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A game theoretical framework for allocating cost and gas emission responsibilities in a collaborative setting*

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Abstract

Global warming poses significant risks to our planet and has a tremendous impact on our daily lives. Unless severe precautions are taken, these adverse effects are most likely to increase drastically and threaten other aspects of our lives and the environment. We consider a shippers' network in a full-truckload transportation setting. We develop a framework to allocate the resulting cost of this network to the shippers' while determining the gas emission responsibilities. We conduct a computational analysis to test the effectiveness and the time efficiency of this mechanism in comparison with the proportional-based allocation method and the Shapley Value allocation method.

Key words: Collaborative logistics, CO2 emissions, cost/CO2 allocation, lane covering problem.

JEL codes: C44, C61, C71, L91, Q53

1. Introduction and literature review

Global warming poses significant risks to our planet and has a tremendous impact on our daily lives. We have already started experiencing these adverse effects and unfortunately, the primary reason for global warming is human activity. Global greenhouse gas (GHG) emissions caused by the activities in (i) electricity and heat production (25%), (ii) agriculture and related activities (24%), (iii) industry (21%),

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(iv) transportation (14%), (v) buildings (6%) and (vi) other (10%) (Based on 2010 data). Carbon dioxide (CO2) accounts for 65% of the global greenhouse gas emissions and burning fossil fuel is the primary cause of CO2 emission. Specifically, in the transportation sector, gas emissions are mostly due to fossil fuels burned for transporting passengers and goods. The main energy source in this sector (%95) is petroleum-based fuels (Environmental Protection Agency, 2018). The contribution of transportation to the GHG emissions is not only high but also has a steady upward trend. Due to the increased demand in passenger and freight transportation, GHG emission in transportation is increased by 23% from 1990 to 2010 (European Commission, 2014a).

Unless severe precautions are taken, the adverse effects due to the GHG emissions, hence global warming, are most likely to increase drastically and threaten other aspects of our lives and the environment. As the transportation activities are responsible for a large chunk of the total GHG emissions and unlike other sectors it is possible to reduce the GHG emission in this sector employing better transportation planning and using environmentally friendly fuels, focusing on transportation sector should be one of the priorities of the legislators. This is, in fact, the case as European Commission Directorate-General for Energy and Transport (2009) urges to take immediate action to mitigate the environmental damage caused by transportation. We propose a framework to allocate the resulting cost of a network of shippers while determining the gas emission responsibilities. Stable allocation of gas emission in a shippers' network has a diminishing effect on the overall gas emission in a twofold manner. First, when the allocation is stable, shippers prefer to stay in the collaboration rather than having an individual network which overall decreases the aggregate distance that shippers have to travel and hence the gas emission. Second, a fair division of gas emission in a collaboration diminishes the negative externalities of the gas emission as shippers have to pay for permission to pollute. That is fair division of gas emission attempts to eliminate the free-rider problem that a public good creates.

There are certain initiatives already in effect to reduce the factors contributing to global warming. For instance, the European Union Emission Trading Scheme (European Commission, 2014b) tries to limit the GHG emissions by the direct and indirect actions of the companies. In this setting, the companies are only allowed to exceed their threshold emission limits, imposed by the authorities, if they acquire additional GHG emission permits from the "market". In that aspect, such an initiative provides economic incentives to monitor their individual GHG emissions, and hence reduce overall GHG emissions.

An example to reduce operational inefficiency in the transportation sector is the "shipper collaboration networks". The main reasons to have operational inefficiencies in full-truckload transportation is the geographical imbalances between load requests and the load volume insufficiencies of a single shipper. In order to explain both phenomena, consider a shipper, possibly a manufacturer of a certain good at a given location. Most of the transportation requests of this shipper will be originated at the location of its manufacturing facility and to the location of the markets. Therefore, trucks should be repositioned to the origin of these loads to pick-up and deliver the goods to their destinations. One might argue that there should be incoming trucks to this manufacturing facility that carry raw materials etc. Even though this is the case, as a general rule for manufacturing environments, inbound logistics volume is typically smaller than the outbound logistics volume, sometimes quite significantly. In order to balance this, one might utilize incoming truck capacity to carry other shippers' loads to the manufacturer's location and it is easier to identify such loads in a shipper collaboration network. In addition to this, most of the shippers by themselves do not have enough volume of transportation request in order to achieve synergies that reduce empty truck movements. Most of the time, each shipper typically has a few load requests at a time. On the other hand, in a shipper collaboration network there exist hundreds (even thousands) active load requests at a given time, increasing the possibility of constructing efficient transportation plans. Etasimacilik (https://www.etasimacilik.com/), Webnak (https://webnak.com.tr/), IBM Sterling Transportation Management System (https://www.ibm.com/) and Transplace (https://www.transplace.com/) are some examples of shipper networks providing an electronic platform for shippers to collaborate and procure transportation services in the most efficient way possible.

Even though the motivation for such collaborative networks does not reduce GHG emission, eliminating unnecessary empty truck movements have a direct consequence of reducing GHG emission. Hence, in that aspect, they provide a side benefit of reducing emissions. On the other hand, even though the travel distance/cost of the transportation service providing trucks is correlated with the GHG emission, it is not directly proportional to neither the cost nor the distance. In addition to this, in a collaborative structure even though efficient transportation planning becomes possible, responsibilities of the individual companies are not well-defined as in the non-collaborative setting. For instance, suppose that a truck moves empty from the destination of a shipment request to the origin of another shipment request in order to reduce empty truck movements and increase utilization as in the alternative, two trucks should handle each shipment request and both should return back to the origin empty. Even though the collaborative planning is much more efficient in terms of costs and also in terms of GHG emissions, it is not clear who is responsible for the empty truck movement cost and the GHG emission associated with that move. Obviously, both the cost and emission responsibilities should be shared among the shippers, it is not clear what would that shares be. In addition to that, the cost and the emission responsibilities should be allocated separately as they are not directly proportional. Therefore, allocating cost and emission responsibilities to the companies is a difficult task, yet it is also the key to maintain a sustainable collaboration and to maximize the effect of GHG emission limiting initiatives such as emission cap and trade.

In this study, we develop an effective framework that determines the cost and emission responsibilities of the shippers in a shipper collaboration network. In this context, shippers form a collaboration to minimize the total cost of serving all their transportation requests. These requests correspond to a full-truckload delivery from the origins to the destinations of the loads. The collaboration first identifies the collaborative solution that serves all the request at minimum cost and then allocates the resulting costs and the GHG emissions to the shippers. The GHG emissions are measured in units of grams of CO2 (gCO2). Both the transportation cost and the GHG emission mainly depend on the fuel consumption of the vehicles, but there are other factors affecting both. Transportation costs depend on driver's salaries, truck maintenances, insurance, etc., whereas GHG emission is main affected by the weight of the vehicle next to the distance traveled.

We develop a dual linear programming (LP) based framework in order to allocate costs and emission to the shippers in a shipper collaboration network. We compare our results to a proportion-based allocation method and an approximation method for the generic Shapley Value allocation framework. We conduct a computational analysis to test the effectiveness and the time efficiency of our proposed mechanism in comparison with the benchmark mechanisms and show that our proposed approach yields significantly better results.

Allocation problems are widely studied in the literature in the context of cooperative games. We refer the reader to Young (1985) and to Borm et al. (2001) for a thorough review of cooperative games and allocation mechanisms. Following the relevant studies in the literature, the quality of a given allocation (cost or emission) scheme is measured mainly based on two criteria: (i) budget balancedness, (ii) stability. The former one dictates that there should be no budget deficit or surplus, hence all the costs/emissions are to be allocated among the members of the collaborative network. The latter one provides a restriction on the allocation to ensure the sustainability of the shipper collaboration and states that no group of members should have a better alternative than being members of the collaboration. That is, they cannot have a better situation outside of the collaboration where they have a lower cost/emission value compared to what they are allocated. The allocations that satisfy both conditions are called the "core" Gillies (1959).

When a core allocation does not exist or to complex to identify, a near-core allocation might be sufficient. In such an allocation either the budget balanced or the stability condition is relaxed (preferably minimally) to identify an allocation. In this study, when we fail to identify a core allocation, we only allow stability restriction to be relaxed as in our context the total costs/emission should be entirely allocated to the members. In that aspect, our works follows the studies in the literature such as Faigle et al. (1998), Pal and Tardos (2003), Engevall et al. (2004), and Goemans and Skutella (2004) in which the stability condition is relaxed when a core allocation does not exist or cannot be computed in polynomial time.

Shipper collaboration networks have been studied by Moore et al. (1991), Ergun et al. (2007a) and Ergun et al. (2007b). These papers attempt to identify the system optimal solution, the minimum cost solution, to the shippers' collaborative transportation problem under various restrictions. Özener and Ergun (2008) study the cost allocation problem for such shipper collaboration networks but neither the gas emission resulted from these transportation actions nor allocation of this emission to the shippers is considered in that study.

We propose a duality-based allocation method for allocation costs/emissions and this approach has been introduced in the context of cooperative games by Owen (1975). Following this work, Kalai and Zemel (1982), Samet and Zemel (1984), and Engelbrecht-Wiggans and Granot (1985) are other examples in the literature, try to establish the relationship between the optimal dual solutions of the given underlying optimization problem and the core allocations of the corresponding cooperative game. Unfortunately, these results only hold for a few numbers of games with relatively simple underlying optimization problems.

Even though cost allocation schemes have been widely studied in the literature in a variety of setting, emission allocation has received limited attention from researchers. Sichwardt (2011), Leenders (2012), Naber (2012) and Özener (2014) consider emission allocation to a group of customers receiving deliveries from a common supplier. As the underlying problem is NP-Hard (unlike our setting), the proposed allocation mechanism in these studies has the "scalability problem" which means that they are not applicable for larger instances of the problem.

Our contribution to the literature with this work can be summarized as follows. We propose methods to simultaneously allocate both the transportation costs and the emissions among the shippers in a collaborative network. To the best of our knowledge, gas emission allocation in a shipper collaboration network has not been studied in the literature before. We propose a time-efficient method to the cost/emission allocation problem, which is scalable for real-life sized instances of the problem with even thousands of shipment requests. Finally, as presented in Section4 our proposed mechanism provides significantly better results compared to the benchmark algorithms from the literature.

The remainder of the paper is organized as follows. In Section 2, we provide a formal definition of the problem and list our assumptions and provide a mathematical model for the underlying optimization problem. In Section 3, we present the solution approaches, proportional, duality-based and Shapley Value, respectively. In Section 4, we computationally demonstrate how all the allocation mechanisms perform in comparison with each other. Concluding remarks are provided in Section 5.

2. Problem definition

In this section, we provide a formal definition of the problem, list our assumptions and provide a mathematical model for the underlying optimization problem.

In a shippers collaboration network, there is a group of shippers requesting transportation services, each corresponds to a full-truckload delivery from a corresponding origin to a corresponding destination. The ultimate motivation in constructing such a collaborative network is to reduce the inefficiencies resulted from the empty truck movements and in turn minimize the total cost of serving all the shipment requests of the members of the collaboration. As the empty truck movements are associated with the imbalance of the shipment requests along with the collaborative network, the possibility of finding cost-efficient routes increases as the number of shippers/shipment requests in the collaboration increases. After the minimum cost solution is identified for the shippers' collaboration network, the resulting costs and emissions are to be allocated to the shippers. Note that even though the emissions are to be allocated, the collaboration does not explicitly try to minimize the gas emission resulted from the transportation activities.

The problem is defined on a complete directed Euclidian graph $G = (N, A)$ where N is the set of nodes $\{1, \dots, n\}$ representing the locations (origins/destinations) in the network. A is the set of arcs connecting these locations and $L \subseteq A$ is the set of arc that has been included in the shipment requests of the shippers. The weight of the shipment on arc (i, j) is represented by w_{ij} and the cost of traversing an arc (i, j) with a full-truckload is represented by c_{ij}. If the same arc is traversed by an empty truck, the corresponding cost is represented as a percentage of the original cost and that percentage is represented by θ. Solving the following model yields the minimum cost solution to the shippers' collaboration network's transportation problem:

$$P: \quad z(L) = \min \sum_{(i,j)\in L} c_{ij}\, x_{ij} + \theta \sum_{(i,j)\in A} c_{ij}\, z_{ij} \qquad (1)$$

$$s.t. \sum_{j\in N} x_{ij} - \sum_{j\in N} x_{ji} + \sum_{j\in N} z_{ij} - \sum_{j\in N} z_{ji} = 0 \;\; \forall i \in N \qquad (2)$$

$$x_{ij} \geq 1 \;\; \forall (i,j) \in L \qquad (3)$$

$$z_{ij} \geq 0 \;\; \forall (i,j) \in A \qquad (4)$$

$$x_{ij} \in \{0,1\} \qquad (5)$$

$$z_{ij} \in \mathbb{Z}. \qquad (6)$$

In the model above, x_{ij} represents whether arc $(i,j) \in L$ is covered with a full truckload and z_{ij} represents the number of times arc $(i,j) \in A$ is traversed for an empty repositioning move. Constraints (2) are the classic flow balance constraints of the network. Constraints (3) ensure that the shipment requirements of the shippers are satisfied. Finally, the objective is to minimize the total cost of covering all the shipment requests in the network.

Even though the formulation above corresponds to an integer linear program, as it has a total unimodular matrix, so it can be solved in polynomial time and solving the corresponding linear programming relaxation is guaranteed to yield integral solutions. The optimal objective function value, $z^*(L)$, represents the characteristic function of the collaboration whereas $(z^*(S))$ represents the optimal cost of covering all the shipment requests in $S \subseteq L$.

After identifying the minimum cost solution of the collaboration the next task is to calculate the resulting emission values. In the truck transportation context, there two main approaches; energy-based and activity-based calculation of the emission values. We follow the activity-based approach used in Özener (2014) and employ a detailed piecewise linearization approach based on the following formula and the carbon emission factor values with respect to payload levels of the trucks given in Table 1 (acquired from McKinnon and Piecyk (2011)).

CO2 emissions = Transport volume × Distance × Ave. CO2-emission factor per ton-km

Table 1
Carbon Emission Factors (gCO2/ton-km) for 40-44 Ton Trucks with Varying Payloads and Levels of Empty Running

Payload in tonnes	**% of truck-kms run empty**										
	0%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
10	81	84.7	88.8	93.4	98.5	104.4	111.1	118.8	127.8	138.4	151.1
11	74.8	78.2	81.9	86.1	90.8	96.1	102.1	109.1	117.3	127	138.6
12	69.7	72.8	76.2	80	84.3	89.2	94.7	101.1	108.6	117.5	128.1
13	65.4	68.2	71.4	74.9	78.9	83.4	88.5	94.4	101.3	109.5	119.3
14	61.7	64.4	67.3	70.6	74.2	78.4	83.2	88.7	95.1	102.7	111.8
15	58.6	61	63.8	66.8	70.3	74.2	78.6	83.7	89.7	96.8	105.3
16	55.9	58.2	60.7	63.6	66.8	70.5	74.6	79.5	85.1	91.7	99.7
17	53.5	55.7	58.1	60.8	63.8	67.2	71.2	75.7	81	87.2	94.7
18	51.4	53.5	55.8	58.3	61.2	64.4	68.1	72.4	77.4	83.3	90.4
19	49.6	51.5	53.7	56.1	58.8	61.9	65.4	69.5	74.2	79.8	86.5
20	48	49.8	51.9	54.2	56.8	59.7	63	66.9	71.4	76.7	83
21	46.6	48.3	50.3	52.5	54.9	57.7	60.9	64.5	68.8	73.9	80
22	45.3	47	48.8	50.9	53.3	55.9	59	62.5	66.5	71.4	77.2
23	44.2	45.8	47.6	49.6	51.8	54.3	57.2	60.6	64.5	69.1	74.7
24	43.2	44.7	46.4	48.3	50.5	52.9	55.7	58.9	62.7	67.1	72.4
25	42.3	43.8	45.4	47.3	49.3	51.7	54.3	57.4	61	65.2	70.3
26	41.5	42.9	44.5	46.3	48.3	50.5	53.1	56	59.5	63.6	68.5
27	40.8	42.2	43.7	45.4	47.3	49.5	52	54.8	58.1	62.1	66.8
28	40.2	41.5	43	44.6	46.5	48.6	51	53.7	56.9	60.7	65.3
29	39.7	41	42.4	44	45.7	47.8	50.1	52.7	55.8	59.5	63.9

The rest of the calculations are carried out as done in Özener (2014), which in a nutshell corresponds to the multiplying the average CO2-emission factor per ton-km with respect to the given payload, t, with the distance traveled and the payload volume. This calculation yields, $g_{ij}(t)$, the gas emission value of traversing with a payload of t from node i to node j. Note that the truck is assumed to be 14-15 tons and the payload values vary between 0 and 30 excluding the truck's weight. Given the minimum cost solution to the collaboration, the corresponding gas emission value is denoted by $e^*(L)$ and similarly for the subset of the collaboration, $S \subseteq L$ the same value is denoted by $e^*(S)$.

3. Cost/emission allocation methods

In this section, we describe our proposed allocation methods, proportional, duality-based and Shapley Value, both for cost and emission allocation among the shippers. Our objective is to identify a core allocation if possible, or a close approximation to the core if not. As the budget balancedness of an allocation is kept as an invariant in this study, a close approximation refers to minimum deviation allocation with respect to the stability condition. Therefore, we calculate the percent deviation from stability over all the subsets of the shippers and based on that criterion determine the closeness to the core allocation.

1.1. Proportional allocation method

The proportional allocation method allocates the costs and the emissions proportional to the distance that has to be covered with a full-truckload from the origin to the destination of a shipment request. As both the costs and the emission value along this direct route depend on the distance, this method is likely to allocate the costs and emissions resulted by the full-truckload movement of the trucks satisfactorily to the shippers. However, the cost and emission responsibilities along the empty repositioning moves are not clear as these do not happen directly as a result of a particular shipment request. The procedure is simple to understand and implement. Additionally, it is perfectly scalable meaning that this method is applicable even when we have thousands of shipment requests in a given collaboration and will yield results in a matter of seconds. We compute $\alpha(i,j)$, the cost allocated, and $\beta(i,j)$, the emission allocated to the shipment request along arc (i,j), as follows:

Procedure: Proportional Allocation Method
For $(i,j) \in L$

Compute $\alpha(i,j) = \frac{c_{ij}}{\sum_{(k,m)\in L} c_{km}} z^*(L)$

Compute $\beta(i,j) = \frac{g_{ij}(t_{ij})}{\sum_{(k,m)\in L} g_{km}(t_{km})} e^*(L)$

End For

Note that t_{ij} represents the payload of the truck along the lane (i,j), which is equal to the weight of the shipment requests, w_{ij} plus the weight of the truck, t_0.

1.2. Duality-based allocation method

Next, we describe the duality-based costs and emissions allocation mechanism. We construct two different dual linear programs, one based on costs and the other based on emission values and allocate costs and emissions based on these the dual LPs respectively. As shown in Özener and Ergun (2008), the duality-based allocation method is proven to yield core allocations for the cost allocation. However, the same cannot be stated for the emission allocation due to a very fundamental difference between these two allocations. As the objective of the collaboration is to minimize the system-wide costs, the duality framework proposed by Owen (1975) perfectly suited to allocate the costs for this particular setting as well. Unfortunately, the same does not hold for the emission allocation as in this case the dual LP has a completely different objective function value compared to the objective of the collaboration. Nevertheless, as shown by this study, it is still a valid method to allocate emission as it assesses the intrinsic relationships between the member of the collaboration and their alternative options better than any other allocation method.

Following the notation in Özener and Ergun (2008), let I_{ij} be the dual variables associated with constraints (3) and y_i be the dual variables associated with constraints (2). The dual LP for the cost allocation problem is given as follows:

$$D: \quad d(L) = \max \sum_{(i,j)\in L} I_{ij} \qquad (7)$$

$$s.t.\ I_{ij} + y_i - y_j = c_{ij} \quad \forall (i,j) \in L \qquad (8)$$

$$y_i - y_j \leq \theta c_{ij} \quad \forall (i,j) \in A \qquad (9)$$

$$I_{ij} \geq 0 \quad \forall (i,j) \in L. \qquad (10)$$

The dual LP for the emission allocation problem is similar to the model above. However, in order to construct that dual LP, we need to first construct the primal problem with the objective function of minimizing the emission values rather than the costs. The updated model below is the primal LP with the objective of minimizing the total emission:

$$PE: \quad f(L) = \min \sum_{(i,j)\in L} g_{ij}\left(t_{ij}\right)x_{ij} + \sum_{(i,j)\in A} g_{ij}\left(t_0\right)z_{ij} \quad (11)$$

$$s.t. \sum_{j\in N} x_{ij} - \sum_{j\in N} x_{ji} + \sum_{j\in N} z_{ij} - \sum_{j\in N} z_{ji} = 0 \ \ \forall i \in N \quad (12)$$

$$x_{ij} \geq 1 \ \ \forall (i,j) \in L \quad (13)$$

$$z_{ij} \geq 0 \ \ \forall (i,j) \in A \quad (14)$$

$$x_{ij} \in \{0,1\} \quad (15)$$

$$z_{ij} \in \mathbb{Z}. \quad (16)$$

Note that t_0 in the formulation above represents the empty weight of the truck. Also, the optimal objective function value of the problem above $f^*(L)$ is not equal to $e^*(L)$, which is the actual total emission value to be allocated among the shippers. Therefore, this allocation method may not yield core allocations, unlike the cost allocation case. Now similar to above, let H_{ij} be the dual variables associated with constraints (13) and u_i be the dual variables associated with constraints (12). The dual LP for the emission allocation problem is given as follows:

$$DE: \quad b(L) = \max \sum_{(i,j)\in L} H_{ij} \quad (17)$$

$$s.t. \ H_{ij} + u_i - u_j = g_{ij}\left(t_{ij}\right) \ \ \forall (i,j) \in L \quad (18)$$

$$u_i - u_j \leq \theta g_{ij}(t_0) \ \ \forall (i,j) \in A \quad (19)$$

$$H_{ij} \geq 0 \ \ \forall (i,j) \in L. \quad (20)$$

Both dual LPs can be solved in polynomial time to yield optimal values of the dual variables for corresponding allocation purposes. Next, we allocate the total cost and total emission values proportional to the corresponding dual variables. The details of the procedure are as follows:

Procedure: Duality-Based Allocation
Solve D to obtain $I_{ij}^* \ \forall (i,j) \in L$
Solve DE to obtain $H_{ij}^* \ \forall (i,j) \in L$
For $(i,j) \in L$
Compute $\alpha(i,j) = \frac{I_{ij}^*}{\sum_{(k,m)\in L} I_{km}^*} z^*(L)$

Compute $\beta(i,j) = \frac{H_{ij}^*}{\sum_{(k,m)\in L} H_{km}^*} e^*(L)$

End For

It is important to note that there might exist several alternative optimal solutions for either of the dual problem. Even though this does not pose a problem for cost allocation purposes as every single one of these alternative optimal solutions corresponds to a core allocation for cost allocation, this might affect the performance of the emission allocation mechanism. On the other hand, in a very vague sense the most balanced solution to the dual linear program is obtained by solving the corresponding LP with the barrier method rather than primal/dual simplex method (this a vague statement in the sense that even the term "balanced solution" is not a well-defined one, however, since the barrier method is an interior point algorithm, it yields a solution with less tendency to biased towards a basic feasible solution). Based on the computational analysis, we observe that this is, in fact, the case for emission allocation purposes.

4. Shapley value

The Shapley Value, proposed by Shapley (1953), is a generic allocation method based on the marginal contribution of the members to the overall collaborative structure. It means that the contribution of a given member to the collaboration is calculated in a step-by-step manner considering all possible subsets of the collaboration and the final allocations will be based on the weight contributions calculated for each member of the collaboration. In that sense, Shapley Value might be perceived as an allocation method that accurately computes the relative responsibilities of the members in a cost allocation situation. On the other hand, the Shapley Value does guarantee to yield core allocations, as the stability condition may not be satisfied even though the budget balancedness restriction is always achieved by construction.

The generic method for calculating the Shapley Value is as follows:

$$\alpha(i,j) = \sum_{S\subseteq N\setminus(i,j)} \frac{|\, S \,|\,!\;|\, N\setminus(S \cup (i,j)) \,|\,!}{|\, N \,|\,!} m^{(i,j)}(S),$$

$$\beta(i,j) = \sum_{S\subseteq N\setminus(i,j)} \frac{|\, S \,|\,!\;|\, N\setminus(S \cup (i,j)) \,|\,!}{|\, N \,|\,!} l^{(i,j)}(S).$$

where $m^{(i,j)}(S)$ represents the marginal cost of adding (i,j) to the subset S and similarly $l^{(i,j)}(S)$ represents the marginal emission value of adding (i,j) to the subset S.

Even though Shapley Value is a promising allocation method in terms of solution quality and quite simple to implement, it is not a scalable method for larger instances of the shipper collaboration networks. As we need to calculate the marginal contribution of each member to all possible subsets, this task becomes quite difficult as the number of subsets becomes really large. For instance, even in a shipper collaboration network with 100 shipment requests, this value corresponds to 2^{100} which is greater than 10^{10} subsets. As such calculations cannot be performed with this magnitude, we propose a modification to the original Shapley Value. Instead of considering every possible subset, we only consider the nearest 10 shipment requests for performing such calculations. Here, the term "nearest" refers to the closest distance between the origin of a given shipment request to the destination of all possible shipment requests as the truck moves empty between a destination of a load to an origin of another load and having such distances as small as possible basically determines the quality of the given collaborative solution. The details of the procedure are as follows:

Procedure: Shapley Value

For $(i,j) \in L$

Let $N_{i,j}$ be the set of the shipment requests including the nearest 10 shipment requests and (i,j)

Compute $\alpha(i,j) = \sum_{S \subseteq N_{i,j} \setminus (i,j)} \frac{|S|!|N_{i,j} \setminus (S \cup (i,j))|!}{|N_{i,j}|!} m^{(i,j)}(S)$

Compute $\beta(i,j) = \sum_{S \subseteq N_{i,j} \setminus (i,j)} \frac{|S|!|N_{i,j} \setminus (S \cup (i,j))|!}{|N_{i,j}|!} l^{(i,j)}(S)$

End For

5. Computational study

We performed a detailed computational analysis to compare the performance of our proposed method with respect to the benchmark algorithms, proportional allocation method, and Shapley Value. We use randomly generated instances on a square map with relatively denser regions representing populated areas as well as less dense regions representing rural areas. The transportation cost between locations is based on the Euclidean distance among them. The emission values are calculated using the formula presented above. Based on the costs and emission values, we first solve the problem to determine the minimum cost collaborative transportation plan that serves all the shipment requests of the shippers in the collaborative network. Next, we apply all the cost and emission allocation methods to determine the respective allocations using each method.

We performed our analysis on ten 25-nodes/250-shipment requests instances and ten 50-nodes/500-shipment requests instances. The trucks' payload capacity is

30 tons and the shipment weights are uniformly generated between 1 ton and 30 tons. The shipment volumes are assumed to be compatible with the truck capacity with respect to volumes, which means that each of the shipment requests can be handled by a single truck. Technically, this is basically the case in the full-truckload shipping industry.

As mentioned before, the first stage is to identify the best solution for the shipper collaborative network's underlying logistics problem. To this end, we solve the corresponding lane covering problem, which is shown to be solved in polynomial time as the corresponding matrix is total unimodular. Then, we run all the allocation algorithms to obtain cost and emission allocations for each of these instances. Finally, all the algorithms are implemented using C++ and CPLEX Concert Technology and the experiments are performed on a 64-bit Windows Server with two 2.4 Ghz Intel Xeon CPU's and 24 GB RAM.

The real challenge, unfortunately, is about how to evaluate the performance of each allocation mechanism. As mentioned before, the allocations preferably satisfy two criteria: budget balancedness and stability. As the former condition cannot be relaxed, we relax the latter condition in a limited way and rank the performance on the allocation mechanism on how small relaxation they need to yield feasible allocations. In other words, we calculate the percentage deviation from stability and conclude that the best allocation method is the one with the lowest stability value. Even though this might seem straightforward at first, given the fact that we need to check the stability condition for all potential subsets of the collaboration, this task requires an exponential effort. Therefore, we need a quick yet effective method for such an evaluation. Hence, we first use the method proposed in the literature by Özener et al. (2013), which performs a similar function in a different problem setting. The main idea behind this procedure is to test the stability of the allocation methods without having to generate all of the possible subsets of the collaboration. To this end, the algorithm creates subsets in a smart manner due to the assumption that the subsets that have relatively high expected interactions/synergies among them are more threatening to the collaboration compared to an entirely random subset. As the algorithm is proposed for a milk-run based problem environment, the high synergy potential among collaborators is due to the geographical closeness. Hence, the assessment algorithm starts by randomly generating a base point on the map and select elements into the subset based on the probabilities calculated by the relative location of the collaborator to this base point. After the subsets have been created, the percentage deviation from stability value is determined by calculating the difference between the cost of a given subset and the sum of the assigned costs to the members of that subset.

We first modify the procedure above to use it in our context. Even though geographical synergies are still important in our context, it is not as clear as the milk-run type problem since our shipment requests may even need transportation from one end to the exact opposite end of the map. Hence, being close to a point on the map is not a well-defined concept in our full-truckload shipment setting. Nevertheless, we choose the closest of the ends of the shipment requests, which is either the origin or the destination, and assign selection probabilities based on this distance. The details of the procedure are as follows:

Procedure: Stability Assessment I
For $t = 1, \dots, nSubsets$
Pick a random point on the map, p^t
For $(i,j) \in L$
Compute the closest distance between the random point and the origin/destination of the shipment between (i,j), d_{ij}^t
Assign the selection probabilities as follows:

$$sp_{ij} = \begin{cases} 0.9, & d_{ij}^t \leq 100 \\ 0.5, & 100 \leq d_{ij}^t \leq 200 \\ 0.1, & d_{ij}^t > 100 \end{cases}$$

Select shipment requests into the subset S^t based on the sp_{ij}^t values.

End For

End for

In the procedure above "nSubsets" is the parameter representing the number of subsets to be generated by the procedure. We select this value quite high in order to assess the performances of the allocation methods accurately, hence in 25-nodes instances, this value is equal to 25,000 and in 50-nodes instances, it is equal to 50,000. Next, we try to design a better modification of the procedure, a one that is more suitable for the task at hand. The subsets that have the highest synergy potential in our context are again based on the geographical locations however these locations should be inline in such a way that the destination of the former shipment request should be close to the origin of the later shipment requests to be handled by the same truck. With this idea, the amount of empty repositioning of the truck would be minimized if we were to identify all such good subsets. Accordingly, we first define what is "close enough" in our context. To this end, we sort the distance values for each pair of nodes in the network in ascending order and selected value that corresponds to 15 percentile. Note that this percentage is an arbitrary value and based on our preliminary computational study, we find that this is a reasonable value to work with. However, one may try different values to observe the results under different benchmark distance values. Next, we randomly select a shipment request out of all shipment requests. Based on the destination of that shipment request, we randomly select another shipment request as long as the distance from the destination of the former shipment request to the origin of the latter shipment request is below the threshold value. We continue adding shipment requests to the subset until there is no other request remaining to be added to the subset. The details of the procedure are as follows:

Procedure: Stability Assessment II
Calculate the benchmark distance, bmd
For $t = 1, \dots, nSubsets$
    Initialize count for unsuccessful iterations, $nUns^t = 0$
    Pick a random maximum chain length, c^t
    Pick a random shipment request, (i, j), and set as previous shipment request
    For $l = 1, \dots, c^t$
        Pick another random shipment request, (k, m)
        Calculate the distance between the destination of the previous request, j, and the origin of the current request, k, d_{jk}
        If $d_{jk} \leq bmd$
            Add the current request to the subset
        Else
            $nUns^t = nUns^t + 1$
            l = l - 1
        End If
        If $nUns^t > limit$
            break
        End If
    End For
End For

Table 2 summarizes the performance of the cost allocation methods using Stability Assessment I procedure. The first column presents the instance number from one to twenty, the next three columns present the total number of instable subsets of all generated subsets in each allocation method, referred to as “Prop.”, “Dual.”, and “Shap.”, which correspond to the proportional allocation method, the duality-based allocation methods, and the Shapley Value. Similarly, the next three columns present the average percent instability of each cost allocation method. Finally, the last three row presents the maximum percent instability of cost allocation methods. The first 20 rows, on the other hand, present the corresponding values for each of the 20 instances. The row “Ave 25” presents the average values for the 25-nodes instances whereas “Ave 50” presents the average values for the 50-nodes instances. Similarly, “Max 25” and “Max 50” rows present the maximum values for the 25-nodes and 50-nodes instances respectively.

Based on the results of the computational analysis, the duality-based method performs considerably better than the benchmark allocation methods. Even though duality-based method performance, finding the core solution for the cost allocation problem, is known due to the analytical results proved in the literature, we observe that the performance of the proportional allocation method and the Shapley Value is quite worse. For instance, the maximum percentage deviation of the proportional allocation method is equal to 9.66% and 5.37% in 25-nodes and 50-nodes instances respectively. The Shapley Value’s performance is even worse and the maximum percentage deviation is equal to 39.91% and 12.00% in 25-nodes and 50-nodes instances respectively.

Table 3 presents the performance of the emission allocation method assesses using Stability Assessment Procedure I. This time, there is no theoretical result proved in the literature suggesting that the duality-based allocation method yields solutions in the core, the budget balanced and stable. However, we observe that in all of the instances, the duality-based allocation method yields a core allocation as all the instability related values are equal to zero. Note that without performing a full-scale stability check, we may not definitely conclude that it is, in fact, a core allocation. This statement is solely based on the assessment method used which is also the method used for testing performance of the benchmark allocations. The performance of the proportional allocation method and the Shapley Value is again worse. The maximum percentage deviation of the proportional allocation method is equal to 4.56% and 2.59% in 25-nodes and 50-nodes instances respectively. The Shapley Value’s maximum percentage deviation is equal to 22.38% and 7.01% in 25-nodes and 50-nodes instances respectively.

Table 2
The Performance of the Cost Allocation Methods Assessed Using Stability Assessment Procedure I

	# of Instable Subsets			Ave. % Instability			Max. % Instability		
Ins	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**
1	2004	0	2560	1.51	0.00	2.21	5.48	0.00	10.23
2	2941	0	4494	2.42	0.00	3.14	7.87	0.00	12.68
3	1609	0	5501	1.63	0.00	9.00	7.83	0.00	39.91
4	141	0	2049	0.58	0.00	5.89	2.65	0.00	18.68
5	4323	0	4578	2.55	0.00	4.56	9.66	0.00	20.29
6	196	0	1117	0.68	0.00	3.30	2.96	0.00	15.34
7	692	0	1736	1.22	0.00	3.08	5.14	0.00	14.73
8	2654	0	4517	1.65	0.00	4.17	6.38	0.00	13.33
9	1473	0	3677	1.33	0.00	3.31	5.87	0.00	16.10
10	691	0	1389	1.09	0.00	1.94	5.24	0.00	8.93
11	2428	0	4310	1.00	0.00	1.68	3.81	0.00	7.99
12	442	0	2018	0.49	0.00	2.96	2.25	0.00	9.88
13	635	0	8349	0.63	0.00	3.35	2.82	0.00	12.00
14	4013	0	7506	1.30	0.00	2.55	5.37	0.00	10.77
15	3228	0	5570	1.14	0.00	2.07	5.35	0.00	7.76
16	84	0	2586	0.39	0.00	2.30	1.60	0.00	9.97
17	221	0	1236	0.44	0.00	1.16	2.31	0.00	6.49
18	715	0	2101	0.74	0.00	1.60	4.81	0.00	9.15
19	1247	0	3085	0.73	0.00	4.15	3.27	0.00	11.59
20	220	0	2032	0.47	0.00	1.59	2.00	0.00	5.73
Ave 25	1672.40	0	3161.80	1.47	0.00	4.06	5.91	0.00	17.02
Ave 50	1323.30	0	3879.30	0.73	0.00	2.34	3.36	0.00	9.13
Max 25	4323	0	5501	2.55	0.00	9.00	9.66	0.00	39.91
Max 50	4013	0	8349	1.30	0.00	4.15	5.37	0.00	12.00

Table 3
The Performance of the Emission Allocation Methods Assessed Using Stability Assessment Procedure I

	# of Instable Subsets			Ave. % Instability			Max. % Instability		
Ins	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**
1	2010	0	2802	0.73	0.00	1.29	2.57	0.00	5.75
2	2936	0	4980	1.16	0.00	1.76	3.70	0.00	6.80
3	1610	0	5912	0.80	0.00	5.06	3.71	0.00	22.38
4	127	0	2519	0.30	0.00	3.83	1.26	0.00	11.69
5	4321	0	4943	1.22	0.00	2.64	4.56	0.00	10.83
6	195	0	1753	0.32	0.00	2.10	1.36	0.00	10.74
7	706	0	2389	0.60	0.00	2.15	2.50	0.00	8.74
8	2652	0	4928	0.81	0.00	2.43	3.03	0.00	7.60
9	1482	0	4195	0.64	0.00	1.98	2.81	0.00	10.23
10	691	0	1753	0.51	0.00	1.08	2.41	0.00	5.25
11	2428	0	5564	0.48	0.00	1.04	1.81	0.00	5.35
12	454	0	2432	0.23	0.00	1.87	1.08	0.00	5.86
13	632	0	10061	0.30	0.00	2.16	1.34	0.00	7.01
14	3984	0	8577	0.63	0.00	1.51	2.59	0.00	5.76
15	3269	0	6171	0.56	0.00	1.16	2.54	0.00	4.82
16	77	0	3654	0.19	0.00	1.49	0.75	0.00	5.82
17	223	0	2178	0.21	0.00	0.73	1.11	0.00	3.88
18	713	0	2750	0.36	0.00	0.94	2.27	0.00	4.95
19	1257	0	3799	0.34	0.00	2.35	1.53	0.00	6.61
20	230	0	2493	0.22	0.00	0.84	0.92	0.00	3.43
Ave 25	1673.00	0	3617.40	0.71	0.00	2.43	2.79	0.00	10.00
Ave 50	1326.70	0	4767.90	0.35	0.00	1.41	1.59	0.00	5.35
Max 25	4321	0	5912	1.22	0.00	5.06	4.56	0.00	22.38
Max 50	3984	0	10061	0.63	0.00	2.35	2.59	0.00	7.01

Table 4
The Performance of the Cost Allocation Methods Assessed Using Stability Assessment Procedure II

	# of Instable Subsets			**Ave. % Instability**			**Max. % Instability**		
Ins	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**
1	2417	1	2848	1.43	0.00	1.79	8.11	0.00	14.05
2	3059	2	3364	1.83	0.00	2.09	10.52	0.00	16.42
3	2165	12	5825	1.70	0.00	4.57	10.22	0.00	53.50
4	106	0	497	0.70	0.00	1.50	2.19	0.00	24.11
5	5883	13	6099	2.70	0.00	3.21	11.40	0.00	27.22
6	71	2	357	0.66	0.00	1.38	5.23	0.00	17.79
7	505	11	684	1.07	0.00	1.32	8.03	0.00	12.12
8	2344	6	3155	1.53	0.00	2.17	9.00	0.00	19.45
9	1429	6	2815	1.21	0.00	2.05	5.65	0.00	13.26
10	686	0	847	0.93	0.00	1.21	4.94	0.00	8.83
11	2494	0	3080	0.91	0.00	1.06	6.03	0.00	20.74
12	201	4	685	0.39	0.00	0.67	2.06	0.00	7.75
13	618	0	1631	0.57	0.00	0.94	5.57	0.00	19.47
14	4352	0	5103	1.11	0.00	1.41	8.31	0.00	20.36
15	3846	0	4839	1.02	0.00	1.30	7.03	0.00	15.38
16	109	0	331	0.46	0.00	0.67	1.78	0.00	3.49
17	370	0	660	0.48	0.00	0.60	5.63	0.00	3.01
18	1251	4	1046	0.80	0.00	0.74	5.85	0.00	14.21
19	1030	0	2213	0.57	0.00	0.97	5.25	0.00	18.31
20	484	0	1155	0.50	0.00	0.77	2.59	0.00	13.33
Ave 25	1866.50	5.30	2649.10	1.38	0.00	2.13	7.53	0.00	20.68
Ave 50	1475.50	0.80	2074.30	0.68	0.00	0.91	5.01	0.00	13.61
Max 25	5883	13	6099	2.70	0.00	4.57	11.40	0.00	53.50
Max 50	4352	4	5103	1.11	0.00	1.41	8.31	0.00	20.74

Table 5
The Performance of the Emission Allocation Methods Assessed Using Stability Assessment Procedure II

	# of Instable Subsets			**Ave. % Instability**			**Max. % Instability**		
Ins	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**	**Prob.**	**Dual.**	**Shap.**
1	2403	8	3151	0.69	0.00	1.00	3.78	0.00	11.07
2	3076	3	3467	0.89	0.00	1.08	4.89	0.00	8.71
3	2168	15	6190	0.83	0.00	2.57	4.82	0.00	29.07
4	107	10	833	0.34	0.00	0.93	1.06	0.00	17.19
5	5910	1	6261	1.30	0.00	1.71	5.27	0.00	16.82
6	69	12	545	0.32	0.00	0.85	2.42	0.00	20.90
7	505	11	898	0.52	0.00	0.84	3.80	0.00	17.51
8	2347	7	3469	0.75	0.00	1.20	4.26	0.00	12.09
9	1437	0	3287	0.59	0.00	1.23	2.75	0.00	13.24
10	697	1	1026	0.44	0.00	0.68	2.30	0.00	6.68
11	2512	0	3486	0.44	0.00	0.60	2.84	0.00	10.88
12	196	0	1060	0.20	0.00	0.43	1.00	0.00	5.79
13	626	4	2199	0.28	0.00	0.56	2.62	0.00	11.31
14	4368	4	5602	0.54	0.00	0.77	3.91	0.00	10.73
15	3843	3	5324	0.50	0.00	0.72	3.30	0.00	10.70
16	113	0	552	0.22	0.00	0.42	0.82	0.00	11.10
17	364	0	853	0.24	0.00	0.33	2.63	0.00	1.97
18	1247	3	1145	0.38	0.00	0.39	2.82	0.00	4.93
19	1039	3	2836	0.27	0.00	0.58	2.43	0.00	17.86
20	484	0	1544	0.24	0.00	0.43	1.25	0.00	10.05
Ave 25	1871.90	6.80	2912.70	0.67	0.00	1.21	3.54	0.00	15.33
Ave 50	1479.20	1.70	2460.10	0.33	0.00	0.52	2.36	0.00	9.53
Max 25	5910	15	6261	1.30	0.00	2.57	5.27	0.00	29.07
Max 50	4368	4	5602	0.54	0.00	0.77	3.91	0.00	17.86

Next, we present the performance analysis results under Stability Assessment Procedure II. As mentioned before, this procedure generates subsets with higher synergy potential therefore we expect to see the performance of all allocation algorithms to deteriorate to some extent with the exception of cost allocation with the duality-based method. Table 4 and Table 5 summarizes the performances of the cost and emission allocation method assessed using Stability Assessment Procedure II. As mentioned before, the performances of the benchmark allocation algorithms are worse as this is a better assessment of the stability condition using sampling bases subset generation. In cost allocation (Table 4), the maximum percentage deviation of the proportional allocation method is equal to 11.40% and 8.31% in 25-nodes and 50-nodes instances respectively. The Shapley Value's maximum percentage deviation is equal to 53.50% and 20.74% in 25-nodes and 50-nodes instances respectively. In emission allocation, the maximum percentage deviation of the proportional allocation method is equal to 5.27% and 3.91% in 25-nodes and 50-nodes instances respectively. The Shapley Value's the maximum percentage deviation is equal to 29.07% and 17.86% in 25-nodes and 50-nodes instances respectively. One interesting result here is that even though the average and maximum deviation from stability values of the duality-based allocation is equal to zero for all instances in both cost and emission allocation, the number of instable subset values is not equal to zero in some cases. The explanation for this is that the allocation values are rounded using computational methods, hence there might be small inconsistencies due to these numerical procedures. Therefore, even though it might show a few instable subsets in the results, there is actually none while using duality-based procedure.

In terms of computational times of the allocation methods; the proportional and the duality-based allocations are computed instantly whereas the Shapley Value take around on average 15-30 minutes in 25-nodes instances and 4-5 hours in 50-nodes instances.

6. Concluding remarks

In this paper, we propose an effective and time-efficient mechanism for the cost and emission allocation arising in a shipper collaborative network. As transportation activities are listed as one of the major contributors to global warming, determining the gas emission responsibilities have a key to reduce overall gas emission and the adverse effects of global warming.

We develop a duality-based cost and emission allocation method to achieve a sustainable shipper collaboration network. Based on the computational analysis, we show that our proposed method outperforms the benchmark allocations methods, the proportional allocation method, and the Shapley Value.

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Özet

İşbirlikli bir ortamda maliyet ve gaz emisyon sorumluluklarının tahsis edilmesi için oyun teorik yaklaşım

Küresel ısınma, gezegenimize ciddi riskler oluşturmakta ve günlük hayatımızı etkilemektedir. Ciddi önlemler alınmadıkça, bu olumsuz etkilerin büyük ölçüde artması ve hayatımızın ve çevrenin diğer yönlerini tehdit etmesi muhtemeldir. Bu çalışmada bir yükleyicinin şebekesini tam kamyon yükü taşıma ortamında dikkate alıyoruz. Gaz salınım sorumluluklarını belirlerken bu ağın ortaya çıkan maliyetini göndericilere tahsis etmek için bir mekanizma geliştiriyoruz. Bu mekanizmanın etkinliğini ve zaman verimliliğini orantılı temelli tahsis metodu ve Shapley Değer tahsisi yöntemine göre test etmek için bir hesaplama analizi yürütüyoruz.

Anahtar kelimeler: İşbirlikçi lojistik, CO2 emisyonları, maliyet/CO2 tahsisi, şerit örtme problemi.

JEL kodları: C44, C61, C71, L91, Q53