service levels and manufacturing flexibility and more than 10% reduction in GHG emissions are realized. Another project is the Mars-United Biscuit case which involve the effective consolidation in supply chain activities of retailing operations. In this project, a number of suppliers collaborate through their delivery operations made to a number of common retailers. In the project common DC's are constructed and trucks are loaded with goods of different suppliers and routed through a specified network of retailer to make deliveries. This is a good example for vehicle routing consolidation. Besides financial and environmental benefits, this case also aims to develop an effective gain sharing methodology (Verstrepen & Jacobs, 2014)

The idea of forming coalitions in some business activities like shipment, comes along with its issues. One of these important issues is how to allocate the costs and benefits of these cooperative activities among the members of the coalition. Allocation schemes are the schemes describing how to share the joint costs and benefits of a coalition among the members. The allocation schemes should possess some properties so that distribution of gains is made on a fairly basis. It is important for the members of a potential cooperation as they might avoid collaborative action otherwise. At this point, cooperative game theory may provide good guidelines for the allocation efforts.

Guajardo and Ronnqvist (2016) discusses the allocation methods in their review study. They note that there are more than 40 allocation methods applied in collaborative logistics. In the study, these allocation methods are discussed under both traditional and ad hoc (specific to the problem studied) methods. The traditional methods consists of Shapley value, proportional, nucleolus, shadow price based, and marginal cost based allocations. Some important ad hoc methods include Aumann-Shapley, core centre, and τ-value methods.

There is vast amount of work done so far related to the advantages of the collaboration in different areas including shipment activities, and the allocations schemes. Most of them covers both topics together, because cost or gain allocation is an essential step after savings are achieved as a result of collaboration. For example, Verdonck et al. (2016) studies a cooperative facility location problem and in their study the authors note that the fair allocation of the costs is essential for the sustainability of the collaboration. They provide different allocation methods in the same study. Oussoren et al. (2018) discuss a collaborative transportation problem. This study also emphasizes the importance of fair allocations and provides a new gain allocation method called linear rule.

In our study we describe a cooperative shipment problem in which there are a number of shippers which are willing to send loads from the same origin to the same destination. Within this setting we describe a profit and an emission game. In the first one we aim to maximize the profit. In the latter, under the optimal settings for the profit game, the outcomes regarding the emission amounts are discussed. Then, with the goal of contributing to the gain allocation literature and providing new insights to the practical organizations, we introduce 5 different allocation schemes. These are namely the core based, Shapley value, truck based, individual rationality, and steady state allocation schemes (SS1 and SS2). Then, we analyze the performance of these allocation schemes under different performance criteria determined with the help of previous studies based on cooperative game theory. In this study, we firstly define the characteristic function of the profit and emission games. Then, we want to answer the questions if the core is available for the profit and emission games, and if it is possible to define cost and emission allocation schemes providing core allocations. Lastly, we discuss the performance of the cost allocation schemes.

The remainder of the thesis is as follows: In Chapter 2, we discuss some important studies from the related literature. Then, we give the problem definition. After the problem statement, we define the cooperative games and discuss properties of these games in Chapter 4. In Chapter 5, we introduce the allocation schemes. In the subsequent chapter we discuss performance measures proposed to compare allocation schemes. After all, we discuss the results related to our numerical study in Chapter 7. The thesis ends with concluding remarks and extensions.

CHAPTER 2

LITERATURE REVIEW

Considering the supply chain activities, collaboration has emerged as a promising method for the reduction of costs and undesired environmental effects. As a result, main focus of the related literature is the potential benefits of collaboration in supply chain activities like transportation and inventory management. Considerable amount of the studies also covers the efforts to allocate the resulting costs and benefits of collaboration among the stakeholders besides with defining performance criteria to evaluate the fairness of these allocations.

There is considerable amount of work discussing the inventory management and replenishment activities under collaboration. Our work is also closely related with joint inventory replenishment problem in the way that we consider a group of shippers coming together for shipping their goods on shared trucks which is a process where the decisions related to the replenishment and dispatch of the truck are made jointly by the coalition formed by these shippers. There is also plenty amount of work conducted on collaborative transportation and cooperative games. Some of the effort in the area is put on finding ways to integrate the environmental costs with classical supply chain models like transportation problems. To do so, emissions are usually considered as costs or some restrictions over the emission amounts are introduced to the models. Some studies discuss allocation schemes which is inevitably a required part of cooperative games. Lastly, some other studies focus on the emission considerations in other operational activities. In the following parts of this chapter we present key points about some of the studies belonging to these 5 groups.

2.1 Joint Replenishment & Cost Allocation

Our work is closely related with joint replenishment and cos allocation problems, since the arrival and acceptance of the shipment requests to the truck is a joint process involving a number of shippers. The waiting, and setup costs we consider also related with the costs in joint replenishment problems. As in the works discussed below, our study also involves the allocation of the costs.

Meca et al. (2004) considers a group of firms collaborating for their inventory replenishment activities, where the aim is to minimize the joint replenishment cost of the group. The setting considered is an extension of the basic EOQ inventory model. In the study, also a method to allocate the joint costs to the collaborating firms is provided using the tools from cooperative game theory.

In the study of Dror and Hartman (2007) an EOQ inventory model in which replenishment of multiple items is considered. In this system the consolidation of the shipments of different items are allowed. First the optimal policy is determined, then the problem of cost allocation among the different items is analysed and the conditions in which the fair cost allocations are possible are determined.

Guajardo and Rönnqvist (2015) introduces inventory considerations into the collaborative forest transportation problem. The study also involves the problem of coalition formation under the cost considerations. A number of methods to partition the players to form different coalitions are defined. The problem is then solved under the consideration of core stability and strong equilibrium criteria.

Anily and Haviv (2007) introduces an infinite horizon deterministic joint replenishment model where a group of retailers place orders together for a single item. In the model, there is a retailer independent setup cost, and besides, some minor setup costs depending on each retailer. The study provides the optimal-power-of-two (POT) policy for this problem and deals with the cost allocation problem for all subsets of the retailers under the POT policy. The characteristic function of this cooperative game is defined to be the average time total cost of the POT policy for the possible subsets of the retailers. The game is shown to be concave and to have a nonempty core. The study also provides a core allocation method for the costs of the joint replenishment activities.

Fiestras-Janeiro et al. (2012) considers an inventory problem involving a number of players giving joint orders for a single item. The ordering locations are assumed to be on a single line. To make the cost allocations, a new method, called line rule, is proposed. This method is shown to provide allocations in the core under some specific circumstances.

In another study of Fiestras-Janeiro et al. (2013) under the same problem setting of Fiestras-Janeiro et al. (2012) it is shown that the discussed inventory transportation problems can be decomposed into smaller inventory transportation problems which are shown to be solved with less effort. In this study a new allocation method, namely average of the marginal vectors with an extreme agent first, is also introduced. This method is also proven to generate allocations in the core under specific conditions.

Korpeoglu et al. (2013) considers the joint replenishment activities of a number of firms under a non-cooperative game with asymmetric information. In this game, a model similar to EOQ is applied. In the game, the private information involving demand rate requested payment amount of each firm is sent to a central authority. Then, this authority makes decisions regarding which shipments to consolidate and shipment frequencies under the fixed replenishment costs. It is shown that under this setting the Bayesian Nash equilibrium exists and the characteristics of this equilibrium are defined. One of the main findings of the study is that the information asymmetry reduces the potential gains of collaboration compared to the share full information.

Fiestras-Janeiro et al. (2018) study another inventory problem with a single item. In this study the EOQ model was applied for a number of collaborating companies having warehouses of limited capacities. In the study it is shown that the companies are better of forming a coalition and make joint decisions. The study also provides a method to allocate the benefits of the coalition to the members.

In our study, we try to maximize the profit of the shippers per unit time under fixed dispatch cost, waiting cost, and minor dispatch cost which can be considered as a shipper specific setup cost. We assume the demand (order requests of the shippers) is stochastic. Under this setting we introduce a Markov decision model and provide the optimal solution of the problem. Then, we introduce the cooperative profit game and cooperative emission game. We also introduce new allocation schemes and compare their performance under the performance measures which are also introduced in this study.

2.2 Collaborative Transportation

In our study, we consider a problem environment where, the shipment of the goods is made from the same origin to the same final destination. We discuss the characteristics of the optimal policy in case of collaboration under stochastic demand rates. We provide an analysis of the effect of the problem parameters on the optimal policy. Besides, we also provide allocation schemes with evaluation of their performances under reasonable criteria. The characteristics of the optimal policy together with the allocation schemes we discuss may be used as guidelines in real life applications.

One of the studies in the field of collaborative transportation is by Xu et al. (2012) where a multi-echelon supply chain network is considered. Related to this network, the pooled-supply-networks optimization problem is introduced. To allocate the benefits of the collaboration approach in terms of both operational and environmental costs, a cooperative game theoretical model is also discussed. This model allocates the benefits to the players after the pooled-supply-networks problem is solved. For the allocation, Shapley value method is used and proven to be fair and stable. The experimental results suggest that the suggested method can be used as an effective tool to reduce transportation costs and environmental costs.

Ozener et al. (2013) discuss the vendor managed inventory and transportation system in their study. In the scope of this concept a vendor manages transportation routings, frequencies and inventories of its customers. Such an effort requires instant flow of information and difficult set of decisions to stay competitive. Because as a result of applied policies the cost amounts are determined and these should be allocated to each customer. The first part of this decision-making process involves inventory routing problem. In this stage delivery routings, frequencies and quantities are to be determined. In the scope of the work a real-life company which adopted vendor managed inventory policy is studied. Regarding the difficulties associated with solving an inventory routing problem, some approximation methods are used to obtain good results instead of exact methods. The allocation process in the study is modelled a cooperative game. The allocation methods are classified into three: proportional, per route based, and duality-based cost allocation methods. It is noted in the study that the stability of these simple allocation categories may be low or non-existent, so that as a measure of accuracy they defined the concept of “instability value” to compare the performances of the allocation methods. Experimental results show that the allocation schemes which take the “synergies between the players” into account give better results compared to proportional methods.

In Ozener (2014)’s study, a delivery network with multiple customers is considered as well. In this work, besides with total distribution costs, carbon emissions are also considered. The study, also provides a number of cost and emission allocation schemes. Regarding these allocation schemes, some performance criteria are defined. These are budget “balancedness” (allocation of the entire cost/emissions), individual rationality, stability, fairness and approximation to the core. Then, the allocation schemes are compared under these criteria. The experimental results of the study show that when the carrier takes the joint responsibility of both transportation costs and emission before allocating them to the customers, the emission amounts tend to decrease.

Sun et al. (2015) covers a route optimization problem. On one route there are multiple customers on different nodes and their demand are to be satisfied. The transportation cost for a truck, which visits all the customers and return to the plant, is allocated to the costumers. For the allocations there are five fairness criteria defined to be satisfied. Some of these are the allocation of all the costs, non-negativity of the cost allocation, and monotonicity of the allocations. Then proportional allocation, Shapley value, moat model, and contribution constrained packing model allocation methods are discussed.

In the study by Kimms and Kozeletskyi (2017), a multi-objective travelling salesman problem (TSP) is considered. In the problem there are players which cooperate to satisfy their orders on a specific route in the same network. The cooperative TSP in the first part needs a mathematical programming model to be solved while for the cost and utility allocations, authors developed a cooperative game theoretical solution procedure. The solutions to the first multi-objective TSP is evaluated under the pareto optimality concept. The allocation procedure is based on a bi-allocation core-based solution which involves obtaining non-dominated set of allocations among all the pareto optimal result obtained in the first part. The study introduces new concepts for the multi-objective nature of the cooperative games and a structured two staged solution procedure to deal with the problem.

We also introduce a collaborative transportation model where shipments are made from the same origin to the same destination. We aim to contribute the related literature by introducing the optimal policy for the problem we discuss, expressing the cooperative games involved in this collaboration process, providing new allocation schemes and performance measures, and evaluating the performance of the allocation schemes under the defined performance criteria.

2.3 Studies that Consider Emissions in Transportation

Our study extends to cover considerations related to emissions resulting from transportation activities. The emission amounts are introduced as a part of initial Markov decision model in our study. To calculate the emission amounts we introduce a basic model in which we take the emissions caused by both the empty truck and the load in the truck into account.

One of the other studies in the related field is by Ozener et al. (2008) in which a set of shippers collaborating to obtain better rates for their shipment operations are considered. They employ a common carrier through optimized routes covering all the demand by all the shippers. As a result of increased utilization, the costs decrease. The goal of the study is to determine cost allocation mechanisms such that the coalition stays sustainable, that is the allocations are stable. In the study the cost minimization problem is defined as a lane covering problem. Then to obtain core allocations they first make use of duality. Besides this nucleolus, Shapley Value, and cross-monotonic cost allocation methods are discussed. Other desirable properties of a good allocation are also discussed in the study, though authors note that it may not be possible to find an allocation method promising good results for all these desirable aspects.

In Diabat et al. (2013) a multiechelon multicommodity facility location problem is considered. In the study, this system operates under the cap and trade policy of the government. Under this setting the remanufacturing decisions of a company is analysed in terms of profitability and environmental effects. The work provides a numerical study in which the effects of carbon prices on costs, optimal policy, remanufacturing of the goods and environment are discussed.

The study by Jin et al. (2014) discuss the sourcing and network design problem of a group of retailers. The problem is modelled as a minimum cost network problem. The study analyses the effects of carbon emission tax, inflexible cap, and cap-and-trade policies on carbon emissions and company costs. These are the most commonly applied policies to reduce the carbon emissions. The models developed in the study are evaluated with the real data of a retail company. Using the results, authors highlight some key points for setting parameter values under the three carbon policy mentioned for reducing the carbon emissions to desired levels.

Demir et al. (2014) discus the bi-objective pollution routing problem as an extension of the pollution routing problem. In this problem they try to minimize both the fuel consumption and the driving time. In the study the fuel consumption is considered to be a function of the vehicle load and the vehicle speed. The CO_2 emissions, on the other hand, is considered to be constant rate of fuel consumption, so that the study also provides a tool for analysing the cost of delivery performance in terms of CO_2 emissions, as higher vehicle speed results in higher fuel consumption.

The emission amounts are introduced as a part of initial Markov decision model in our study. We take the emissions caused by both the empty truck and the load in the truck into account. As a result, the emission amount at the time of dispatch of a truck is a function having a constant amount due to empty truck and a variable amount resulting from the total load in the truck. This assumption firstly provides with the reduction and simplicity in model creation and evaluation efforts, since it simply requires us to update the original model without changing the basic structure of it. The fact that, the variable emission amount is defined to be a function of the total load in the truck, and the distribution of the load in the truck is known at any time also plays an important role for the allocation phase. Secondly, such an emission model reflects the real life conditions, so that it helps to derive common and applicable results.

In the emission discussion part of our study we introduce two alternative methods for emission calculations. We discuss the emission considerations in relation with the primary objective of the coalition which is the profit maximization. We provide two different approaches to link the profit considerations with the emission considerations. In the first one the emission amount is not included in the objective of the coalition, but it is a result of the optimal policy of the profit maximization problem. We also introduce a game with carbon tax policy where the emission amount is a part of the objective function. Under both cases, we provide discussions for allocation of the emissions to the members of the coalition by using allocation schemes we define. Then, we discuss the performance of the allocation schemes.

2.4 Emission Allocations

In our work, we consider the emissions as a part of the shipment activities taking place. Our efforts include the allocation of these emissions among the members of the coalition. In this part, we discuss other studies related with the emission allocation methods.

Benjafaar et al. (2011) discuss the methods to integrate the carbon emissions with the models developed in decision-making areas like production and inventory management. The focus of the study is based on making it possible to account for emission considerations by making small modifications on the parameters of the classical models. The impact of these modified models on carbon emission and operational costs is also analyses in the study. Regarding the emerging environmental policies, the study also addresses the extent to which expensive investments to prevent carbon emissions can be avoided. The discussion also includes the contribution of collaboration on decreasing operational and environmental costs.

Frisk et al. (2010) discuss a supply chain collaboration model for transportation activities of a number of forest companies. In the study, they express the fact that collaboration is possible only if the participants are agreed on a plan for sharing the costs and savings. In the study several allocation methods are investigated. These are Shapley value, the nucleolus, separable and non-separable costs, shadow prices and volume weights as well as equal profit method. After these methods are explained, they are compared with each other according to some performance criteria.

Lozano et al. (2013) also study a horizontal cooperation model involving a number of different companies that come together to achieve cost savings from transportation operations. To solve the cost savings problem a mixed integer linear model is offered. This study also involves a second stage effort in which joint savings obtained in the first part are allocated to the companies under the cooperative game theoretical tools. After the cost savings model is solved, different rules are used for allocating the savings to the players. These involve, Shapley value, the nucleolus, the τ-value, the core-centre, minmax core, and the two LC variants allocation schemes. Then, the performances of these allocation rules are discussed.

The study by Vanovermeire and Sörensen (2014b) involves the distribution activities of a number of collaborating shippers on a specific route. In the study, a combined model for distribution route optimization and cost and benefit allocation is introduced. In the work, the Shapley value allocation method is integrated with the transportation optimization model in a way that the outcoming results are acceptable for all the members.

Naber et al. (2015) introduced new methods for allocation of CO_2 emission to the customers on a distribution route. These are Shapley Value, nucleolus, Lorenz, equal profit allocation, and star allocation methods. In the study there are four different performance measures discussed to compare the allocation results of these methods.

These measures are stability, consistency, robustness, and computational time. The experimental results in the study show that in terms of computation time the Star method is more preferable. In terms of stability and consistency Lorenz and equal profit allocation methods outperform other. For the stability and robustness, on the other hand, the nucleolus method has given the best results. All of these works emphasize the importance of allocation methods. Another important thing is to define performance measures to compare the allocation methods with each other. It is important to note that, there are multidimensional aspects to be considered to measure the quality of an allocation method. In our study, besides with new allocation methods, we also define some performance measures and test the results generated by these allocation methods under the performance measures introduced.

Leenders et al. (2017) study the CO_2 allocation problem in a routing problem. The authors seek to find new cost allocation methods as classical methods would not work well due to the problem nature. In the study 4 new allocation schemes are introduced.

Allocation of common benefits is at least as important as the collaboration which is commonly intended for commercial benefits and reducing negative environmental effects of industrial operations. That is because the allocation policy is expected to be a prerequisite for an agreement on collaboration. Since we consider a collaborative model, we also deal with the issue of allocating costs and benefits resulting from the collaboration. To do that, we define 6 different allocation schemes and performance measures. We also provide a detailed analysis of the allocations made under defined performance measures.

2.5 Emission Considerations in other Problem Settings Involving Collaboration

We consider a market characterized by uncertain shipment requests where shippers are willing to collaborate for their shipment activities. They also compete for truck space within this collaboration process. In this study, we derive the baselines for forming such a collaboration and discuss some important properties of the coalitions formed in detail. These properties highlight the benefits of collaborative action in terms of cost advantages which is one of the most important findings that could help encouraging the collaboration.

Vanovermeire and Sörensen (2014a) also discuss the ways of encouraging the firms for collaboration. In the study, the benefits of forming a coalition for supply chain activities are discussed. The work shows that by relaxing some of the terms of the firms like delivery time and order size, a better base for the coalition may be constructed. They argue that the players offering more flexible terms contribute more to the benefits of the coalition than the other players. The authors suggest that the members may be convinced to relax their terms by offering them more reward. This way, flexible behaviour is encouraged and coalition benefits are increased more. In the study, a method is introduced to measure and analyse the effect of a relaxing the delivery terms on the benefits of the coalition so that the reward amounts can be determined.

In the study of Chabot et al. (2018) a model in the aim of encouraging partnership between different firms is considered. The shipment activities of these companies are done with shared trucks which have standard capacities to satisfy the demand on a specific network having directed arcs. This capacitated vehicle routing problem involves the environmental costs as well as the other fixed and variable costs related to transportation activities. In the study four different collaboration schemes offered. The problems are formulated as mixed integer programming problems with objectives changing according to the defined schemes. The findings show that consolidation of shippers would yield better results in terms of monetary costs, traffic, mileage and service levels. Also, it is seen that environmental benefits may be up to 65-80% reduction in GHG emissions.

In our work, we assume that the companies aim to minimize transportation and waiting costs as well as carbon emissions while maximizing the revenue obtained from each shipment. We assume that the decisions regarding acceptance of a shipment request and the dispatch of the truck are made jointly by the member of the coalition. To ensure a fair and stable allocation of the savings we develop allocation schemes that require low computational effort. We evaluate and compare these schemes based on several performance criteria.

CHAPTER 3

PROBLEM DEFINITION AND MODEL

We consider a group of shippers, $N=\{1, 2,\ldots,n\}$ a subset of which may agree on collaborating through using a common carrier truck for their shipments. All of the items are to be shipped from the same origin to the same destination. Each shipment request from each shipper $m \in N$ arrives randomly and independently according to a Poisson process with parameter λ_m. Associated with each shipment request from shipper m, there is a potential of unit revenue gain R_m obtained if the shipment request is accepted. If the shipment request of a shipper is rejected, the load attached with this request cannot take place in the truck. Once a request from a shipper is rejected, the shipper is assumed to be able to deal with the shipment of this request by itself. Remember the Tupperware and P&G case mentioned in the previous chapter. In the scope of the explained project, these companies collaborate for sending their shipments once the transportation lanes are similar. Note that, it is not meaningful to accept all shipment requests of these companies to any truck. The composition of the loads on a truck should be determined carefully to achieve higher benefits, so that the companies are better not to be captive to send all of their loads with shared trucks. Other means for making these shipments, which cannot be sent with shared trucks, might be managing their own truck fleet or working with a third-party logistic organization. In our model, for each shipment request accepted, the revenue is obtained upon the dispatch of the truck. When a shipment request from a shipper arrives, it may join the queue of waiting requests. All the shipment requests in the truck wait until the current truck dispatches. Associated with each shipment request by shipper m, there is a waiting cost c_m incurred per unit time of waiting in the truck. This waiting cost amount is assumed to be associated with the delivery schedule of the shipments. There is also a shipper dependent fuel cost, f_m, which incurs proportionally to the amount of load accepted from the shippers. Associated with the dispatch of the truck, there are two fixed costs involved: the fixed dispatch cost A, and minor dispatch cost d_m. The fixed dispatch cost is included as the cost of operating the truck which involve the costs like the salary of the driver. The minor dispatch cost is incurred only when there is at least one shipment request in the truck from shipper m which is independent of the total load. Together with the fixed dispatch cost mentioned the shipper dependent minor setup cost constitute the first order interaction cost as Anily and Haviv (2007) discuss in their study. Each truck has a capacity of K, and each shipment request is assumed to consume a single unit of the truck space. A truck is readily available upon the dispatch of the previous truck, so that the shipment requests never have to wait for a truck to arrive. Upon dispatch of the truck, all accepted shipment requests must be fulfilled.

Suppose that a coalition of shippers $S \subseteq N$ jointly make decisions i.e. we assume that all shippers in the coalition make the decisions together. They decide on whether to accept or reject the shipment requests that have arrived (requests outside the coalition are not considered). They also decide on whether to dispatch the truck or wait for more shipment requests at the time of making the accept/reject decisions. In line with the arrivals, the decision-making takes place over continuous time points. Figure 3.1 pictures this joint decision-making process.

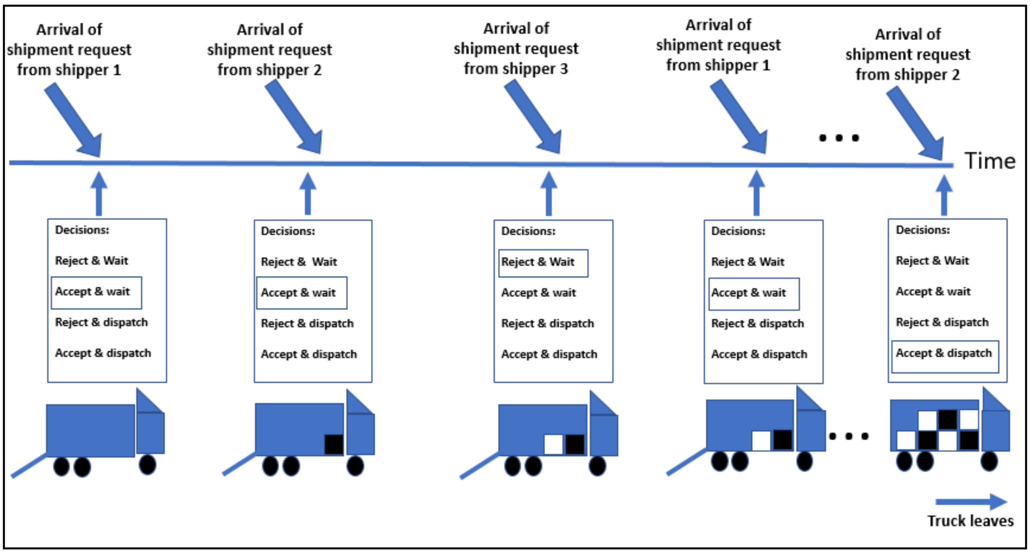

Figure 3.1. Joint decision-making process

Note that, due to the waiting cost c_m, it might be more profitable not to use the truck space capacity at full utilization. Indeed, truck capacity may never be used at all. For example, when there are only two shippers whose unit revenue gains are less than their minor setup costs, the trivial solution to the profit maximization problem is zero, so that no capacity is utilized in such a case.

The profit maximization problem of the shippers in a coalition $S \subseteq N$ can be modelled as a continuous time Markov Decision Process (MDP). In the following part, the states, actions transition probabilities and one-stage expected reward of the MDP are presented. Then, we introduce the MDP characteristics of the discrete time functional equations to derive the optimal average reward per period.

The state of the MDP is defined as the number of waiting shipment requests for each shipper in the truck at a given time t. The decisions are whether to accept an arriving request or reject, and whether to dispatch the truck at a given time t. Note the accept and reject decisions are only defined upon customer arrival. Furthermore, due to the Markovian nature of the problem, it is not optimal to take dispatch decisions when there is no arrival. Thus, the time index can be omitted from the state definition. Furthermore, the continuous-time process can equivalently be described as a discrete-time process by observing the system only at the points of arrivals.

Under the discrete-time MDP, the state can be defined as $(\boldsymbol{Z},Y)$, where $\boldsymbol{Z}$ is a vector: $\boldsymbol{Z}=(Z_1,Z_2,\ldots,Z_{|S|})$ with Z_m denoting the number of shipment requests that belongs to shipper m, which are waiting to be dispatched on the truck (excluding the arriving request), where $m = 1,2,\ldots,|S|$, and $Z_m \in \{0,1,..,K-1\}$, and with, $Y \in \{1,2,\ldots,|S|\}$ denoting which shipper the arriving request belongs to.

We let,

$S_{\boldsymbol{Z}}$: State space of $\boldsymbol{Z}$, $S_{\boldsymbol{Z}} = \{(Z_1, Z_2, \ldots, Z_{|S|}): \sum_{m \in S} Z_m \leq K-1, m \in S\}$

S_Y: State space of Y, $S_Y = \{1,2,\ldots,|S|\}$.

B: The set of possible states, $B = S_{\boldsymbol{Z}} \times S_Y$.

At the time of any shipment request arrival, there are two sets of decisions to be made:

1. Determine whether to accept (A) or reject (R) the arrived shipment request.
2. Determine whether to dispatch (D) the truck or wait (D) for another arrival.

Then, we can denote the set of all possible actions, $S_A = \{A, R\}x\{D, W\}$.

We note that, reject and dispatch (RD), decision is dominated by the accept and dispatch (AD) decision, since it always decreases the profit. That is because, between consecutive shipment requests the waiting cost incurs and it is possible to avoid this additional cost simply by dispatching just after the last accept decision.

Let *D(**j**,l)*, denote the action taken at state *(**j**,l)*, where, □=(□*1*,□*2*,...,□*|□|*) denotes the number of shipment requests from each shipper which are already waiting in the truck at the time of a new shipment request arrival, □∈*{1,2,...,|*□*|}* denotes the shipper that an arriving shipment request belongs to. Then, we can define the set of nondominated actions as follows:

$$D(\boldsymbol{j}, l) = \begin{cases} AD, AW, RW & for \ \sum_{m=1}^{|S|} j_m < K - 1 \\ AD, RW & for \ \sum_{m=1}^{|S|} j_m = K - 1 \end{cases} \tag{1}$$

Let, $\boldsymbol{e_m}$ be the S-dimensional vector whose mth element is 1 and others are 0.

Let, $\Lambda_S = \sum_{m \in S} \lambda_m$ be the sum of arrival rates of shippers in the coalition S.

Let, $P(\boldsymbol{j_2}, l_2 | \boldsymbol{j_1}, l_1, a)$ denote the one-step transition probability. That is, while in state (j_1, l_1) if the decision a is made, the state (j_2,l_2) is visited with probability $P(\boldsymbol{j_2}, l_2 | \boldsymbol{j_1}, l_1, a)$. The one step transition probability, $P(\boldsymbol{j_2}, l_2 | \boldsymbol{j_1}, l_1, a)$ can be expressed as:

$$P(\boldsymbol{j_2}, l_2 | \boldsymbol{j_1}, l_1, a) = \begin{cases} \frac{\lambda_m}{\Lambda_S}, \ if \ l_2 = m, & \begin{matrix} (\boldsymbol{j_1} = \boldsymbol{j_2}, a = \{RW\}) \\ or \left(\boldsymbol{j_2} = \boldsymbol{j_1} + \boldsymbol{e_{l_1}}, a = \{AW\}\right) \\ or \ (\boldsymbol{j_2} = 0, a = \{AD\}) \end{matrix} \\ 0, \ otherwise \end{cases} \tag{2}$$

Consider equation (2). Suppose the current state is (j_1,l_1) and decision made is a. The probability that the next arrival is from shipper m is $\frac{\lambda_m}{\Lambda_S}$. The state in the next stage, (j_2,l_2) depends on this probability besides with the decision made in the current stage. If reject decision is made, the composition of the loads in the truck does not change, so that, in the next stage $\boldsymbol{j_1} = \boldsymbol{j_2}$. If the current request is accepted, the load from the current arrival is added to $\boldsymbol{j_1}$, and $\boldsymbol{j_2} = \boldsymbol{j_1} + \boldsymbol{e_{l_1}}$ holds for the next stage. If AD decision is made, all the current load is dispatched so that in the next stage $\boldsymbol{j_2} = \boldsymbol{0}$.

Let, $\theta_m(\boldsymbol{j}, l)$ be defined as follows:

$$\theta_m(\boldsymbol{j}, l) = \begin{cases} 1, & if\ j_m > 0\ \ or\ \ l = m \\ 0, & otherwise \end{cases} \tag{3}$$

Then, one-stage expected rewards can be defined as follows.

$$For \sum_{m \in S} j_m < K - 1:$$

$$r(\boldsymbol{j}, l, a) = \begin{cases} \sum_{m=1}^{|S|} j_m (R_m - f_m) + R_l - f_l - A - \sum_{m=1}^{|S|} \theta_m(j, l) d_m\,, & if\ a \in \{AD\} \\ -\frac{\sum_{m=1}^{|S|} j_m c_m}{\Lambda_S}, & if\ a \in \{RW\} \\ -\frac{\sum_{m=1}^{|S|} j_m c_m + c_l}{\Lambda_S}, & if\ a \in \{AW\} \end{cases} \tag{4}$$

$For\ \sum_{m \in S} j_m = K - 1:$

$$r(\boldsymbol{j}, l, a) = \begin{cases} \sum_{m=1}^{|S|} j_m (R_m - f_m) + R_l - f_l - A - \sum_{m=1}^{|S|} \theta_m(j, l) d_m\,, if\ a \in \{AD\} \\ -\frac{\sum_{m=1}^{|S|} j_m c_m}{\Lambda_S}, if\ a \in \{RW\} \end{cases} \tag{5}$$

Consider equation (4). When the total load in the truck including the last arrival is less than the full capacity, there are 3 set of decisions that can be made. When AD decision is made, all the revenue related to the loads in the truck is collected. At the same time, associated with each load, the fuel costs incur. At the time of dispatch, also the fixed dispatch cost and the total minor dispatch cost incur. For the determination of total minor dispatch cost amount, the availability of load(s) from each shipper for the current truck is evaluated. When RW and AW decisions are made, only the waiting costs are calculated. The total waiting cost calculated at each stage depends on the total load on the truck and waiting cost parameters of the shippers. If the total load on the truck before an arrival is one less from the capacity of the truck, for the next arrival of a shipment request, the AW decision cannot be made, since once the load is accepted the truck capacity is full. Therefore, for this case, only decisions that can be made are AD and RW decisions. Equation (5) accounts for this case. The cost and revenue calculations under these decisions are made as in (4).

Let, g_S be the optimal average profit per unit time when $|S|$ shippers make decisions jointly.

Then, functional equations under the average reward criteria are:

$$For \quad \sum_{m\in S} j_m < K-1:$$

$$h(\boldsymbol{j},l)+\frac{g_S}{\Lambda_S}$$

$$= max\begin{cases} \dfrac{-\sum_{m\in S} j_m c_m - c_l}{\Lambda_S} + \sum_{m\in S}\dfrac{\lambda_m}{\Lambda_S} h(\boldsymbol{j}+e_l,m), \\ \sum_{m\in S} j_m(R_m-f_m)+R_l-f_l-A-\sum_{m\in S}\theta(\boldsymbol{j},l)d_m+\sum_{m\in S}\dfrac{\lambda_m}{\Lambda_S}h(\boldsymbol{0},m), \\ -\dfrac{\sum_{m\in S} j_m c_m}{\Lambda_S}+\sum_{m\in S}\dfrac{\lambda_m}{\Lambda_S}h(\boldsymbol{j},m), \end{cases} \tag{6}$$

$$For \quad \sum_{m\in S} j_m = K-1:$$

$$h(\boldsymbol{j},l)+\frac{g_S}{\Lambda_S} =$$

$$max\begin{cases} -\frac{\sum_{m\in S} j_m c_m}{\Lambda_S}+\sum_{m\in S}\frac{\lambda_m}{\Lambda_S}h(\boldsymbol{j},m), \\ \sum_{m\in S} j_m(R_m-f_m)+R_l-f_l-A-\sum_{m\in S}\theta(\boldsymbol{j},l)d_m+\sum_{m\in S}\frac{\lambda_m}{\Lambda_S}h(\boldsymbol{0},m) \end{cases} \tag{7}$$

In (6) and (7) $h(\boldsymbol{j},l)$ denotes the bias function under the optimal policy of coalition S, and g_s is the profit per unit time. In the expressions, $h(\boldsymbol{j},l)$, $r(\boldsymbol{j},l,a)$, and $P(\boldsymbol{j_2},l_2|\boldsymbol{j_1},l_1,a)$ all depend on S, but for simplicity the index *S* has been omitted.

Example 3.1: For the model parameters listed in Table 3.1., we calculate the optimal average profit per unit time when the coalition consists of 3 shippers.

Table 3.1. *Problem parameters for Example 3.1*

Shippers	**c**	**R**	**d**	**λ**	**A**	**K**
Shipper 1	11.49	46.59	0	5.25	50	11
Shipper 2	7.95	11.10	0	2.45		
Shipper 3	12.83	35.01	0	6.70		

For this problem, the optimal profit per shipment request under optimal policy is:

$$\frac{g_{\{1,2,3\}}}{\Lambda_{\{1,2,3\}}} = 7.59$$

Where, the optimal profit per unit time is:

$$g_{\{1,2,3\}} = 109.30$$

Considering the optimal policy for the mentioned problem, under $j_2=0$, the set of optimal decisions made when $l = 1, 2,$ and 3 are shown in Figures 3.2, 3.3, and 3.4 respectively.

For example, in Figure 3.2. we see that the optimal decision made when $\boldsymbol{Z}=(3,0,2)$ and $Y=1$ is AW. That is, under the optimal policy, when number of waiting shipment request in the truck is 3, 0 and 2 from shipper 1, shipper 2 and shipper 3 respectively, if a shipment request from shipper 1 arrives the optimal decision made is AW.

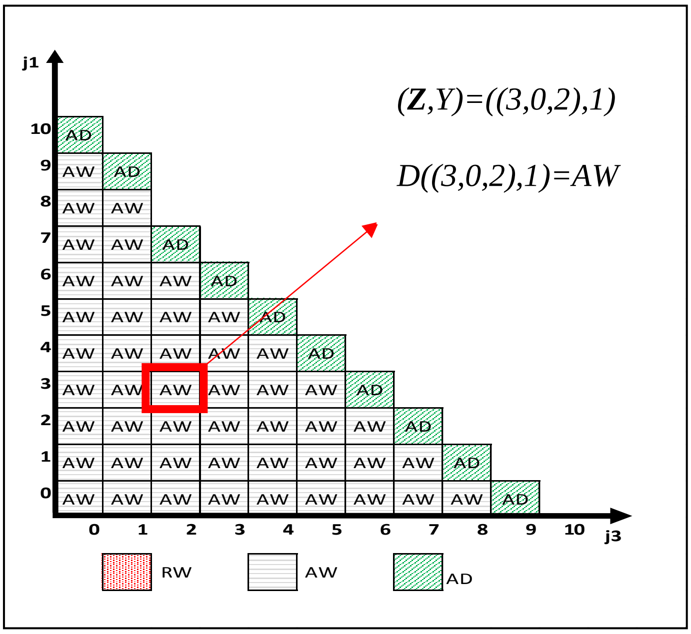

Figure 3.2. Decisions made under the optimal policy when $j_2 = 0, l = 1$ (a request from shipper 1)

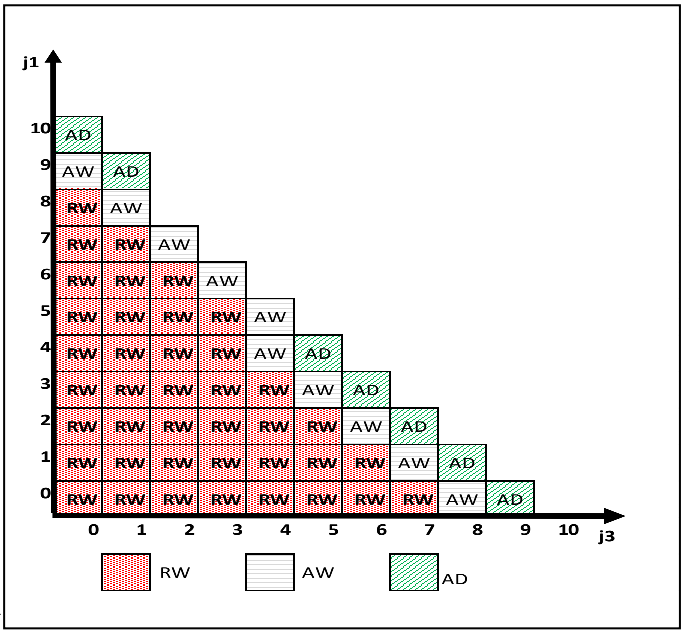

Figure 3.3. Decisions made under the optimal policy when $j_2 = 0, l = 2$ (a request from shipper 2)

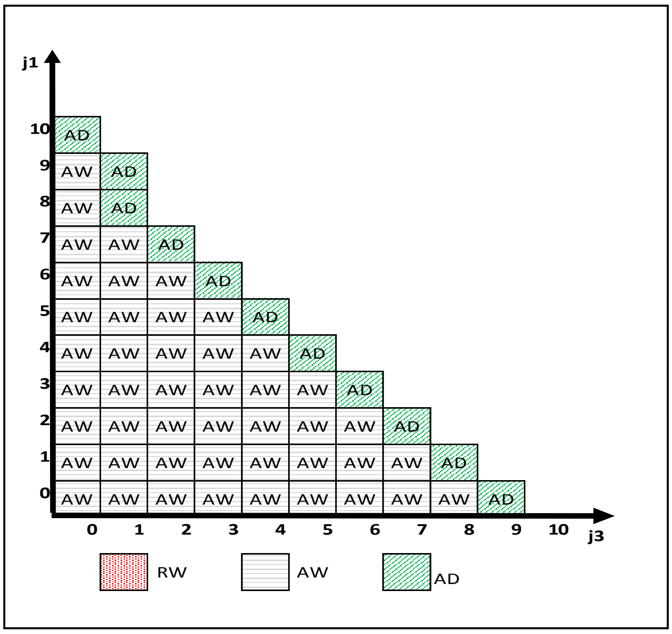

Figure 3.4. Decisions made under the optimal policy when $j_2 = 0, l = 3$ (a request from shipper 3)

In the optimal policy for these settings, the requests from the first and the third shippers are never rejected. On the other hand, more than 84% percent of the requests of shipper 2 are rejected. That is, when steady state probabilities are considered under the optimal policy, the ratio of RW decisions to all decisions made when a request from shipper 2 arrives is above 0.84. Let $\pi(j_1, j_2 j_3, l, a)$ denote the steady state probabilities. Then,

$$\frac{\sum_{\forall j_1, j_2, j_3} \pi(j_1, j_2 j_3, 2, RW)}{\sum_{\forall j_1, j_2, j_{3,a}} \pi(j_1, j_2 j_3, 2, a)} = 0.8424$$

This is reasonable because the second shipper has the least potential for the profit contribution, i.e. its revenue is considerably low compared to other shippers while its waiting cost is rather close to the waiting costs of the other shippers.

Considering the optimal decisions made, we note that the reject decisions are made when the capacity utilization is low. However, as the truck load increases, the coalition tends to accept the shipment requests. This is resulting from the fact that, at the time of any arrival request, the waiting costs for all the accepted requests incur, so that any reject decision results in increased cost of waiting, which is increasing itself with the increasing number of requests waiting to be dispatched. Hence, the coalition is more likely to avoid the reject decisions when the truck is near full. Figure 3.5 shows the percentage of AW, RW, AD decisions made under the optimal policy when shipment request from shipper 2 arrives at different capacity utilization levels.

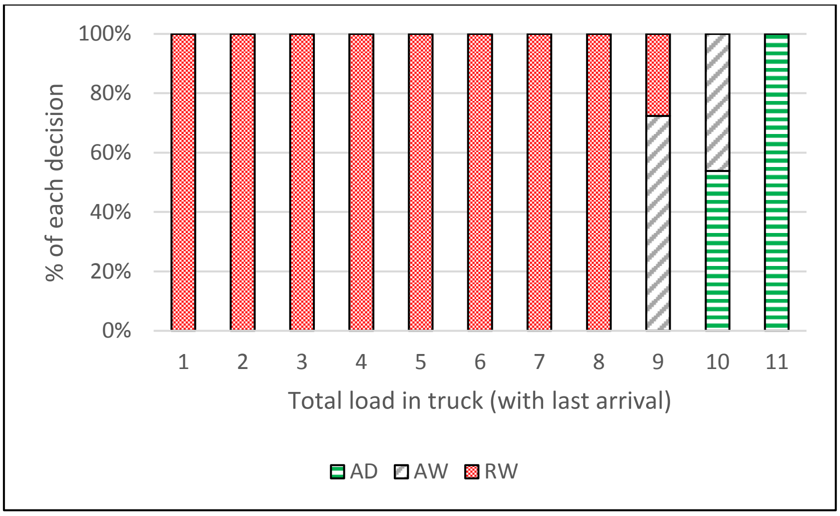

Figure 3.5. Decisions made under the optimal policy for the requests of shipper 2 (*K=11; A=50*)

In Figure 3.6, all of the decisions made under the optimal policy at different utilization levels are summarized. Similarly, we can note that when the truck load increases the rate of reject decisions are decreasing. When the truck load is below 9, there is no dispatch decision, while when the load is 9, more than 90% of the decisions made are AD type. When the load is 10, all of the requests are accepted. That is because, when the load is at low levels, the waiting cost per the arrival of a request is low and the coalition tend to wait for a more profitable request rather than accepting the request of shipper 2. However, at high load, the waiting cost becomes so high that, spending extra time waiting for another request becomes disadvantageous despite the potential of additional revenue.

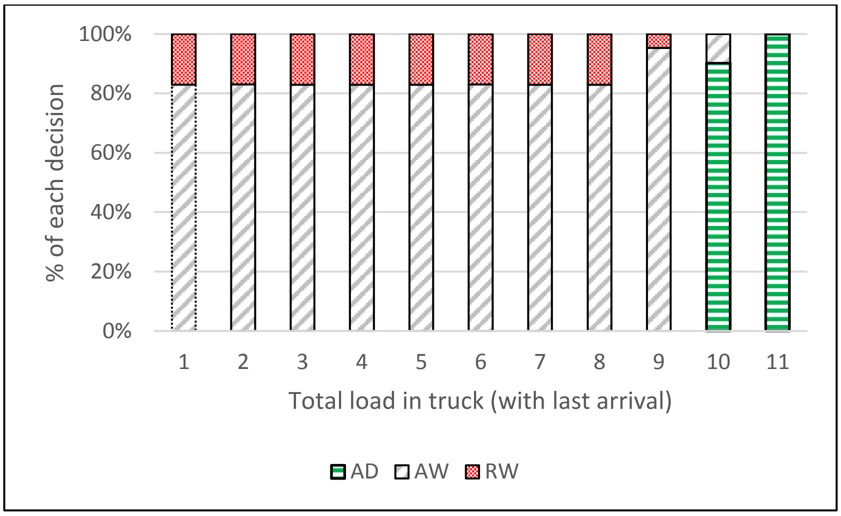

Figure 3.6. Decisions made under the optimal policy for all of the shipment requests ($K=11; A=50$)

CHAPTER 4

THE COOPERATIVE SHIPMENT AND PROFIT GAMES

In this chapter, we firstly provide some basic information about some of the properties of cooperative game theory which have close relation with our study. Then, we introduce three cooperative games associated with the problem under consideration: the profit game, the emission game and the game with carbon tax. The profit game involves the joint decision-making process of the shippers for sending randomly arriving shipment requests with shared trucks. These decisions are made by the coalition to maximize the expected profit per unit time. Upon defining the profit game, we discuss the existence and non-existence of four important properties related to cooperative games, namely monotonicity, superadditivity, the existence of the core and the convexity.

The profit game is defined in a way that it also constructs a baseline for the emission game. In the emission game, the emission amounts are obtained considering the activities taking place as a result of the decisions made to maximize the expected profit in the profit game. For the emission game, we also discuss the monotonicity property and the existence of the core. In the game with carbon tax, we update the objective function so that the total emission amount is penalized with a factor. This penalty amount is considered to be the carbon tax amount applied under a carbon tax policy.

4.1 Preliminaries of the Cooperative Game Theory

4.1.1 Definition of Cooperative Games

A cooperative game (N, v) which is also called a coalitional game, is a game in which the players are able to make binding agreements. Let, $N=\{1,2,\ldots,n\}$ be a finite set of players. We call N the grand coalition. Any subset of N is called a subcoalition. Any cooperative game is specified with its characteristic function. The characteristic function v is defined for any subset $S \in N$ as the amount of profit that members of S can achieve by forming a coalition together, which is given by $v(S)$: $2^N \rightarrow R$ (Winston, 2004).

4.1.2 Monotonicity

Monotonicity of a cooperative game implies that any coalition would yield better overall gain compared to any of its subcoalitions. That is, the cooperative game, (N, v) is monotonic iff for any $S \subset T$, the following condition is satisfied:

$$v(S) \leq v(T),\ for\ \forall\ S \subset T \subseteq N \tag{8}$$

4.1.3 Superadditivity

In a superadditive game the total amount of profit which can be achieved by disjoint subcoalitions is always less than or equal to the profit amount that can be achieved by the union of these coalitions.

A cooperative game, *(N, v)* is superadditive if the following condition holds for $\forall\ S, T\ \subset\ N, S \cap T = \emptyset$:

$$v(S) + v(T) \leq v(S \cup T),\ where\ \mathrm{S} \cap \mathrm{T} = \emptyset \tag{9}$$

4.1.4 Imputation and the Existence of the Core

Consider a game involving $N=\{1, 2, ..., n\}$ shippers. Let $\boldsymbol{x} = \{x_1, x_2, \dots, x_n\}$ be a vector such that the allocation amount for the n^{th} player is x_n. **x** is called an imputation if it satisfies the following (Winston, 2004):

$$v(N) = \sum_{m=1}^{m=n} x_m \qquad \text{(Efficiency)} \tag{10}$$

$$x_m \geq v(\{m\})\ ,for\ \forall m \in N \qquad \text{(Individual rationality)} \tag{11}$$

The core is the set of all imputations under the grand coalition N, which assures that none of the members of N can achieve better allocations under any subcoalition of N. In other words, we say that an imputation $\boldsymbol{x} = \{x_1, x_2, \dots, x_n\}$ is in the core iff for each $S \subset N$, the following condition is satisfied (Winston, 2004):

$$\sum_{m \in S} x_m \geq v(S),\ S \subset N \qquad \text{(Group Rationality)} \qquad (12)$$

Note that, the core may be empty.

4.1.5 Convexity

As introduced by Shapley (1971), a cooperative game is convex if the contribution of additional players presents increasing returns to scale. In other words, a game *(N, v)* is convex iff the following condition holds:

$$v(S) - v(S \cap T) \leq v(S \cup T) - v(T), where\ S, T \subseteq N \qquad (13)$$

In other words, let S_1, S_2 be two sets such that $S_1 \subset S_2 \subseteq N$. Then, a cooperative game is convex iff,

$$v(S_1 \cup \{\mathrm{m}\}) - v(S_1) \leq v(S_2 \cup \{\mathrm{m}\}) - v(S_2)$$

$$\text{, for } \forall \mathrm{m} \notin S_1, S_2\ ;\ \forall\, S_1, S_2, \{m\} \subseteq N\ ; S_1 \subset S_2 \qquad (14)$$

Shapley (1971) has also proven that the core of any convex game is non-empty.

4.2 The Profit Game

When the shippers act in a coalition to perform shipment activities and make joint decisions, the overall benefits increase as a result of the increase in truck space utilization and shared fixed costs. Besides identifying the optimal policy, the allocation of the costs and benefits among the shippers forming the coalition remains an issue. In this part, with the aim of finding adequate answers to these questions, we introduce the profit game played by shippers $m \in N$. We note that the optimality equations of the profit game are given by (6) and (7).

Let v be a real valued function where $v{:}2^N \rightarrow R$. Given a subcoalition S such that $S \subseteq N$, let $v(S)$ denote the amount of profit per unit time achieved by S. Note that, $v(S)$, which is simply the g_S in (6) and (7), is the characteristic function of the profit game.

In the remaining parts of this chapter, some properties are discussed under capacitated and uncapacitated settings separately. We consider an instance to be uncapacitated if in the optimal policy the truck capacity is never fully utilized. That is, an instance is uncapacitated if the following holds at the time of any dispatch under the optimal policy:

$$\frac{\sum_{\forall m} j_m}{K} < 1 \tag{15}$$

In the following sections of this chapter, we will be explaining some important properties of the profit game.

4.2.1 Monotonicity of the Profit Game

Note that in the profit game the decisions are made by the coalition and the acceptance criterion for a shipper depends on its potential contribution to the overall benefits. Any shipper whose acceptance reduces the profits would simply be rejected. Thus, it is not possible to end up with a larger coalition with less profit, so that the profit game is monotonic regardless of the value of any parameter.

Proposition 4.1: The profit game is monotonic.

Proof: Note that for any $S \subset T \subseteq N$, any policy that can be applied for S, can also be applied for T. For example, the following is always a feasible policy for T:

- Always reject the requests from shipper $m \in T \backslash S$.
- Apply the optimal policy for the subcoalition of T consisting of remaining shippers, S.

As a result, we conclude that $v(S) \leq v(T)$ always holds for any $S \subset T \subseteq N$.

■

4.2.2 Superadditivity of the Profit Game

Considering the definition of superadditivity property, the profit game is superadditive if shippers or a coalition of shippers get better off joining with other shippers or coalitions.

Proposition 4.2: The uncapacitated profit game is superadditive.

Proof: Suppose S, $T \subset N$ and suppose at least one of S and T achieves zero profit by itself. Note that, for the coalition $S \cup T$ the following is a feasible policy:

- If a coalition makes zero profit, then reject all the requests from the members of this coalition.
- If there is any coalition with positive profit, apply the optimal policy for the shippers of this coalition.

Applying this policy would result in a profit amount of $v(S) + v(T)$. Therefore, Equation (9) is satisfied:

$$0 \leq v(S) + v(T) \leq v(S \cup T)$$

Now suppose that each of the coalitions S, $T \subset N$ can achieve positive amount of profit by themselves and the dispatch decisions made under their optimal policy are shown in Figure 4.1.

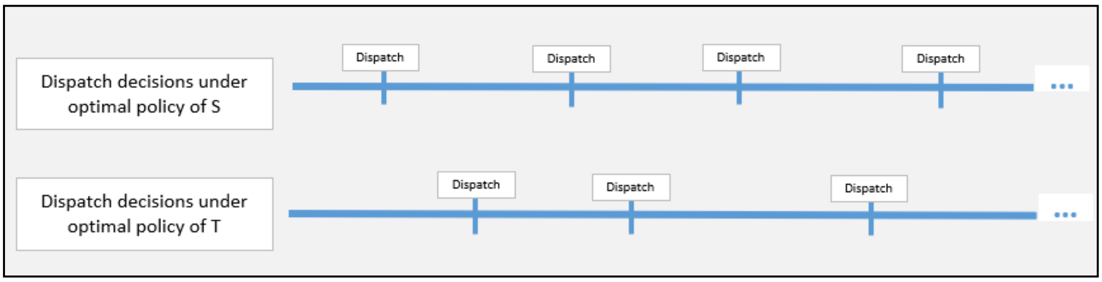

Figure 4.1. Dispatch points under optimal policies of S and T

Consider an arbitrary sample path, and the optimal dispatch times of both coalitions together on this path. Suppose that for coalition $(S \cup T)$ same set of decisions are made as in the decentralized case as presented in Figure 4.2. Note that, this policy is non-Markovian, and the profit achieved under this policy is more than the total of the profit amounts coalitions S and T can achieve separately, since total revenue amount and total dispatch cost does not change while total waiting cost is decreasing. Because, it is expected that under the optimal policy of coalition $(S \cup T)$ more profit can be achieved compared to the non-Markovian policy mentioned, (9) is always satisfied.

■

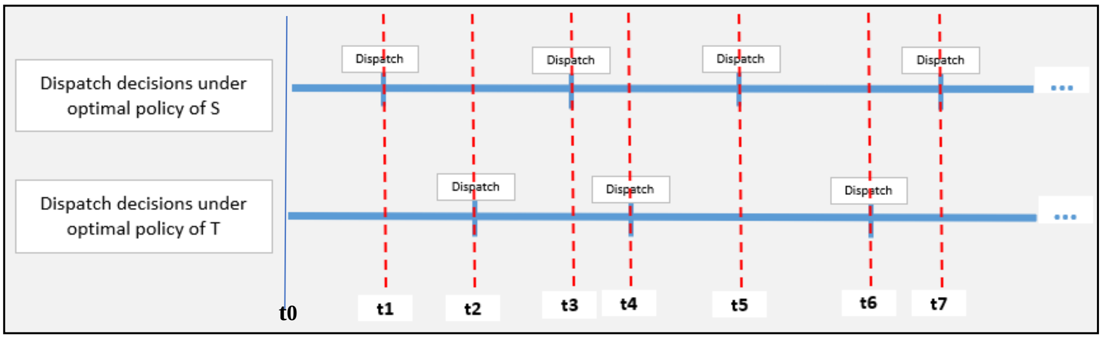

Figure 4.2. The feasible set of dispatch points for the coalition $(S \cup T)$

Observation 4.1: The capacitated profit game may not be superadditive.

Discussion: When the trucks are capacitated the shippers compete on truck space and the coalition tends to accept more profitable requests. Example 4.1. shows that Equation (9) may not be satisfied for the capacitated profit game.

Example 4.1: Consider the problem instance in Table 4.1.

Table 4.1. *Superadditivity problem parameters*

Shippers	**c**	**R**	**d**	**f**	**λ**	**A**	**K**
Shipper 1	2	50	2	10	50	50	5
Shipper 2	1	75	1	10	50		

For this problem, the grand coalition yields a profit of 4189 per unit time under the optimal policy.

For the same parameters, $v(\{1\}) = 1476$, $v(\{2\}) = 2738$, so that:

$v(\{1\}) + v(\{2\}) = 4214 > v(\{1\} \cup \{2\}) = 4189$, which is a counter example for Equation (9). Hence, the capacitated game may not be superadditive.

■

4.2.3 The Existence of Core and Convexity of the Profit Game

The profit game may possess different characteristics under different settings in terms of existence of the core and convexity. In the following part, these settings are further discussed.

Conjecture 4.1: In the uncapacitated profit game the core exists, and the game is convex.

Discussion: When there is no capacity constraint, additional shippers tend to contribute more to larger coalitions. That is a result of the fact that, in a bigger coalition the broadening effect of a new shipper to the feasible set of decision points is higher considering the possible elements of state space.

This conjecture is supported by the scenario results presented in Chapter 6.

■

Observation 4.2: In the capacitated profit game, when there is no minor dispatch cost, the core always exists while the game may not be always convex.

Example 4.2: Consider the problem instance in Table 4.2.

Table 4.2. *Convexity/problem settings*

Shippers	**c**	**R**	**d**	**f**	**λ**	**A**	**K**
Shipper 1	3.7	24.62	0	10	7.26	200	15
Shipper 2	2.79	32.34	0	10	5.24		
Shipper 3	2.64	31.06	0	10	3.90		

Under optimality conditions, the profit values for this problem setting are listed in Table 4.3.

Table 4.3. *Profit per unit time for possible coalitions for the setting in Table 4.2.*

Coalition $S \in N$	***v(S)***
{1}	0.00
{2}	27.66
{3}	11.65
{1,2}	35.39
{1,3}	19.36
{2,3}	58.25
{1,2,3}	65.30

Note the following expression which suggests that this game is not convex.

$$v(\{2,3\} \cup \{1\}) - v(\{2,3\}) = 7.05 \ \ngeq v(\{2\} \cup \{1\}) - v(\{2\}) = 7.73$$

However, for the discussed settings the core exists. For example, the following allocation is in the core:

$$(x_1, x_2, x_3) = (4.92, 38.20, 22.18)$$

Observation 4.3: In the capacitated profit game, when there is minor dispatch cost the core may not exist.

Observation 4.4: In the capacitated profit game, core may not exist when *d > 0.*

In Example 4.3. below, we discuss instances that exemplifies these observations.

Example 4.3: Consider the problem instance in Table 4.4.

Table 4.4. *Problem settings to show the non-existence of core and convexity under d>0 and finite capacity*

Shippers	**c**	**R**	**d**	**f**	**λ**	**A**	**K**
Shipper 1	7.7	59.3	25.0	10	23.9	50	7
Shipper 2	10.1	51.5	25.0	10	24.9		
Shipper 3	12.0	30.1	25.0	10	15.3		

Under optimality conditions the profit values for this problem setting are listed in Table 4.5.

Table 4.5. *Profit per unit time for possible coalitions for the setting in Table 4.4.*

Coalition *S* ∈ *N*	***v(S)***
{1}	89.9
{2}	73.5
{3}	10.8
{1,2}	149.0
{1,3}	91.0
{2,3}	74.6
{1,2,3}	149.0

The core does not exist for this problem setting. Also note that, this game is not convex since:

$$v(\{3\}) - \emptyset = 10.8 \ngeq v(\{2\} \cup \{3\}) - v(\{2\}) = 1.1$$

■

4.3 The Emission Game

In this part of the study, we introduce the emission considerations to the profit game. In the emission game, while shippers are aiming to maximize their total profits, the resulting carbon emission amounts from the shipment of the goods are shared among them. Any dispatch activity of the trucks from the shipment area causes some amount of carbon emissions. In our study, we consider two sources of emissions. First is the result of the additional fuel consumption due to loads. The other is due to the empty truck.

Let j_m, *EPL*, *E*, and s denote the workload due to shipper m upon dispatch, the emission per load, the emission amount due to the empty truck, and the number of players in a coalition $S \subseteq N$ respectively.

Then, the total emission amount per dispatch, $EPD(j_1, j_2, \dots, j_s)$, is defined as:

$$EPD(j_1, j_2, \dots, j_s) = \text{EPL} \sum_{\forall m} j_m + E \tag{16}$$

Note that the total emission amount is a result of the decisions made to maximize the expected profit in profit game. In the emission game, we do not optimize the emission amount, but we seek reasonable allocation methods to share the resulting emissions from the optimal policy of the profit game.

Let $\pi(j_1, j_2, \dots, j_n, l, a)$ be the steady state probabilities under the optimal policy for the grand coalition. Then, the characteristic function of the emission game, *e(S),* is defined as follows:

$$e(S) = \Lambda_S \sum_{\forall j,l} EPD(j_1, j_2, \dots, j_s)\, \pi(j_1, j_2, \dots, j_n, l, AD) \tag{17}$$

In the study by Liao et al. (2009) an activity-based emission model is discussed. In this model, the total amount of emission for a transportation activity is calculated based on a linear function of total distance travelled, total load carried and a vehicle specific emission factor. In this model the emission caused by the empty truck is not taken into account separately, but its effect on emission amounts is considered in the emission factor. Considering the model, we introduced in (16), the discussed model in this study is a specific case where $E=0$, and *EPL* is a function of distance travelled and vehicle specific emission factor.

Let *TD* be the distance in kilometers the truck travels for the delivery of the shipments.

Let *W* be the unit weight of the loads in the truck in tons including the last arrival at the time of the dispatch.

Let *EF* be the mode specific emission factor i.e. tons of CO_2 per ton per km.

The EPL can be calculated as follows:

$$\text{EPL} = (TD)(W)(EF) \tag{18}$$

Proposition 4.3: In the uncapacitated setting the emission game is monotonic.

Proof: Remember that the profit game is monotonic so that Equation (8) always holds. In the supercoalition, none of the shipments that are accepted in the earlier coalition would be rejected. Thus, when the coalition size increases, if the dispatch regime does not change, on the average, higher number of loads would be waiting in the truck and higher number of loads would be in the truck upon dispatch. Note that, increasing total truck load decreases the fixed costs per load, which would lead to more frequent dispatches. Since both number of dispatches per unit time and total number of shipments made per unit time would increase, the emission amount per unit time would also increase.

■

Observation 4.5: The core may not exist for the emission game.

Example 4.4: Consider the problem setting in Table 4.6. under *E=10*, and *EPL =1*.

Table 4.6. *Problem settings to show the core non-existence in the emission game*

Shipper	c	R	d	f	λ	A	K
Shipper 1	11.49	46.59	0	10	5.25	50	20
Shipper 2	7.95	11.10	0	10	2.45		
Shipper 3	12.83	35.01	0	10	6.70		

For this problem setting, the emission yield for the grand coalition per unit time is 245. The emission amount per unit time for all of the possible coalitions are listed in Table 4.7.

Let x_m^e be the emission amount allocated to shipper *m*. Note that the following inequalities cannot be satisfied at the same time:

$$x_1^e \leq 120$$

$$x_{\{2,3\}}^e \leq 81.2$$

$$x_1^e + x_2^e + x_3^e = 245$$

Therefore, the core does not exist for the given settings.

■

Table 4.7. *Emission amounts under optimal policy for Example 4.4*

COALITION (S)	e(S)
{1}	120.0
{2}	0.0
{3}	81.1
{2,3}	81.2
{1,3}	245.0
{1,2}	120.0
{1,2,3}	245.0

4.4 Profit and Emission Game with Carbon Tax

Many countries charge carbon taxes for the carbon emissions of the organizations resulting from their business activities. Plumer and Popovich (2019) provides a detailed study on this topic. This study involves the current carbon prices applied in countries all over the world.

Within the scope of this work, we seek for an approach for integrating the profit and emission games. To make the profit and emission amounts compatible terms, we transform the emissions into monetary unit by using the carbon taxes.

With these considerations we introduce a game with carbon policy in which the objective is to maximize the profit of the coalition under the carbon tax policy. Then, we evaluate the effect of carbon tax policy on the core of the games and the performance of the allocation schemes.

Let P be the carbon tax amount charged per tons of CO_2 emitted due to the dispatch of the trucks. Then the total carbon tax incurred per dispatch, with a load $(j_1, j_2, \dots, j_s)$, in a coalition S is as follows:

$$P\ EPD\ (j_1, j_2, \dots, j_s)$$

The reward function for this game, $r(\boldsymbol{j}, l, a)_S^{tax}$ is given as follows:

$$r(\boldsymbol{j}, l, a)_S^{tax} = \begin{cases} \sum_{m \in S} j_m (R_m - f_m) + R_l - f_l - A - \sum_{m \in S} \theta(\boldsymbol{j}, l) d_m - P\ EPD(\boldsymbol{j}),\ if\ a = \{AD\} \\ 0, otherwise \end{cases} \tag{19}$$

Note that the characteristic function for the game with carbon tax, $V^{tax}(S)$, would be the average profit per unit time under the reward function $r(\boldsymbol{j}, l, a)_S^{tax}$.

CHAPTER 5

ALLOCATION SCHEMES

Allocation of costs or benefits is an essential part of cooperative practices. As we may notice, the satisfaction of core conditions is an important criterion for the evaluation of the performance of an allocation. However, for large coalitions it may be difficult to determine the core of the game because it requires to solve $2^n - 1$ optimization models, where n denotes the number of members in the coalition.

Efficiency, individual rationality and group rationality concepts are important for making allocations in cooperative games. These concepts construct the main baselines for the allocation schemes we define. In all of the allocations made, we satisfy the efficiency criteria. To be able to achieve this, the grand coalition profit game is solved to obtain the optimal settings for each run.

In the scope of this work, we offer 6 different allocation schemes which requires relatively low computational efforts. In this part of the study, we also define some performance measures to compare the performance of the allocation schemes.

In the following sections of the study, x_m will be referred as the allocation made to shipper $m \in S$. Also, let s and n be defined as follows:

s: number of players in a coalition $S \subseteq N$.

n: total number of players in N.

5.1 Allocation Schemes for the Profit Game

In this section we define the allocation schemes for the profit game.

5.1.1 Core Allocation Scheme

In core based allocation method, the contribution of each shipper to all possible coalitions are calculated to be used as a base case. For each shipper, a threshold value which is indeed the minimum value a shipper must be allocated to satisfy the core conditions is found. Let this first stage allocation amount be u_m. Let u_m^* denote the optimal solution to the following minimization problem.

(Corebased):

$$\min \mathrm{z} = \sum_{\forall m \in N} u_m \tag{20}$$

$$subject\ to: \tag{21}$$

$$\textstyle\sum_{m \in S} u_m \geq v(S) \ , \forall\, S \subset N \tag{22}$$

$$u_m \geq 0 \ \ , \forall\, \{m\} \in N \tag{23}$$

Let z^* be the optimal solution to the (Corebased). Then, the grand coalition profit is found and excess (deficit) amount, *EP*, is calculated to be shared in the second phase:

$$EP = v(N) - z^* \tag{24}$$

The *EP* is shared among the shippers proportional to $\lambda_m c_m$ values. Final allocation amount is:

$$x_m = u_m^* + \lambda_m c_m \frac{EP}{\sum_{\forall i \in N} \lambda_i c_i} \tag{25}$$

This scheme requires $2^{|n|-1}$ many optimization models to be solved (for each coalition) to obtain the right-hand side values of (22). If the core is available, the core allocation scheme always makes core allocations.

5.1.2 Shapley Value Based Allocation Scheme

Shapley (1953) proposed a cost allocation method satisfying the symmetry, inessential player, and additivity properties. We call an allocation symmetric if it guarantees to allocate the same amount to identical players. An inessential player is a player in a cooperative game which never contributes to a coalition. In profit game, inessential player property is satisfied when the shipper is assigned 0 allocation (it is either rejected always or its acceptance provides no additional profit). Lastly, additivity property states that the allocation made to a coalition S, should be equal to the total allocation amount that would be made to any combination of subcoalitions of S.

Shapley (1953) showed that the only imputation satisfying the three properties is the following:

AC_m^S: Additional contribution of a player $m \notin S$ to the S, $AC_m^S = v(S \cup \{m\}) - v(S)$

Then, the allocation made to shipper m is defined as:

$$x_m = \frac{1}{n!} \sum_{S \subseteq N-\{m\}} (s!)(n-s-1)!\, AC_m^S \tag{26}$$

In Shapley based allocation scheme, the allocations are made according to (26).

5.1.3 Truck Based Allocation Scheme

In truck based allocation scheme, shippers are identified as null (O), partial (P) and full (F) shippers according to the optimal decisions made in grand coalition. Null shippers are the inessential players, whose shipment requests are always rejected under optimal policy of grand coalition, so that null shippers have no contribution to the coalition. Partial shippers are the ones whose shipment requests are rejected at least once and accepted at least once as well under the optimal policy of grand coalition. In truck based allocation, null shippers and partial shippers are made 0 allocation. Full shippers are the shippers whose shipment requests are always accepted. In this scheme, all of the allocation is made among the full shippers. That is, the costs and revenues of the null and partial shippers are shared among the full shippers. Note that, at least one of the shippers must be a full shipper in any policy.

As the name suggests, in truck based allocation scheme, the allocations are made at truck level at the dispatch point. At any decision point, costs and revenues are allocated to all of the shippers according to their classification and according to the cost and revenue parameters under the decision made. The waiting cost, minor dispatch cost, fuel cost and revenue amounts of each shipper are allocated to itself according to the total number of accepted requests from that shipper. The common cost A, on the other hand is shared proportionally among the full shippers according to their total loads in the truck at the time of dispatch. As a second stage effort, these truck level allocations are multiplied by steady state probabilities to obtain the final allocation.

Upon the arrival of any shipper when the decision made, the corresponding truck based cost and profit amounts are allocated as follows.

Let $cl_m \in \{O, P, F\}$ denote the class of a shipper m, and $\delta_{l=m}$ be the function taking value of 1 if l=m, 0 otherwise.

Then, $\bar{x}_m(j_1, j_2, \dots, j_s, l, a)$, the allocation made for shipper $cl_m \in \{F\}$, is:

$$\bar{x}_m(j_1, j_2, \dots, j_n, l, a)$$
$$= \begin{cases} \dfrac{1}{\Lambda}\left(c_m\,(j_m + \delta_{l=m}) + \dfrac{j_m + \delta_{l=m}}{\sum_{\forall cl_i \in \{F\}} j_i + \delta_{cl_l \in \{F\}}} \displaystyle\sum_{k \in \{O,P\}} j_k c_k\right), if\ a\ \in \{AW, RW\} \\ \dfrac{1}{\Lambda}\left((j_m + \delta_{l=m})\left(R_m - f_m + \dfrac{\left(\sum_{\forall cl_k \in \{O,P\}} (j_k + \delta_{l=k})(R_k - f_k) - d_k\right) - A}{\sum_{\forall cl_i \in \{F\}} (j_i + \delta_{l=i})}\right) - d_m\right) \\ \qquad , if\ a \in \{AD\}, (j_m + \delta_{l=m}) > 0, cl_m \in \{F\} \\ 0, otherwise \end{cases}$$

(27)

The final allocation made to shipper *m* is:

$$x_m = \sum_{\forall j,l,a} \bar{x}_m(j_1, j_2, \dots, j_s, l, a)\,\pi(j_1, j_2, \dots, j_n, l, a) \tag{28}$$

5.1.4 Individual Rationality (IR) Based Allocation Scheme

Individual rationality implies that imputations should be fair enough so that the players do not lose any advantage considering what they can obtain without participating in the grand coalition.

In IR based allocation we firstly classify the shippers as null, partial and full shippers with respect to the grand coalition behavior. Then, we calculate the following values for each shipper $m \in N$.

Marginal Profit (mp_m): the contribution of a shipper to the grand coalition.

$$mp_m = v(N) - v(N - \{m\})$$

Individual Rationality Ratio(IRR_m): the ratio determining the imputation amount of a shipper.

$$IRR_m = \begin{cases} \frac{v(\{m\}) + mp_m}{\sum_{\forall j}(v(\{j\}) + mp_j)}, m, j \in N, cl_m \in \{F\} \\ 0, \; otherwise \end{cases} \tag{29}$$

In IR based allocation scheme, the allocations are made based on IRR values and allocation made to shipper m is defined as:

$$x_m = v(N) IRR_m \tag{30}$$

5.1.5 Steady State Allocation Scheme 1 (SS1)

In steady state allocation schemes, steady state probabilities are taken into consideration to be used in the allocation stage. Firstly, the optimal policy for grand coalition is obtained and steady state probabilities are found. The steady state probabilities are used to calculate the following:

Let λ_F^m denote the long-run number of accepted requests per unit time from shipper m. It is given by:

$$\lambda_F^m = \Lambda_N \sum_{a \in \{AW, AD\}} \sum_{\forall j} \pi(j_1, j_2, \dots, j_n, m, a) \tag{31}$$

SR_m: Denotes the rate at which the truck dispatches with at least 1 unit of load from shipper m.

$$SR_m = \Lambda_N \sum_{a \in \{AD\}} \sum_{\forall j, l} \pi(j_1, j_2, \dots, j_n, l, a) \left(\delta_{(\delta_{l=m} + j_m) > 0}\right) \tag{32}$$

In *SS1* the allocation is made in an aggregate manner except for the minor dispatch costs of the shippers.

Allocation made to shipper m in *SS1*:

$$x_m = \lambda_F^m ((v(\mathrm{N}) + \sum_{\forall i} d_i SR_i) \frac{c_m}{\sum_{\forall i} \lambda_E^i c_i}) - d_m SR_m \tag{33}$$

5.1.6 Steady State Allocation Scheme 2 (SS2)

In SS2 besides minor dispatch cost, revenue amounts, and fuel costs are allocated to shippers individually using λ_F^m and SR_m. Since these parameters are shipper specific, this allocation method is expected to result in better results in terms of individual rationality.

Allocation made to shipper m in SS2:

$$x_m = \lambda_F^m((v(\mathrm{S}) + \textstyle\sum_{\forall i}(d_i - R_i + f_i)SR_i)\ \frac{c_m}{\sum_{\forall i}\lambda_E^i c_i}\ -\ (d_m - R_m + f_m)SR_m \quad (36)$$

5.2 Emission Allocations

The emission allocations in the emission game and the game with carbon tax are made using the Shapley value based allocation scheme, steady state allocation scheme 2, and truck based allocation scheme. The formulations are similar, but this time instead of profits and costs, the total emission amounts are allocated to the shippers.

Let x_m^e, denote the emission allocation made to shipper m.

To calculate the Shapley value based emission allocation we first define $ACE_m{}^S$ as the additional emission amount a player $m \notin S$ causes when entered to the coalition.

$$ACE_m{}^S = EPL(S\ U\ \{m\}) - e(S) \quad (34)$$

Then the Shapley value based emission allocation can be expressed as:

$$x_m^e\ = \frac{1}{n!}\sum_{\mathrm{S} \subseteq \mathrm{N}-\{\mathrm{m}\}}(s!)(n-s-1)!\,ACE_{\mathrm{m}}{}^{\mathrm{S}} \quad (35)$$

Truck based emission allocation is also made in two stages.

Let $\overline{x_m^e}(j_1, j_2, \ldots, j_s, l, a)$ be the emission allocation made to shipper cl_min $\{F\}$ when the truck dispatch. We calculate $\overline{x_m^e}(j_1, j_2, \ldots, j_s, l, a)$ as follows:

$$\overline{x_m^e}(j_1, j_2, \ldots, j_s, l, a) = \begin{cases} \frac{1}{\Lambda}\left((j_m + \delta_{l=m})\left(\mathrm{EPL} + \frac{E + EPL\sum_{\forall cl_k \in \{O,P\}}(j_k + \delta_{l=k})}{\sum_{\forall cl_i \in \{F\}}(j_i + \delta_{l=i})}\right)\right) \\ \qquad\qquad\qquad , if\ a = \{AD\}, (j_m + \delta_{l=m}) > 0, cl_m \in \{F\} \\ \qquad\qquad 0, otherwise \end{cases}$$

(36)

That is at each dispatch event, each shipper is allocated an emission amount of $\overline{x_m^e}(j_1, j_2, \ldots, j_s, l, a)$. Considering the whole time horizon, the total emission allocated to a shipper can be found by multiplying the amounts allocated to that shipper at each dispatch by the steady state probability of the corresponding state.

Then the final emission allocation made to shipper m is:

$$x_m^e = \sum_{\forall j,l,a} \overline{x_m^e}(j_1, j_2, \dots, j_s, l, a)\, \pi^s(j_1, j_2, \dots, j_n, l, a) \tag{37}$$

The steady SS2 allocation of the emissions as follows:

$$x_m^e = \lambda_E^m \left(\left(e(\mathrm{S}) - \mathrm{EPL} \sum_{\forall i} j_i\, \lambda_E^i. \right) \frac{c_m}{\sum_{\forall i} \lambda_E^i c_i} + j_m \mathrm{EPL} \right) \tag{38}$$

5.3 Performance Measures

To measure the quality of the defined allocation schemes we suggest 6 different performance measures. This way, we can compare the performance of the allocation schemes in some aspects. These performance measures are explained in the following part of the study.

Number of Instances in the Core: Practically, we may note that the boundaries of the core identify the threshold values for the individual shippers to form a coalition, so that, the core performance of an allocation scheme is one of the most important performance measures for the cooperative games. The core performance of each allocation is evaluated on a binary scale; taking value of 1 if the allocation is within the core, 0 otherwise.

Maximum Gap Amount (MAXG): The maximum gap amount is a measure to approximate the maximum distance of a specific allocation from the core region.

To determine the maximum gap amount, profit amounts of all possible subcoalitions are calculated and these are compared with the total allocations made to the members of these subcoalitions in the grand coalition. If the profit of a subcoalition is higher than the total amount its members get in the grand coalition under a specific allocation scheme, this deviation is identified as a gap. Among these, the highest absolute value is identified as the maximum gap.

$$MAXG = \max_{S \in N} \left(v(S) - \sum_{\forall m \in S} x_m \right)^+ \tag{39}$$

Example 5.1.

Assume that in a game with 3 shippers the total profit amounts for all possible coalitions are given in Table 5.1.

Table 5.1. *Example 5.1. problem settings*

Coalition	Profit
{1}	2
{2}	3
{3}	3
{1,2}	7
{1,3}	5
{2,3}	8
{1,2,3}	10

Note that the grand coalition profit amount is 10. A possible allocation of the profit for the grand coalition is 4, 2, and 4 for the shippers 1, 2, and 3 respectively. According to this allocation, the gaps are shown in Table 5.2.

Table 5.2. *Allocation example for example 5.1*

Coalition	Coalition Profit	Total Grand Coalition Allocation	Gap
{1}	2	4	0
{2}	3	2	1
{3}	3	4	0
{1,2}	7	6	1
{1,3}	5	8	0
{2,3}	8	6	2
{1,2,3}	10	10	0

For this allocation, the maximum gap amount is 2.

Minimum Gap Amount (MING): Similar to the maximum gap amount, minimum gap amount is also related to the deviations from the core. However, on the contrary to *MAXG*, it states the minimum deviation from the core, so that instead of the highest gap, here the lowest absolute deviation is noted as the minimum gap amount.

$$MING = \min_{S \in N}\{(-v(S) + \textstyle\sum_{\forall m \in S} x_m), 0\} \quad (40)$$

Consider example 5.1. For the same settings, the minimum gap amount would be 1.

Number of Gaps (NG): Consider the grand coalition allocation amounts of the shippers. If any set of shippers can achieve better total profit than their grand coalition allocation totals by forming a subcoalition, there is an unwelcome deviation amount for this subcoalition. We name this deviation as the gap. Number of gaps is the number of cases for which there is a gap when considered all of the possible subcoalitions. For instance, the number of gaps for Example 5.1. is 3.

Percent Gap (PG): It is simply the percentage of number of gaps.

$$PG = \frac{NG}{2^{|N|-1}} \times 100\% \quad (41)$$

Note that, the maximum number of gaps for any allocation can be $2^{|N|} - 1$ since the empty set of shippers does not form a coalition. For Example 5.1, the maximum number of gaps is $2^3 - 1 = 7$. Since the *NG=3* for this example, the percent gap is 42.86%.

Average Gap (AG): It is the mean value of the gap amounts, which is calculated by dividing the total gap amount by the total number of gaps.

$$\frac{\sum_{\forall S \in N} (v(S) - \sum_{\forall m \in S} x_m)^+}{NG} \quad (42)$$

In Example 5.1. the total gap amount is 4 while the number of gaps is 3. Therefore, the average gap is 1.33.

CHAPTER 6

NUMERICAL ANALYSIS

Within the scope of this study we address a number of research questions with the aim of checking the availability of the core and for the profit and emission games. We also want to acquire the answers related to the possibility of defining allocation schemes which provides core allocations. Lastly, we want to observe the performances of the allocation schemes based on performance measures we introduce. In this chapter, we provide a numerical analysis to make further investigation on these topics.

In all of the instances discussed in this chapter, the grand coalition, *N*, consists of 3 shippers. For the profit game and the emission game we create different scenarios based on different ranges and values of *A, K, R, c,* λ, and *d.* The values and ranges of these parameters are determined in a way that a wide variety of cases like capacitated and uncapacitated settings are paid regard in our analysis.

The parameter values corresponding to these instances are listed in Table 6.1.

Table 6.1. Parameter values for the profit game in different scenarios

Parameter	Value/Range
A	10, 50, 200
K	7, 15, 20
R_i	U[5, 45], U[30, 70]
λ_i	U[2, 10], U[15, 25]
c_i	U[1, 5], U[7, 15]
f_i	U[2, 8]
d_i	0, A/2, A/4

For each of these scenarios, firstly the MDP model is solved for each possible coalition and optimal policy is obtained. Then, under the optimal policy we execute the defined allocation schemes. After obtaining the allocation results, we analyze the performance of each allocation scheme for each scenario both with respect to the core existence and with respect to the other defined performance measures. In the following sections, the scenarios created for the profit game and the emission game, and related performance results are discussed separately.

6.1 Numerical Analysis of the Profit Game

For the profit game a total of 216 scenarios are created. The results show that, while the parameter values have important effect on core availability, the performance of the allocation schemes is rather robust to changes in parameter values.

6.1.1 Core Performance of the Allocation Schemes

We discuss the existence of core and performance of each scheme in capturing the core. Out of total 216 scenarios, the number of instances in the core is 132. In 14 of the instances, no coalition is formed due to the fact that no profit can be achieved even under the grand coalition. For the remaining 70 instances, the core does not exist i.e. in 34.6% of the instances the core does not exist. The core performance of the allocation schemes is calculated as the percentage of the core allocations made out of 132 instance having core. That is:

$$\begin{aligned}&Ratio\ of\ instances\ where\ scheme\ yields\ the\ core\\ &\qquad = \frac{Number\ of\ Core\ Allocation\ Made\ by\ Allocation\ Scheme}{Total\ Number\ of\ Instances\ Having\ Core}\end{aligned}$$

The results are given in Figure 6.1.

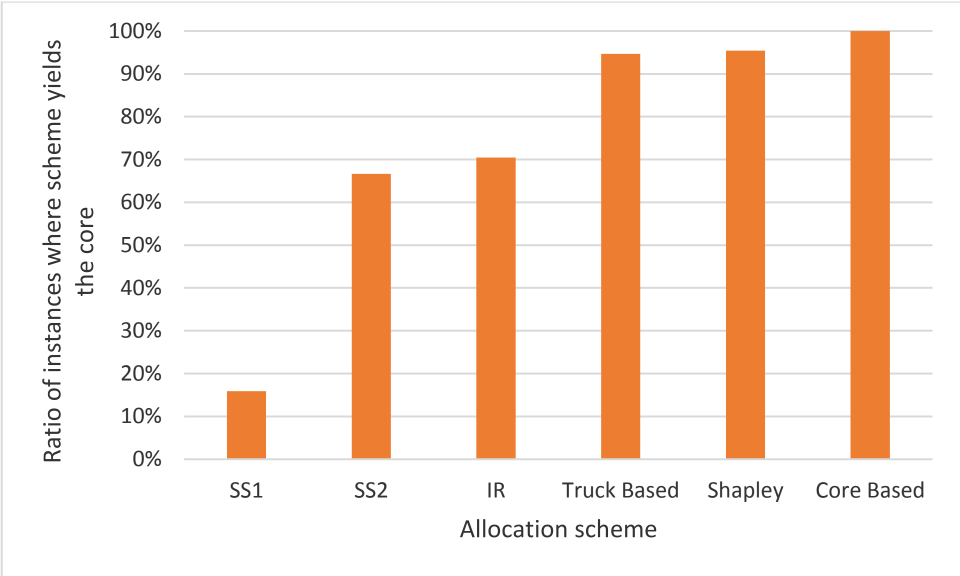

Figure 6.1. Core performance of the schemes (in percentages)

Besides the core performance of the allocation schemes, we discuss the effect of the parameters on the existence of core and on the performances of the schemes. We first note that in the instances where the truck capacity is not fully utilized (the uncapacitated setting) the core always exists independent of the other parameter settings. When minor dispatch cost, $d = 0$, core always exists for both capacitated and uncapacitated settings independent of the values of other parameters. This implies core may possibly exist only when $d>0$ and the setting is capacitated.

The effect of the dispatch cost (A)

For the different values of A, i.e. $A=10$, $A=50$, and $A=200$ the number of instances having core is 59, 41 and 32 respectively. The fixed dispatch cost seems to have a worsening effect on existence of the core in that, the number of instances in the core decreases with increasing values of the fixed dispatch cost as seen in Figure 6.2(a).

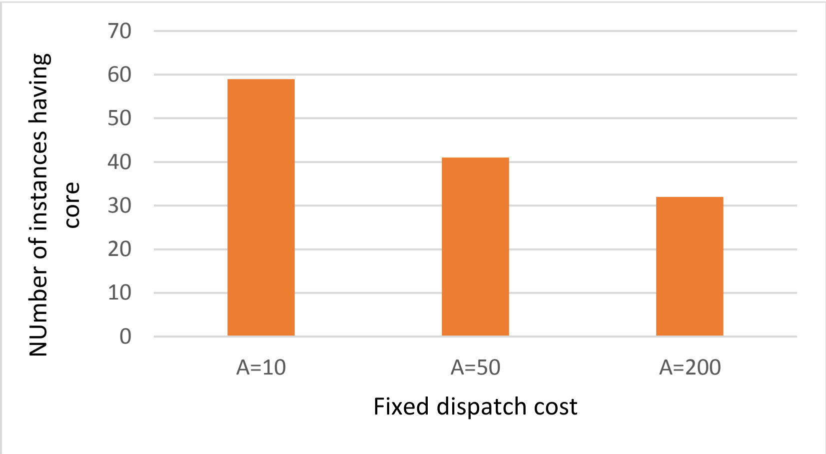

Figure 6.2(a). Fixed dispatch cost vs. number of instances having core

That is probably because of the fact that an increase in the A makes the truck capacity more valuable, as a result the competition among the shippers gets heated.

The core performance of the allocation schemes with changing values of fixed dispatch cost is seen in Figure 6.2(b). In the uncapacitated setting, the Shapley allocation is always in the core, which hints that the uncapacitated game is convex. Under uncapacitated settings, the allocations under the truck based scheme are always in the core as well. From the same figure we also see that, the change in the fixed dispatch cost amount does not have a significant effect on core performance of the allocation schemes.

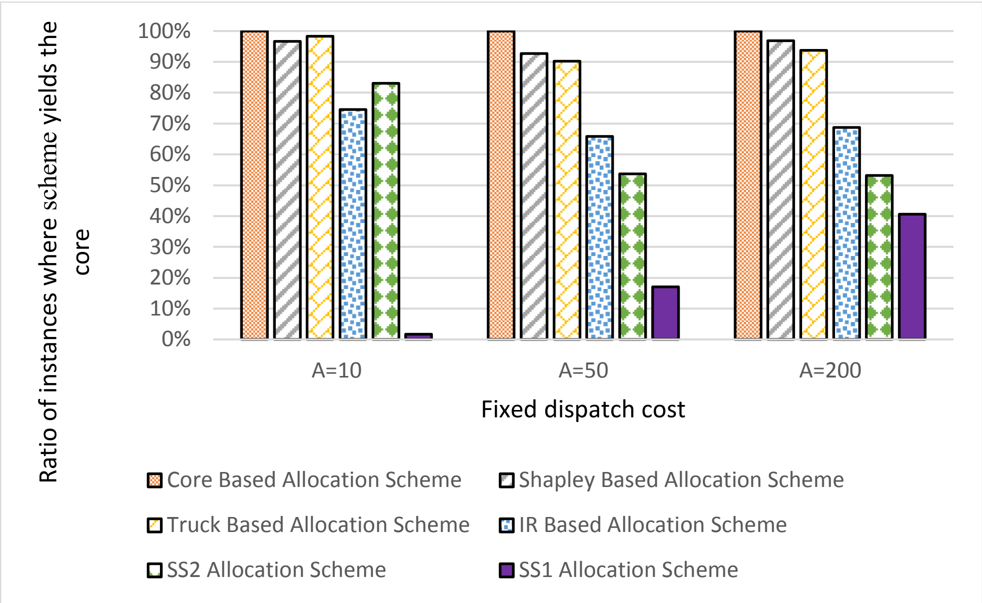

Figure 6.2(b). Fixed dispatch cost vs. core performance for the profit game

The effect of truck size (K)

The change of the core availability with changing values of K is shown in Figure 6.3(a). The number of instances having core is increasing with increasing truck capacity. Note that, this finding is in line with our discussion about the effect of increasing fixed dispatch cost on core availability in the way that with increasing truck capacity the model approaches to the infinite capacity setting. In 55 of the instances the truck capacity is never fully utilized. For these 55 uncapacitated instances the core always exists supporting the discussion made in *Conjecture 4.1* related to the existence of the core.

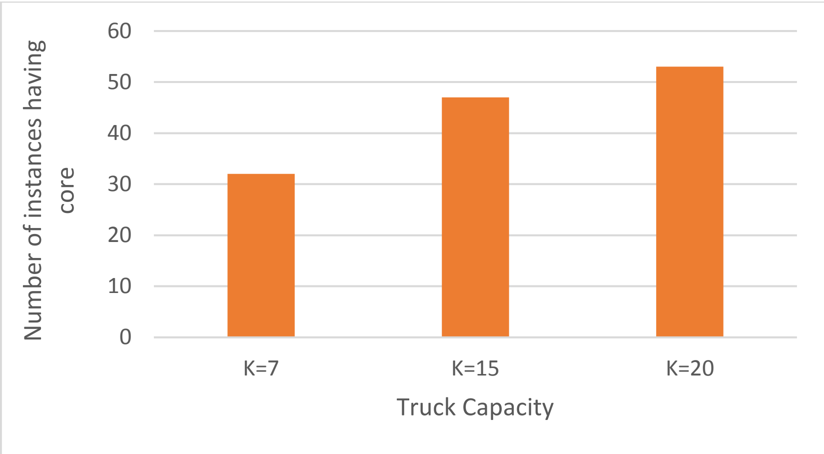

Figure 6.3(a). Truck capacity vs. number of instances having core

As we may note from Figure 6.3(b). under all levels of *K*, the truck based allocation scheme and Shapley based allocation scheme presents the best core performance. We also note that, the change in the truck capacity has no significant effect on core performance of the allocation schemes.

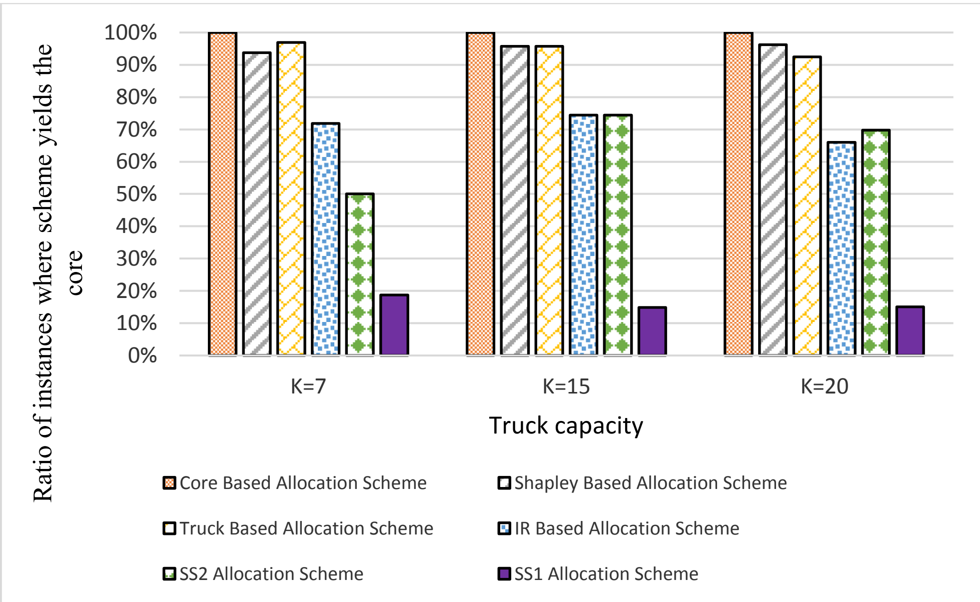

Figure 6.3(b). Truck capacity vs. core performance for the profit game

The effect of arrival rate (λ) and waiting cost (c)

The effect of the arrival rate on the core availability can also be discussed based on its effect on capacity utilization. As arrival rate increases, relatively the waiting cost decreases. This results in increased capacity utilization. As a result, on the average, increasing values of arrival rates have worsening effect on core availability. Figure 6.4(a). justifies this discussion.

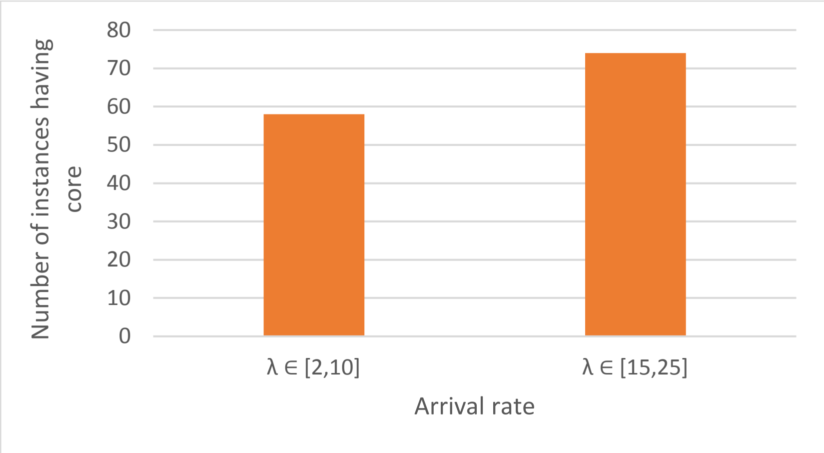

Figure 6.4(a). Arrival rate vs. number of instances having core

Figure 6.4(b) shows the core performance of the allocation schemes under different value ranges of arrival rate. We note that the performance of the allocation schemes is also robust to the changes in arrival rate parameter values.

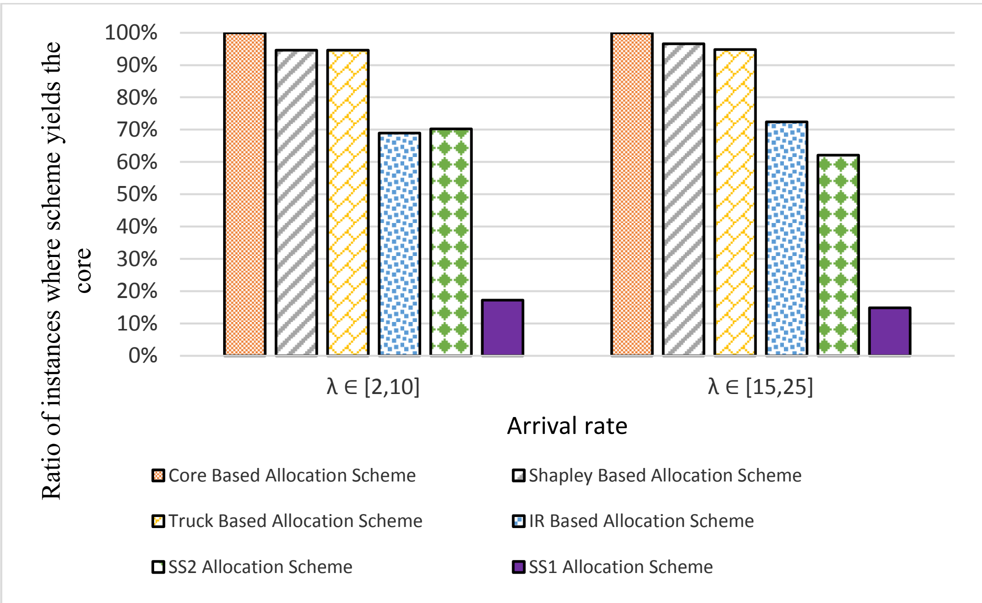

Figure 6.4(b). Arrival rate vs. core performance for the profit game

Increasing values of the waiting cost also discourages the use of capacity at high utilization. Capacity utilization drops with increasing waiting cost. As a result, under high values of waiting cost, the capacity constraint tends to relax. As can be seen in Figure 6.4(c). under low waiting cost, increased core availability is presented.

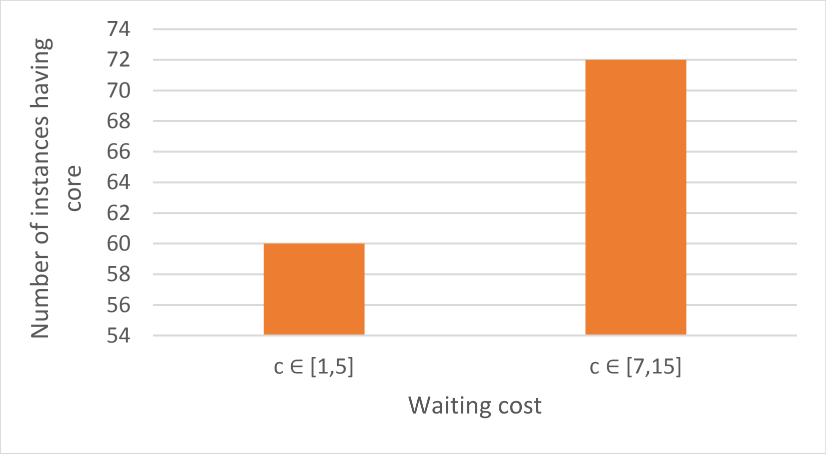

Figure 6.4(c). Waiting cost vs. number of instances having core

In Figure 6.4(d) we see the core performance of allocation schemes for changing waiting cost values. We note the effect of the waiting cost amount on performance of the allocation schemes is also limited.

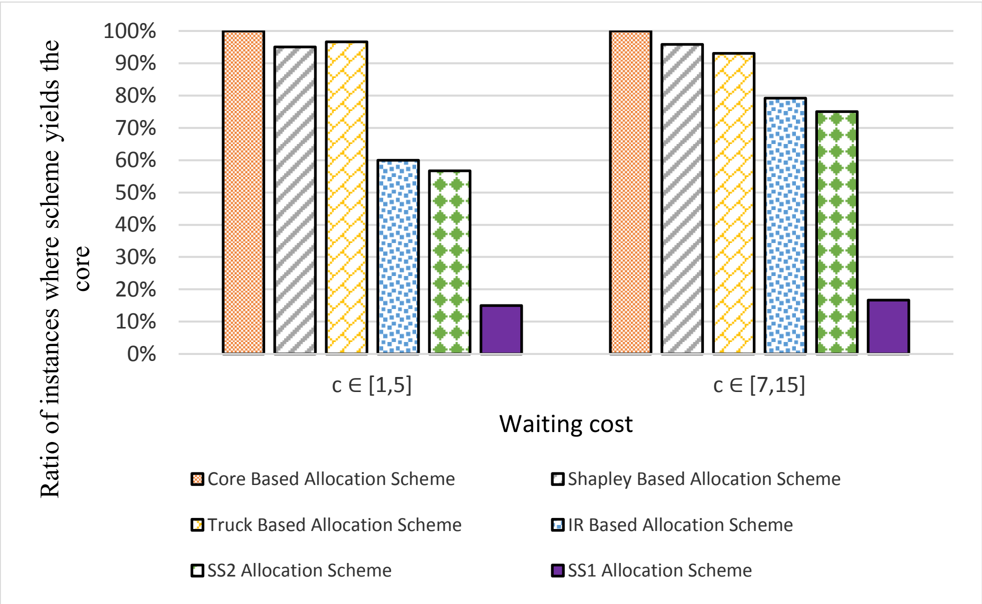

Figure 6.4(d). Waiting cost vs. core performance for the profit game

The effect of minor dispatch cost(d)

Figure 6.5(a). shows the core availability under different values of minor dispatch cost, d. In the instances where there is no minor dispatch cost, the core performance is the highest. When the minor dispatch cost is increased the core availability decrease. This is an expected result since, the effect of minor dispatch cost would be similar to the effect of fixed setup cost.

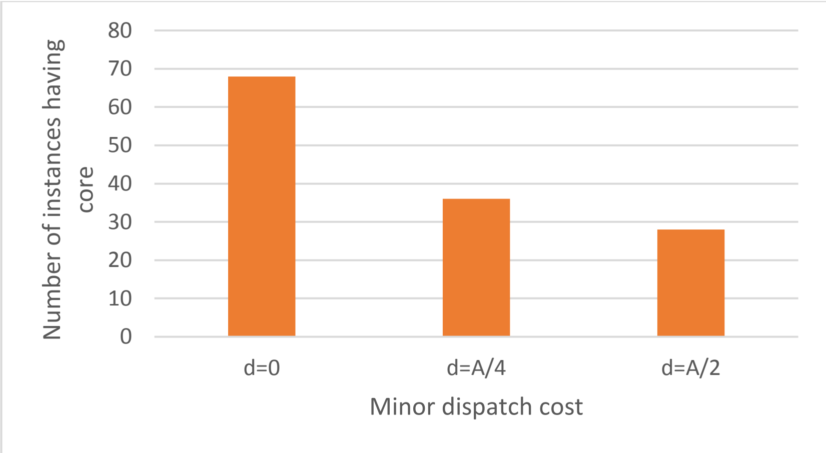

Figure 6.5(a). Minor dispatch cost vs. number of instances having core

The performance of allocations schemes under different values of minor dispatch cost is seen in Figure 6.5(b). When there is no minor dispatch cost, Shapley value based allocation and truck based allocation methods always provide core allocations. Note that when $d>0$, the core performance of these two allocation schemes decrease, while performance of the other allocation schemes increases with increasing values of minor dispatch cost. Remember that, the minor dispatch cost is shipper specific and allocated individually to all shippers, so that there is no interaction between shippers in terms of minor dispatch cost. When the dispatch cost amount increase, it might be dominating the effects of the way the other costs are allocated. As a result, the efforts to satisfy core equations would lose importance. If we continue to increase the minor dispatch cost amount, we would probably see more misleading effects on the core performance of the allocation schemes.

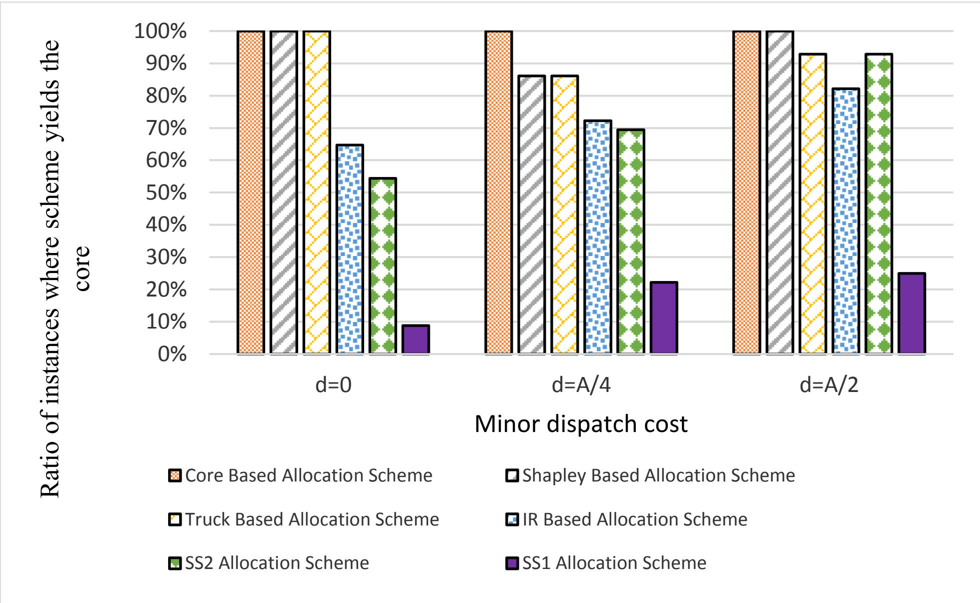

Figure 6.5(b). Minor dispatch cost vs. core performance for the profit game

6.1.2 Fairness Analysis of the Allocations

The gap analysis study aims to compare the performances of the allocation schemes in terms of the fairness of allocation when core does not exist. The numerical results show that an allocation scheme which is powerful in identifying a core allocation in the presence of core, may not be well-performing in achieving "fairness" in the absence of core.

In Table 6.2. the list of abbreviations belonging to fairness measures are listed for ease of tracking.

Table 6.2. *Abbreviations of fairness measures*

Fairness Measure	**Abbreviation**	**Explanation**
Average Gap	AG	Mean value of the gap amounts
Percent Gap	PG	Percentage of number of gaps
Maximum Gap Amount	MAXG	Maximum distance of a specific allocation from the core
Minimum Gap Amount	MING	Minimum deviation from the core
Number of Gaps	NG	The number of cases for which there is a gap when considered all of the possible subcoalitions

To compare the allocation schemes in terms of fairness, we calculate the average values of fairness measures yielded in all instances under the allocations made by each allocation scheme considered. These average values are calculated for each allocation scheme as follows:

$$Average\ value\ of\ fairness\ measure\ under\ an\ allocation\ scheme = \frac{Sum\ of\ Values\ of\ fairness\ measure\ under\ an\ allocation\ scheme}{\begin{array}{c}Total\ number\ of\ instances\ having\ no\ core\ out\ of\\ instances\ for\ which\ profit\ can\ be\ achieved\end{array}}$$

The average of NG values generated by each allocation scheme through all scenario are presented in Figure 6.6.(a). The allocations made by the SS2 allocation scheme results in minimum number of gaps. The SS1 allocation scheme on the other hand is the worst performing scheme. The performance of Shapley value based allocation is slightly worse than the SS2 allocation results while other allocation schemes generates similar results under NG consideration. The summary of average of PG values according to different allocation schemes is seen in Figure 6.6.(b). As expected, the results are similar with the *NG* analysis.

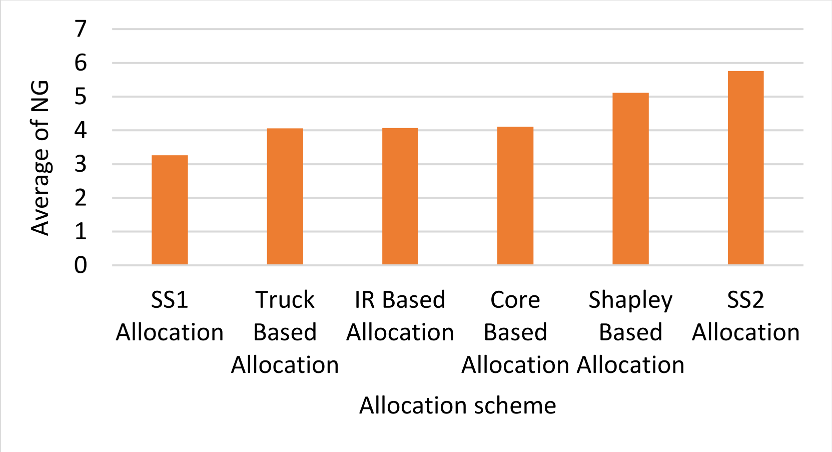

Figure 6.6(a). Average of *NG* over all scenarios having no core

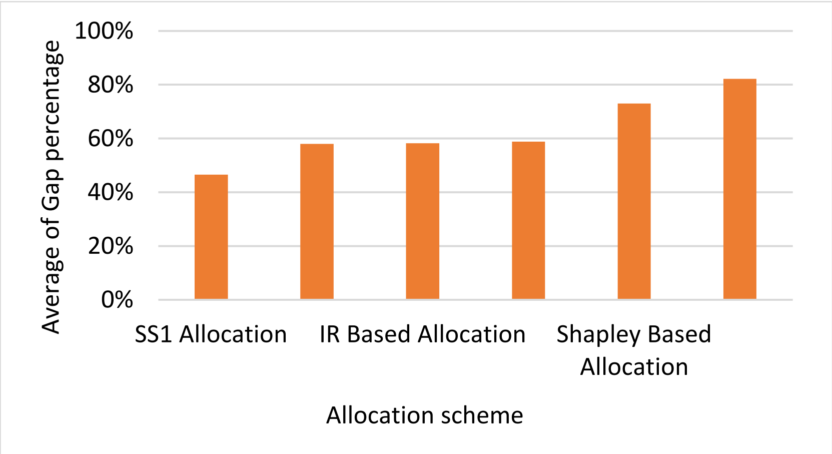

Figure 6.6(b). Average of *PG* over all scenarios having no core

In Figure 6.7. the average of *MAXG* values over all scenarios resulting from the allocations made according to each scheme are presented. In terms of maximum gap amounts, the Shapley value based allocation performs the best while steady state allocation schemes are the worst performing schemes.

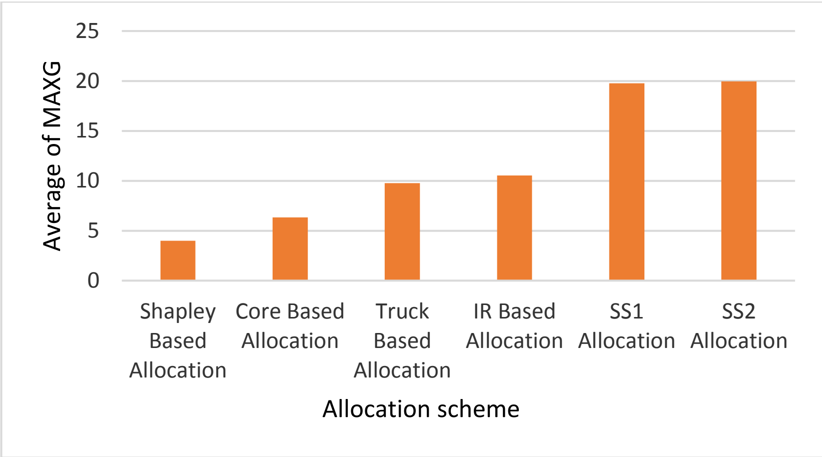

Figure 6.7. Average of *MAXG* over all scenarios having no core

Similarly, considering all of the 202 scenarios the average values of *MING* amounts are calculated for each allocation scheme. The results are presented in Figure 6.8. In contrast with the general trend, SS2 allocation scheme performs the best in terms of *MING*.

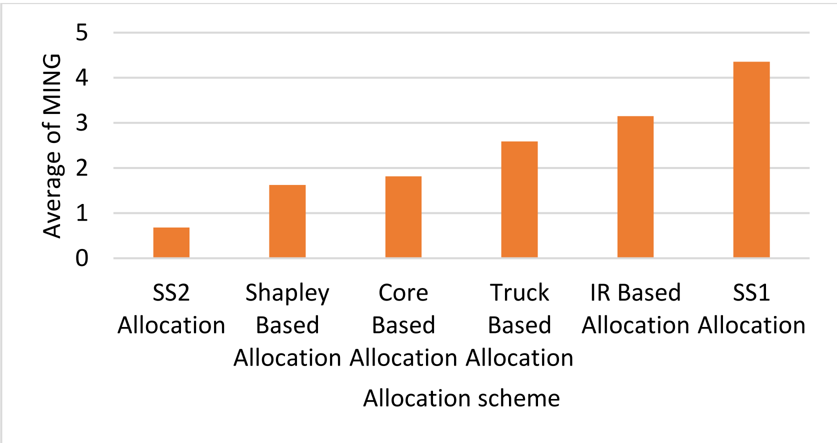

Figure 6.8. Average of *MING* over all scenarios having no core

In Figure 6.9. the average of AG amounts is presented for each allocation scheme. Truck based and IR allocation scheme allocations result in similar amounts of *AG*.

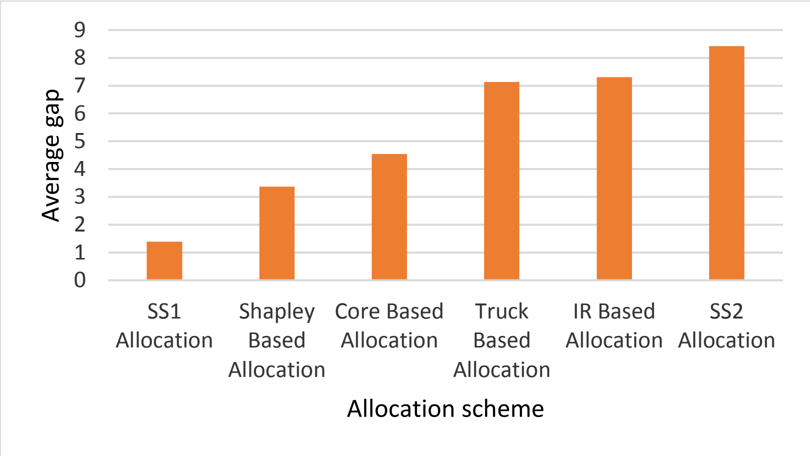

Figure 6.9. Average of AG over all scenarios having no core

6.1.3 Core Performance Analysis for the Emission Game

For the numerical analysis of the emission model, under the profit game having the objective of maximization of the coalition profit we use the parameter setting in Table 7.3. The *EF* value is adopted from the values announced for different transportation means by Environmental Protection Agency (2017). Note that, in the original text, the value is 161.8 grams of CO_2 per ton-mile, and in our study, conversion of this value to 110.8 grams of CO_2 per ton-km is made for calculation purposes. For adopting the unit weight of the loads, we analyze the study of Satır et al. (2018), which is based on the real life data of two different logistics companies from Turkey. 1.125 tons is the average weight of the shipments made by one of the companies in the study for a one month time period. For the *TD* we determined to use the total travel distance from Ankara to İstanbul which is 454 km.

The analysis is conducted over the 216 instances. The values for the other parameters are the same with the ones created for the profit game presented in Table 6.3.

Table 6.3. *Parameter setting for the emission model*

TD (Km)	**W (Tons)**	**EF (tons of CO_2/tons-km)**
454	1.125 / Truck Capacity	110.8

The results show that, under the emission model, in 83.66% of the instances the core exists for the emission game.

The core performance evaluation of the allocation schemes is made over 154 instances for which the core exists. In Figure 6.10. the performance of the allocation schemes in the emission model is summarized. We note that, compared to the previous emission model in which the emission is considered to be caused from the empty truck and total load, the performance of the Shapley value based allocation scheme and SS2 allocation scheme drops. On the other hand, the core performance of the truck based allocation scheme seems to be stable presenting an increase of 0.22%.

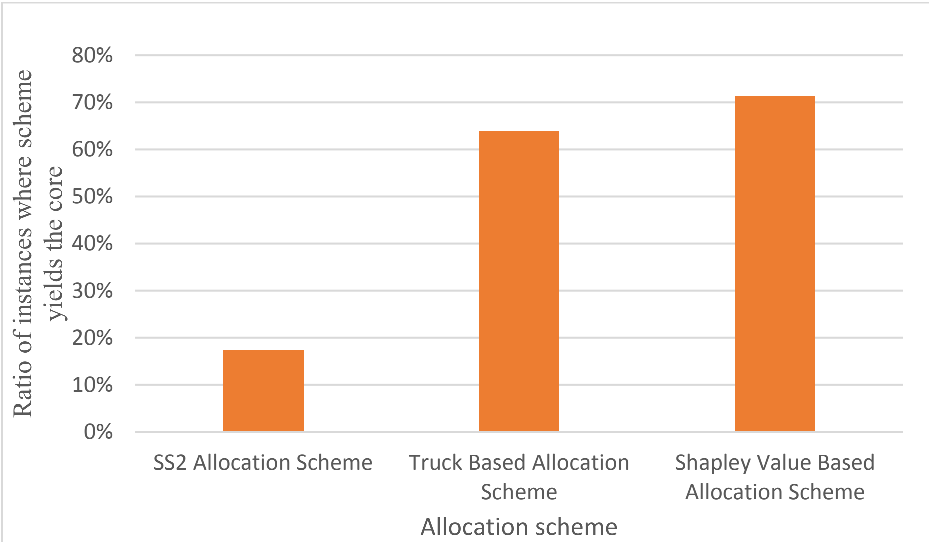

Figure 6.10. Core performance of the allocation schemes for the emission model

In Figure 6.11, the core availability for changing values of fixed dispatch cost, *A* is presented. Increasing value of fixed dispatch cost has worsening effect on the core availability for the emission model as well. Remember that, our discussion for the reasoning of this worsening effect involving the fact that, under the high dispatch cost values the uncapacitated characteristics of the game is lost, and under capacitated settings the core availability falls.

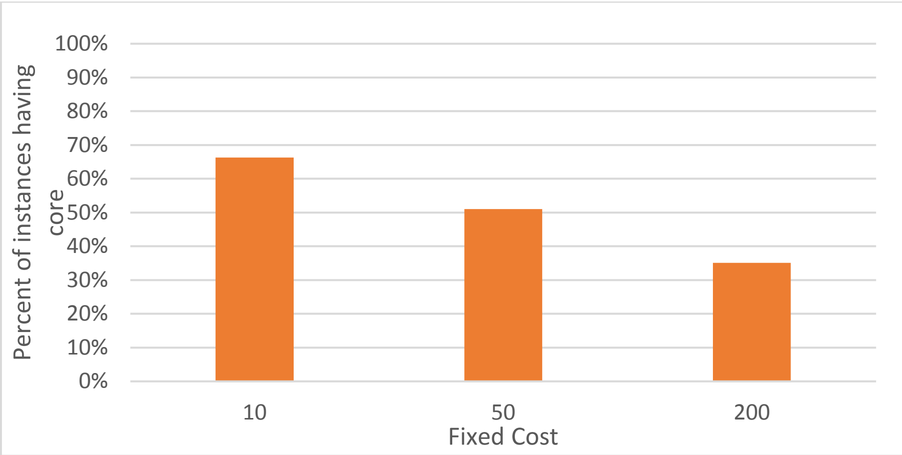

Figure 6.11. Core availability for changing values of A under emission model

6.1.4 Numerical Analysis for the Game with Carbon Tax

For the the game with carbon tax, we conduct the numerical analysis under 3 different values of P, the carbon tax. First one is adopted from the study of Plumer and Popovich (2019). To see the effect of carbon prices under carbon tax policy on the core performance, we perform numerical studies with increasing levels of P values. The values are 30, 100 and 300 (\$/tons of CO_2 emitted). For all of P values, 216 instances are studied.

Considering the results related to 216 instances for $P=30$, in 16 of them no profit can be achieved. Remember that, in the when there is no carbon tax consideration case (case where $P=0$) the number was 14. For the game with carbon tax, we calculate the percent of instances having core as follows:

$$\text{Percent of instances having core} = \frac{\text{Total number of instances having core}}{\text{Total number of instances in which profit can be achieved}} x100\%$$

In the game with carbon tax, percent of instances having core for the profit game is 66%, while the percent of instances having core for the emission game is 76.5% . For the scenarios run without carbon tax consideration, the core availability was 65.4% and 77% respectively for the profit and emission games. This core availability seems not to be affected by the change of the objective function for both of the profit and emission games.

In the model with carbon tax policy, compared to the one without carbon tax policy, the performance of truck based allocation scheme and Shapley based allocation scheme drops by around 7% on average. On the other hand, the SS2 allocation scheme presents 1% improvement, however it still has the worst performance.

Figure 6.12. and Figure 6.13. show the percentage of instances having core for the profit game and emission game, and ratio of instances where scheme yields the core under different P values. These figures suggest that the P value does not have a significant effect on core availability in the games and core performance of the allocation schemes. This is a result of the fact that the part of the objective function involving P changes for all of the possible coalitions. As a result, the maximum profit per unit time each possible coalition can achieve decreases, so that the right hand side values of all of the equations defining the core decrease. This fact reduces the effect of P on the core.

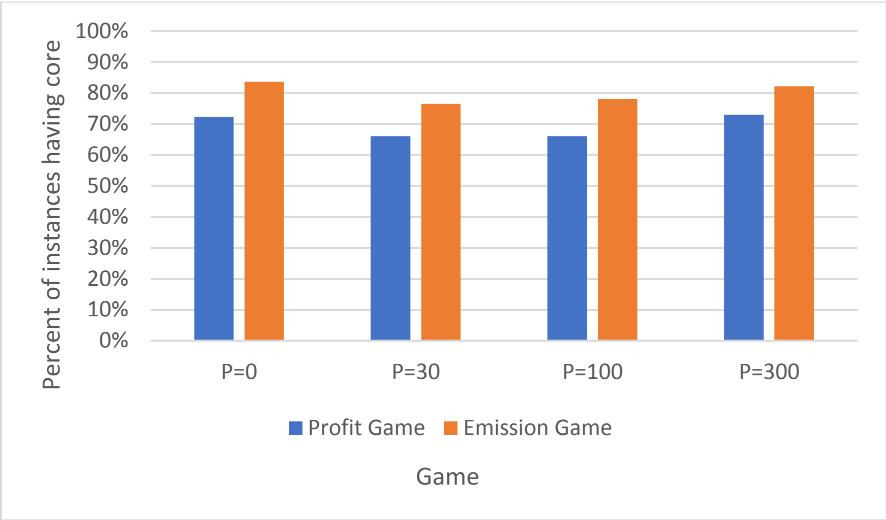

Figure 6.12. Percentage of instances having core for the profit and emission games in the game with carbon tax under different *P* values

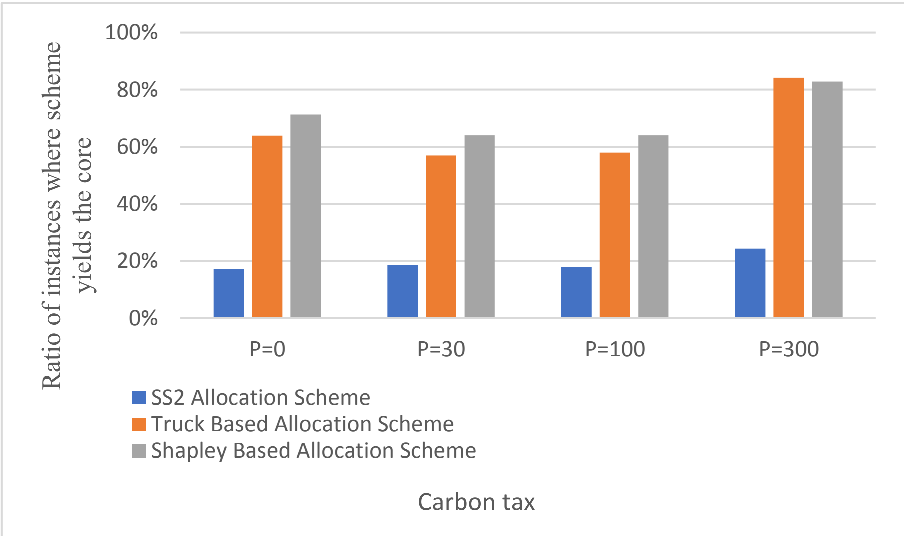

Figure 6.13. Ratio of instances where scheme yields the core in the game with carbon tax under different *P*

CHAPTER 7

CONCLUSION

Collaboration in logistics aims to achieve increased operational and economical efficiencies. It also has the potential for providing environmental benefits by reducing CO_2 emissions. As a result of increasing environmental concerns, and the political enforcements resulting from these concerns, collaboration has become one of the important research topics. Many studies conducted so far, discuss the economical and environmental advantages of collaboration in different problem settings. Some studies also discuss the ways for encouraging the different players in a market for collaboration.

In our study, we consider a market with uncertain shipment requests coming from a number of shippers. These shippers are willing to collaborate for their shipment activities. This collaboration involves the use of a shared truck for the delivery of the shipment requests from the same origin to the same destination. In the scope of the collaboration, the shippers form a coalition. The accept, and reject decisions related with an arriving shipment request and the dispatch decisions for the truck are made by the members of the coalition together. The goal of the coalition is to maximize the total profit per unit time when making these decisions. The profit and emissions resulting from the optimal policy of the coalition are then allocated to the shippers. Since the stability and the fairness of these allocations are critical for the members of the coalition, we defined different allocation schemes and compered them under different performance measures.

For the profit and emission allocation discussion we defined profit and emission games. For both of the games, we have discussed some properties one of which is availability of the core which is an important criterion for the allocations. In the availability of the core the performance of a defined allocation scheme is measured according to the core allocations it makes. For the instances where the core does not exist, we introduced a number of other performance criteria to measure the performance of the allocation schemes.

In numerical analysis of our study, we defined a number of different scenarios by changing parameter values. These values are set to cover many different cases so that, we have had the chance to observe the change in core availability and performance of the allocation schemes under a broad scale of various situations. The numerical analysis results have shown that, for both of the profit and emission games parameter setting has an effect on the core availability. We have also observed that it is possible to make core allocations using the allocation schemes discussed in this study. The numerical results show that, the core performance of different allocation schemes may differ significantly when compared to each other. On the other hand, the performance ranking of the allocation schemes under different parameter setting barely changes. However, the results also show that, when the core is not available, the performance ranking of the allocation schemes may change compared to the instances having core, i.e. an allocation scheme which performs well in the availability of the core, may not be well performing when core does not exist.

In this work, we have shown that in the availability of the core the allocation schemes discussed can make core allocations. We have provided performance measures for comparing these allocation schemes and shown that it may be preferable to use different allocation schemes under different parameter setting.

Our analysis in this study covered 3 players for all the instances. For the future work considerations, this setting may be extended to cover more players. We observed the effect of carbon tax policy on core availability and performance of the allocation schemes while its effects on profit and emission amounts are not analyzed within this study. This discussion can also be a topic for a future work.

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