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Determining collaborative profits in coalitions formed by two partners with varying characteristics

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Abstract

Horizontal logistic collaboration offers a great opportunity for companies to reduce their distribution costs. By forming a coalition and carrying out a joint operational plan, companies are able to achieve a larger profit. The extent of this profit is, however, highly dependent on the partners that form the coalition and the characteristics of their operations. Different companies might have different requirements and could enforce different restrictions on the joint operational plan. In this paper, we discuss a simulation study carried out to analyse the effects of different partner characteristics on the coalition's performance. We evaluate coalitions formed by partners with different characteristics, and analyse how these complement each other. In this way, we are able to identify opportunities for very profitable collaborations that are missed by other studies.

Article classification: Research paper

Keywords: Horizontal collaboration, Cost allocation method, Simulation study, Periodic vehicle routing problem

1 Introduction

The freight transportation sector accounts for a major percentage of the global economy. According to the Organization for Economic Co-operation and Development (OECD, 2006), the transportation of goods and services contributed 1156 billion dollars to the US economy during 2003 (around 11% of that year's GDP). Transportation was ranked the fourth most demanded sector in the US economy (after housing, healthcare and food). During that year only, the EU and the US combined transported around 7707 billion tonne-kilometres. Such a vast economic activity has had a strong environmental impact. In the EU only, this sector accounts for 30% of the total energy consumption and is responsible for 19% of the total greenhouse gas emissions (Campbell, 2007). Figures like these show the importance of the transportation sector, and motivate the enormous effort invested in improving its efficiency and sustainability.

A large fraction of the freight volume is carried via the road network. In the EU, for example, this mode accounts for around 72% of the total freight transportation (Campbell, 2007). One of the main challenges that companies in this sector face is related to the efficiency of their operational plans. These companies need to decide, on a daily basis, which truck delivers which orders and in which sequence. This optimization problem, known as the *vehicle routing problem* (VRP), was proposed by Dantzig and Ramser (1959) and has been widely studied by the operations research community. The development of advanced optimization methods has allowed companies to improve their operational plans considerably. These methods provide the means for companies to reduce their operating costs and become more profitable, as well as more environmentally

friendly (Demir et al., 2014; Lin et al., 2014)[1]. Despite these important advances, the transportation sector still feels an increasing pressure to improve its operational efficiency while maintaining competitive service levels (Global Commerce Initiative and Capgemini, 2008). According to the official statistics of the EU, for instance, around 27% of the trucks in the road network are empty (de Angelis, 2011). The fact that such a large portion of the road-transportation capacity is underused shows that there is still room for improvement.

A recent trend in supply chain management, called *horizontal collaboration*, sees companies join forces to perform their distribution jointly. This kind of cooperation has received increasing attention not only in road transportation (Cruijssen et al., 2007a; Ergun et al., 2007; Hernández et al., 2011), but also in ship (Cruijssen et al., 2007c; Panayides and Wiedmer, 2011), rail (Kuo and Miller-Hooks, 2012; Kuo et al., 2008) and intermodal transportation (Groothedde et al., 2005; Li et al., 2015). The principle behind this trend is straightforward: companies can achieve higher efficiency levels by forming a *coalition* and carrying out a joint operational plan. One of the main motivations for companies to collaborate is, according to a study of EyeforTransport (2010-2011), that the total distribution cost of a coalition is lower than the sum of the stand-alone costs. The difference between these two costs is referred to as the *coalition gain* or *coalition profit*. Several studies show that the synergy achieved by horizontal collaboration can achieve coalition gains of up to 30% (Frisk et al., 2010; Lozano et al., 2013; Vanovermeire et al., 2014). The extent of these gains is, however, highly dependent on the partners that form the coalition and the characteristics of their operations. Different companies might have substantially different requirements, and could enforce different restrictions on the (joint) operational plan. One partner might, for example, require its orders to be delivered on specific days, whereas another partner could be willing to delay some of its orders for a few days. Such differences between the partners' characteristics have a large impact on the performance of the coalition. For that reason, it is important that companies take them into account when choosing the best partner(s) to collaborate with. What might be an ideal partner for a company, might not be so for another one with different characteristics. The task of choosing the best possible partner(s) therefore gives room to the following questions:

- Which partner characteristics have the largest influence on the coalition's performance?
- Which companies are more suitable to collaborate with each other? Or, in a more specific sense: which combinations of partner characteristics lead to a large coalition profit?

The purpose of this paper is to shed some light on the answers to these questions. We study the effects of different partner characteristics on the coalition's performance. To this end, we frame our study in a scenario where companies carry out an operational plan that involves a time horizon of several days. In this sense, the coalition needs to decide on two different levels: first, it needs to determine which orders are served in which days; and second, it requires to solve a VRP for each day in the time horizon. This extension of the VRP, introduced by Beltrami and Bodin (1974), is known as the *periodic vehicle routing problem* (PVRP). For this scenario, we carried out an extensive computational experiment to simulate the gains achieved by several coalitions (formed by partners with different operational characteristics). We then used the data generated to determine the characteristics that have the highest impact on the coalition's performance, and to identify the most promising coalitions.

The study carried out in this paper somehow extends the computational experiment reported by Cruijssen et al. (2007a). They also analyse the extent to which the coalition's performance depends on different operational characteristics of the partners. Their focus is, however, on a coalitional level: they mainly consider scenarios where all the partners have similar characteristics. Instead, we focus on an individual level: we evaluate scenarios where partners have different characteristics, and analyse how these complement each other. Additionally, we perform a case-by-case study to determine the characteristics that different companies (with different characteristics) should look for in a partner. By considering this thorough approach, we are able to identify opportunities for collaboration that are missed by the more general experiment of Cruijssen et al. (2007a). Such detailed analysis comes, however, with a limitation. In order to restrict the size of our computational experiment, we considered coalitions formed by only two companies. Nevertheless, despite

[1]We refer the reader to the book by Toth and Vigo (2014) for a more thorough explanation of the VRP and an extensive review of the most recent optimization methods.

this restricted scope, the results obtained provide useful insights for companies to better choose the partner to collaborate with.

The structure of this paper is as follows. Section 2 presents an overview of the research that has been done to evaluate or determine the benefits of horizontal logistics collaboration. Additionally, this section also reviews a wide range of real cases that serve as motivation for the present study. Section 3 explains the set-up of the computational experiment carried out. Based on the results of this experiment, Section 4 describes a statistical analysis carried out to identify the characteristics that have the strongest influence on the coalition's performance. It turns out that, by considering the interaction effects (i.e., modelling how the characteristics influence each other), the explanatory power of the analysis increases considerably. Section 5 extends the previous analysis by discussing a case-by-case study of the results: for different potential companies, it determines the characteristics of the most promising partners to collaborate with. Finally, Section 6 provides the concluding remarks of the study.

2 Creating collaborative gains

Most of the literature related to horizontal collaboration focusses on discussing its main benefits. Despite the fact that this practice offers other advantages (like improving the service levels and leading to a more environmentally-friendly supply chain), the coalition gain has received most of the attention. A large percentage of the literature discusses several case studies of collaborations that have achieved substantial gains for their partners. See, for example, the papers by Bahrami (2002), Wiegmans (2005), Cruijssen et al. (2007b), Frisk et al. (2010) and Defryn et al. (2016). Another portion of the literature focusses on demonstrating the potential collaborative gains by means of simulation studies. Examples include the papers by Hageback and Segerstedt (2004), Cruijssen and Salomon (2004), Palander and Väätäinen (2005), Le Blanc et al. (2006), Ergun et al. (2007), Zhou et al. (2011), Adenso-Díaz et al. (2014a,b) and Vanovermeire and Sörensen (2014).

A more recent line of research investigates the main characteristics that make a logistics collaboration successful. Many authors argue that a common strategic vision and a high operational compatibility are key factors (Naesens et al., 2007; Ryu et al., 2009). Audy et al. (2012) created the first framework for the implementation of logistics collaboration based on the study of a wide range of cases. One of their most important findings is that partners need to have a relationship built on trust. Such relationship is facilitated when companies have similar size, organizational culture and philosophy. The study carried out by Cruijssen et al. (2007a) pays attention to the operational characteristics of the coalition. They perform a simulation study in order to identify the influence of different characteristics on the coalition's performance. Their study is framed in a scenario where companies carry out an operational plan in which orders need to be delivered within strict time windows[2]. In this context, they study the influence of the partner size, the average and the standard deviation of the order sizes, the width of the time windows, the size of the distribution area and the distribution of the market share. The results of this simulation show that partners of similar size are better suited to collaborate. A joint operational plan seems to be most beneficial when the coalition involves several partners of small to medium size. Furthermore, the coalition gain increases when the order sizes are small compared to the capacity of a standard truck, and when time windows are narrow.

There are several case studies that reflect the operational characteristics suggested by Cruijssen et al. (2007a). For example, Mason et al. (2007) argue that consolidation warehouses are on the rise since the introduction of just-in-time practices. Their case study discusses the operation of a factory gain pricing facility, where the flow of products from several suppliers is collected. The relatively small suppliers (with an average order size lower than 18 pallets) do not deliver their products to the facility itself, but are directed through a local consolidation centre. This strategy led to a reduction of around 23–25% in the total travelled distance.

[2]This extension of the VRP is referred to as the vehicle routing problem with time windows (VRPTW). We refer the reader to Chapter 5 in the book by Toth and Vigo (2014) for an extensive review of the most recent optimization methods to solve this problem.

Another case study discussed by Cruijssen et al. (2007c) describes a coalition formed by eight medium-sized Dutch companies that produce sweets and candies. By implementing cross-docking (i.e, unloading their orders in a common centre, bundling them together and loading them into outbound trucks) these companies were able to reduce their transportation costs and increase their service levels. Other case studies with similar characteristics are discussed by Bahrami (2002) and Krajewska et al. (2008).

In addition to the examples previously mentioned, there exist other case studies that show different operational characteristics (from those suggested by Cruijssen et al. (2007a)) but that have also proven to be very successful. The alliance formed by JSP and HF-Czechforge (Carr, 2011; Verstrepen and Jacobs, 2012) is an interesting example. Despite the fact that both companies have large order sizes, they happened to be very compatible. JSP produces light but voluminous plastic beds, whereas HF-Czechforge manufactures heavy but compact metal automotive brake disks. These kinds of products complement well since, when bundled together, it is possible to take full advantage of the truck's capacity (in terms of both space and weight limit). A similar collaboration between Philips Lighting and Hunter Douglas (Jordans, 2011) also benefits from having products with complementary features. Vanovermeire et al. (2014) discuss a case study of two pharmaceutical companies that transport their orders together from Belgium to Romania. One of the companies requires a larger number of pallets to be delivered in considerably larger batches. However, this company is more flexible as it allows some of its orders to be deferred. This coalition led to a double-digit profit gain, a reduction in the greenhouse gas emissions of almost 50% and a significant increase in the service level. Audy et al. (2011) describes a coalition formed by four furniture manufactures in Canada. In this case, some of the partners shared an important restriction on the joint operational plan: they could not allow their products to be delivered by a regional logistic provider. Despite this constraint, the coalition achieved an important reduction in the transportation costs.

The previous examples illustrate how companies with different operational characteristics can form very successful coalitions. The main challenge is to identify which combinations of characteristics are the most favourable; and more importantly, to determine those that are complementary. Providing insights into this topic would help companies to choose the most beneficial partners to collaborate with. For instance, should a company with a large number of orders prefer a partner of similar size? Or, to the contrary, would collaborating with a smaller partner lead to a larger profit gain? As shown in this section, the current literature is not able to provide concrete answers to these kinds of questions. The previous studies only provide insights about the preferred operational characteristics on a *coalitional* level. In other words, they assume that all partners in the coalition have very similar characteristics. Providing answers to these questions necessitates a more complex analysis: one that evaluates partners with different characteristics and investigates how they interact with each other. To our knowledge, this paper is the first attempt to provide such analysis.

3 Computational experiment

In this section, we describe in detail the set-up of the computational experiment carried out. The main purpose of this experiment is to simulate the performance of several coalitions formed by partners with different characteristics. We consider coalitions with only two companies in order to limit the size of the experiment and provide a more illustrative discussion. By analysing the results of the simulation, our first goal is to identify the partner characteristics that have the highest impact on the coalition's performance, and to determine how they influence each other. Our second goal is to identify the characteristics that different companies (with different characteristics) should look for in a partner in order to form the most profitable coalitions.

As mentioned before, we frame our study in a scenario where the joint operational plan involves a time horizon of several days. In this sense, we assume that each order should be delivered on a specific day within that period. Designing such an operational plan therefore involves solving an instance of the periodic

vehicle routing problem (PVRP). We choose a scenario with these properties for two main reasons. First, we believe that a long-term operational plan might be a better representation of the kind of collaboration that is sometimes looked for on a strategic level. We expect this higher degree of cooperation (compared to a single-day operational plan) to have a greater potential for generating large profits. Second, this scenario allows us to include an important characteristic in our study: the flexibility of the partners' operations. By considering this additional aspect, we expect to identify a larger number of well-performing coalitions, and therefore more promising opportunities for collaboration. We refer the reader to the case study discussed by Vanovermeire et al. (2014) in which it is demonstrated that flexibility plays an important role in the coalition's performance.

Each partner in a coalition is described using three characteristics: 1) the number of orders it needs to deliver, 2) the average size of the orders, and 3) the maximum number of days it allows its orders to be deferred. The first two characteristics are indicators of the partner's operational conditions and cannot be influenced directly. The third characteristic is a strategic choice that represents the flexibility of the partner to adapt its operations. For each of these characteristics, we consider different levels: four levels for characteristics 1 and 3, and five levels for characteristic 2. The information about each characteristic, along with the corresponding notation for two partners, A and B, is summarized in Table 1.

Table 1: Levels of the partner's characteristics

Characteristic	Levels	Partner	Notation
Number of orders	5, 15, 25, 35	A	noA
		B	noB
Average order size	3, 6, 9, 12, 15	A	$aosA$
		B	$aosB$
Maximum number of days an order can be delayed	0, 1, 2, 3	A	mdA
		B	mdB

For the experiment, we generated different coalitions considering all possible partner characteristics (in other words, all possible level combinations). This resulted in a total of $(4 \times 5 \times 4)^2 = 6400$ coalitions. For each coalition, we generated three different planning scenarios; this is, we generated three different instances of the PVRP. The experiment therefore required solving a total of $3 \times 6400 = 19200$ instances. In the following section, we provide a more detailed explanation of the PVRP and how the instances were generated.

3.1 The vehicle routing problem and its periodic extension

The vehicle routing problem (VRP) involves the delivery of goods from a central depot to a set of customers. This problem aims at determining the routes for a fleet a of vehicles, such that the demand of every customer is satisfied and the total travelled distance is minimized. A solution to the VRP must satisfy three constraints: 1) every route should start and end at the depot, 2) every customer should be visited exactly once, and 3) the amount of goods delivered by each vehicle must not exceed the vehicle capacity. In the periodic vehicle routing problem (PVRP), the distribution of goods is carried out over a time horizon of several days. For this purpose, each customer has a set of possible days in which it can be served by a vehicle. A solution to the PVRP must therefore satisfy the following additional constraint: 4) each customer should be served in one of the days it is available.

An instance of the PVRP is defined by a set of orders for each partner in the coalition. Each order represents a customer that needs to be served, and is randomly located within an area of 250×250 distance units. The central depot, which serves as starting and ending point of the routes, is located at the origin $(0, 0)$ of the distribution area. The size of each order is defined by the characteristic of the partner it is associated to. The order size is randomly sampled from a discrete triangular distribution centred in the partner's average order size, and of extreme values located at ± 2 units from the center. Each order needs to be delivered on

one day of a time horizon composed of a week (or 7 days). Initially, the set of service days for each order only includes a single day that is randomly selected. However, this set is extended according to the number of days the partner allows its orders to be delayed. When a delay of i days is permitted, the set of service days for each order is extended to include the following i consecutive days. When necessary, the time horizon was extended to a maximum of 10 days in order to account for potential delayed orders. The fleet of vehicles available comprises 20 trucks with a capacity of 20 load units. This implies that a maximum of 200 routes can be used in order to serve all the customers.

The solution of the PVRP involves two important decisions. First, the day in which each order is to be delivered needs to be determined. Second, for each day of the time horizon, the set of routes to be traversed by the fleet of vehicles must be defined. In order to solve the PVRP, we extend the iterated local search (ILS) algorithm proposed by Palhazi Cuervo et al. (2014) for the vehicle routing problem with backhauls (VRPB). The VRPB involves generating an operational plan for a single day only. For that reason, an extension of the original algorithm was necessary in order to handle the planning for a time horizon of several days. This required implementing additional data structures and performing a few other slight modifications. However, the core optimization components of the algorithm remain the same. The computational experiments described in the paper by Palhazi Cuervo et al. (2014) show that the original ILS algorithm is very competitive. The algorithm is able to find the best known solutions for all the benchmark instances solved. We therefore expect the extension of the ILS algorithm to have also a very good performance. In particular, because the VRPB instances used to test the performance of the original algorithm involve larger numbers of customers than those in the PVRP instances (solved by the extension).

The ILS algorithm implements a metaheuristic that iteratively applies a local search (LS) heuristic and that uses a perturbation operator as a diversification mechanism. In each iteration, a small modification (called perturbation) is performed to the best solution found so far. This modified solution is used as a new starting point for the execution of the LS. For more information about the metaheuristic framework implemented by the ILS algorithm, we refer the reader to the paper by Lourenco et al. (2003). The LS heuristic used by the ILS algorithm has two main features. First, it allows the exploration of solutions that do not satisfy the capacity constraint of the problem. Second, it explores a wide neighbourhood structure produced by the application of four different operators: intra-route and inter-route customer relocation, intra-route and inter-route customers exchange, inter-route crossover and intra-route 2-opt. These operators are described in detail by Kinderwater and Savelsbergh (1997). The inter-route operators are calculated not only for routes within the same day, but also for routes in different days. In this way, both decision levels in the PVRP are taken into account during the entire optimization process. This solution strategy increases the complexity of the algorithm and its execution time. Nevertheless, the LS heuristic implements efficient data structures that attenuate the additional overhead. For more information about the algorithm and the set of parameter values that were used for its execution, we refer the reader to the original paper by Palhazi Cuervo et al. (2014).

3.2 Evaluation of the coalition's performance

Given a planning scenario, the performance of a coalition is measured by the profit it generates. This quantity is denoted by P and is is calculated as the sum of the partners' stand-alone costs, $c(A)$ and $c(B)$, minus the cost of the coalition, $c(A, B)$,

$$P(A, B) = c(A) + c(B) - c(A, B). \tag{1}$$

We consider these costs to be represented as the distance driven by the trucks in each operational plan. The coalition profit can be therefore regarded as the reduction in the travelled distance resulting from the joint operational plan. Additionally, we also consider the percentage that this reduction represents of the total stand-alone costs. This measure, denoted by S and called the *synergy value* by Cruijssen et al. (2007a), is

calculated using the expression

$$S(A,B) = \frac{P(A,B)}{c(A)+c(B)} \times 100. \tag{2}$$

During the execution of the experiment, the values of P and S are calculated for each planning scenario in two separate stages. In the first stage, the ILS algorithm is executed in order to plan the orders of each partner separately and calculate the stand-alone costs. In the second stage, the ILS algorithm is executed to plan the orders of both partners jointly and calculate the coalition cost.

In practice, companies evaluate the performance of a coalition from a more individualistic standpoint. They do not collaborate in order to increase the total coalition gain, but to increase their own gain. For this reason, companies would prefer to join a coalition that maximizes their *allocated profit*. There exist several methods in the literature to determine which percentage of the profit is allocated to each partner. We refer the reader to the paper by Guajardo and Rönnqvist (2015a) for a recent review on allocation methods. In the context of our experiment, methods such as the Shapley value and the nucleolus would allocate to each partner half of the total coalition gain (Aumann and Maschler, 1985). For this reason, in the scenario we investigate, a large value of P also implies a large allocated profit for each partner. It is important to mention, however, that this is not necessarily the case for coalitions involving more than two partners or for other allocation methods.

4 Identifying the most influential characteristics

We evaluate the performance of each coalition (in each planning scenario) by means of the two measures, the coalition profit P (see Equation 1) and the synergy value S (see Equation 2). Using this data, our first goal is to identify the partners' characteristics that have the highest impact on the coalition's performance. To this end, we estimate four linear regression models with the purpose of quantifying the relationship between the different characteristics and the performance measures. We first consider two initial models, one for P and one for S, that involve main effects only. We later extend these models by including interaction effects to increase their explanatory power. In order to be able to compare their effects in a straightforward way, we code each partner's characteristic as a categorical factor. As a result, it is necessary to estimate several coefficients for each factor/interaction in the models. It is by analysing these groups of coefficients (corresponding to each term in the models) that we are able to obtain insights into the most influential characteristics on the coalition's performance. The further the coefficient values are from zero, the higher the influence of the corresponding factor/interaction is. Conversely, the closer the coefficient values are to zero, the lower the impact of the term on the performance measure is. Note that this approach allows for a more appropriate and illustrative analysis than simply considering the p-values (of the statistical tests) that determine the significance of each term in the model. These p-values are usually used to identify the influential factors/interactions in a model. However, in the context of our experiment, small p-values do not necessarily reflect statistical significance as the residuals cannot be assumed to be normally distributed with equal variance[3]. Moreover, the p-values on their own cannot be used to compare the impact of each term on the performance measures as even very small differences in performance may be highly statistically significant. In the following sections, we examine the coefficients of the four regression models. We first focus on the main-effects models, and we carry on with the models including the interaction effects. A general discussion of the most important interaction effects follows in Section 4.3 and a more detailed case-by-case study in Section 5.

[3]We believe that the statistical tests to determine the significance of each term/interaction do not allow for an appropriate analysis of the regression models. However, for the sake of completeness, we calculated their results. For each of the four models estimated, all terms/interactions were identified as significant at a 0.01 level.

4.1 Regression models with main effects only

The models with main effects only, for estimating the coalition profit P and the synergy value S, have coefficients of determination (R^2) equal to 0.3716 and 0.5539, respectively. In other words, the models are able to explain 37.16% and 55.39% of the performance measures' variability by taking into account the partners' characteristics individually. Figure 1 shows the values of the coefficients estimated for each factor in both main-effects models. Observe that, in the model estimating P, both the number of orders (factors noA and noB) and the average order size (factors $aosA$ and $aosB$) are influential. Moreover, both set of factors are equally important as the spread of their coefficient values is relatively similar. In contrast, the coefficient values of the other two factors (mdA and mdB) are very close to zero. The maximum number of days orders are allowed to be delayed has therefore a very low influence on the coalition profit. The coefficients in the model for estimating S follow a different trend: factors $aosA$ and $aosB$ are the the only influential ones. In consequence, the difference in the synergy value can be mainly attributed to the average size of the partners' orders. In fact, a regression model including only these two factors has a coefficient of determination equal to 0.5398. This means that the partners' order size can explain around half of the variability of the synergy value. It is interesting to see that the maximum number of days orders are allowed to be delayed has little or no influence on both performance measures. This suggests that the ability of a company to be flexible, evaluated on its own, does not lead to a better coalition's performance.

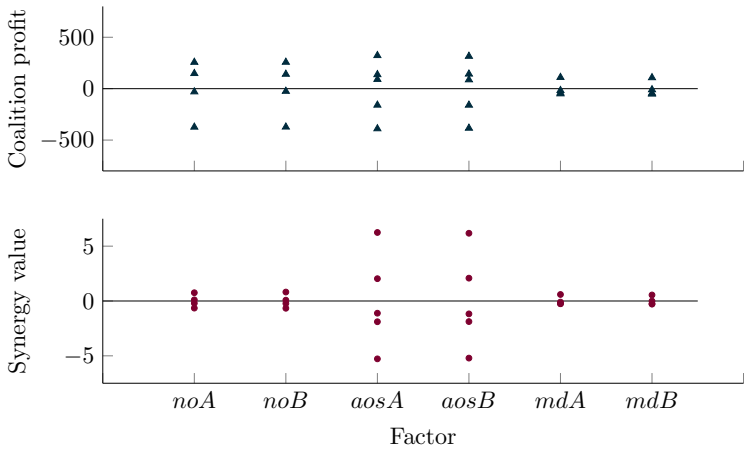

Figure 1: Values of the coefficients in the regression models with main effects.

4.2 Regression models with main effects and interaction effects

The extended models including the interaction effects, for estimating P and S, have coefficients of determination (R^2) equal to 0.7737 and 0.7914, respectively. This means that the models are able to explain an additional 40.21% and 23.75% of the performance measures' variability by including the interactions between the partners' characteristics. Figure 2 shows the values of the coefficients estimated for each interaction in the extended models. The coefficient values of the individual factors are not included since they are equal to those shown in Figure 1. This property follows from the fact that the data used to estimate the models comes from the experiment described in Section 3. Such an experiment was designed as a full factorial experiment (in which all possible factor combinations are evaluated). Therefore, all main effects and all interaction effects can be estimated independently.

Figure 2 shows that the coefficient values of both extended models follow a similar pattern. This means that the interactions between the partners' characteristics influence both performance measures in a similar way. Observe that there are several interaction effects whose coefficient values show large deviations from zero. In

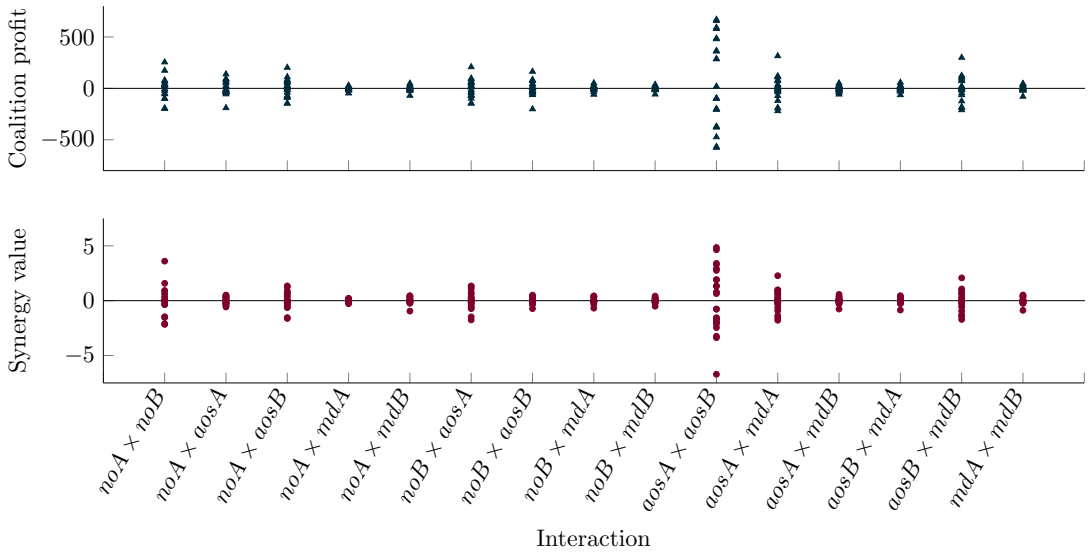

Figure 2: Values of the coefficients in the regression models with main effects and interaction effects.

other words, there are several interactions that have a substantial influence on the coalition's performance. The interaction between the partners' order sizes, $aosA \times aosB$, is clearly the most influential one as its coefficients values are widely spread. The interaction between the partners' numbers of orders, $noA \times noB$, has also a strong impact on the coalition's performance. There are, additionally, two groups of interactions that influence both performance measures, but to a smaller extent: the group of terms $aosA \times mdA$ and $aosB \times mdB$, and the group of terms $noA \times aosB$ and $noB \times aosA$. The first group involves the interaction between the average size of a partner's orders and the maximum number of days the same partner allows its orders to be delayed. The second group involves the interaction between a partner's number of orders and the average order size of the other partner. Finally, the group of interactions $noA \times aosA$ and $noB \times aosB$ has a milder but considerable impact on the coalition profit only. This group involves the interaction between a partner's number of orders and the average order size of the same partner.

The analysis of the extended models shows that the interactions between a partner's characteristics play an important role in determining the coalition's performance. Moreover, it shows that the way in which the partners complement each other has a major impact on the coalition. It is promising to see that the group of interactions $aosA \times mdA$ and $aosB \times mdB$ has shown to be influential. This suggests that, for companies with certain order sizes, the ability to be flexible might lead to a better coalition's performance.

4.3 The most important interactions: a general overview

The data generated by the experiment is very rich and requires a careful analysis. For that reason, Section 5 is devoted to an extensive case-by-case study that allows us to identify the best performing coalitions. Still, examining the interaction effects discussed in the previous section can provide useful insights about very general scenarios. In this section, we take a deeper look at interactions that involve either the same characteristic in different partners ($noA \times noB$ and $aosA \times aosB$) or different characteristics in the same partner ($noA \times aosA$ and $aosA \times mdA$). We believe these interactions to be the most relevant ones in such a general context.

4.3.1 Interactions involving the same characteristic in different partners

Figure 3 shows the average coalition profit and the average synergy for each value of the interaction $noA \times noB$. Observe that coalitions formed by partners with large numbers of customers generate the largest profits. In general, the larger the number of orders a partner needs to transport, the larger its potential to achieve a more profitable operational plan when collaborating with another partner. The synergy value, on the other hand, shows a very different pattern to that shown by the coalition profit. The largest synergy value is achieved by coalitions in which both partners transport a very small number of orders (equal to 5). Additionally, coalitions formed by partners with very different numbers of orders achieve relatively small synergy values. These two observations are in line with the results of the simulation study performed by Cruijssen et al. (2007a).

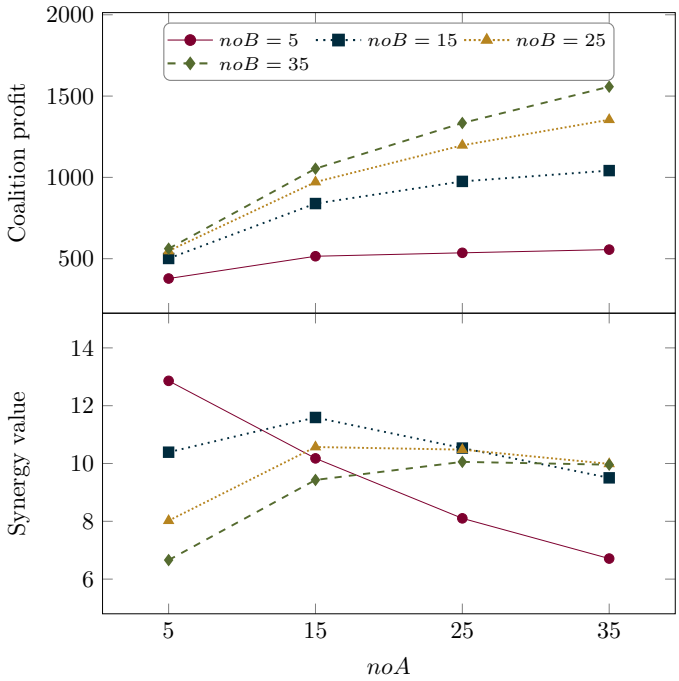

Figure 3: Average profit and average synergy value of coalitions formed by partners with different numbers of orders.

The discrepancy between both performance measures casts some doubts on how appropriate the synergy value is to evaluate the coalition's performance. At least of two-partner coalitions in which the profit generated is equally divided between the partners. Considering this value on its own, as in the simulation study by Cruijssen et al. (2007a), might lead to erroneous conclusions about which partners' characteristics lead to the best-performing coalitions. In case of the results shown in Figure 3, it is clear that coalitions formed by partners with large number of orders have the best performance since they generate the largest profits. Even though these profits might represent a relatively small percentage of the total stand-alone costs, they still result in the most substantial gains. Consider, for example, the coalitions formed by two partners that need to transport 5 orders each. In average, these coalitions lead to a profit equal to 378.01, which represents a reduction of 12.85% in the transportation cost. Alternatively, consider the coalitions formed by two partners that need to transport 35 orders each. Such coalitions lead, in average, to a much larger profit equal to 1557.70. This profit, despite representing a lower reduction of 9.95% in the transportation cost, is around four times larger than that generated by the other coalitions.

Figure 4 shows the average coalition profit and the average synergy for each value of the interaction $aosA \times$

$aosB$. First, note that when the two partners have very large orders, both the coalition profit and the synergy value are very close to zero. This is because, in these cases, most of the trucks can only transport a single order. Carrying out a joint operational plan has therefore no added value in these scenarios. Observe also that coalitions formed by a partner with an average order size equal to 12, and a partner with an average order size equal to 3 or 6, generate the largest profits. In other words, coalitions formed by partners with complementary order sizes achieve the most substantial gains. In these cases, almost all the orders of the first partner are slightly larger than half of the trucks' capacity (20 load units). In consequence, the stand-alone operational plan of this partner requires most of the trucks to carry a single order. When implementing a joint plan, however, close to half of these trucks' capacity becomes available to transport the small orders of the second partner. On the other hand, the coalitions with the largest synergy value are formed by two partners with very small order sizes (equal to 5). This observation is consistent with the results obtained by Cruijssen et al. (2007a). The profit generated by these coalitions, however, is considerably smaller than those achieved by the coalitions formed by partners with complementary order sizes.

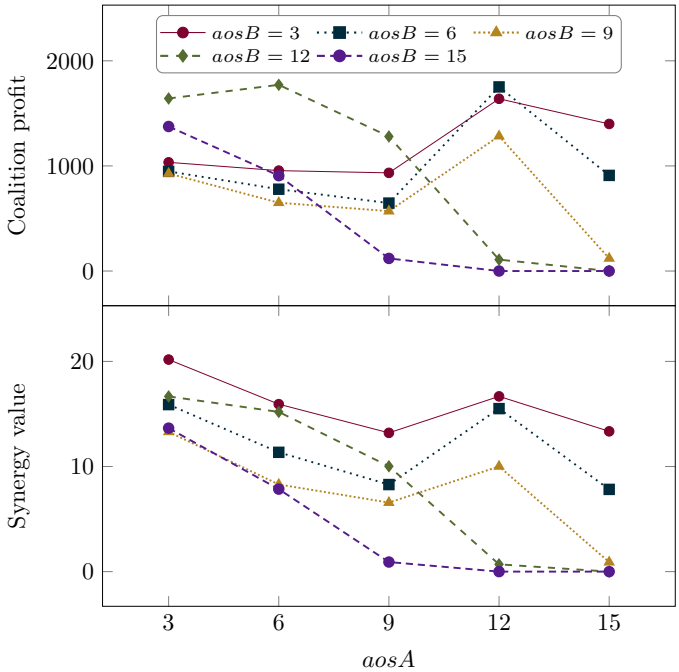

Figure 4: Average profit and average synergy value of coalitions formed by partners with orders of different sizes.

4.3.2 Interactions involving different characteristics in the same partner

Figure 5 shows the average coalition profit and the average synergy for each value of the interaction $noA \times aosA$. Observe that, similarly to that shown in Figure 3, the coalition profit increases with the number of customers the partner needs to serve. This increase is, however, consistently larger when the partner's average order size is equal to 12. Bear in mind that, in the stand-alone plan of such a partner, most of the orders have to be transported in different vehicles since they are too big to be bundled and shipped together. Therefore, a larger number of orders results in a larger left-over capacity that can be used to transport the orders of another partner when collaborating. The coalitions with the largest profits are formed when the partner needs to transport 35 orders and the size of these orders is equal to 3 or 12. In other words, the most considerable gains are achieved when the partner contributes to the joint operational plan in one out of two complementary ways: either by having small orders that can be easily bundled together, or by

providing plenty of additional capacity that can be used to transport the orders of the other partner. The synergy value, on the other hand, shows a more stable pattern than that shown by the coalition profit. The coalitions with the largest synergy values are formed when the partner needs to transport very small orders. Moreover, as suggested by the regression models studied in Section 4.1, the number of orders the partners require to transport has a very low impact on the synergy value achieved by the coalition.

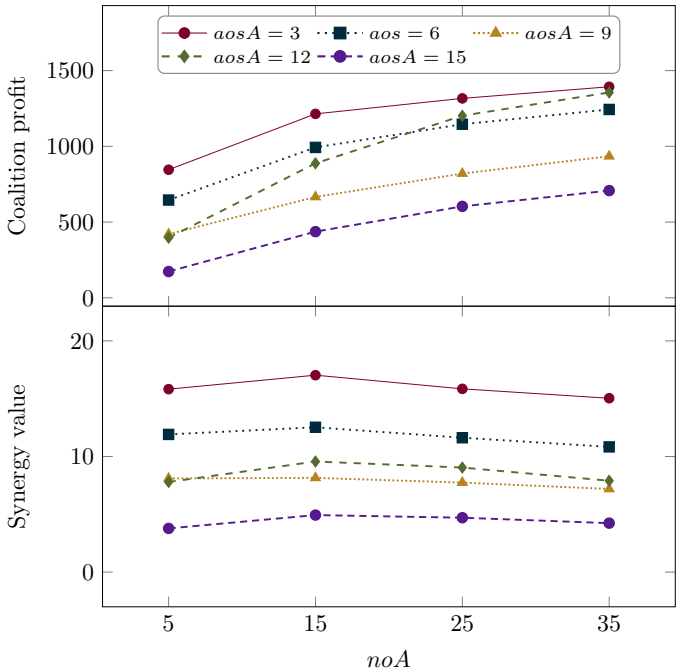

Figure 5: Average profit and average synergy value of coalitions formed when one of the partners has different numbers of orders and these orders have different sizes.

Figure 6 shows the average coalition profit and the average synergy for each value of the interaction $aosA \times mdA$. Observe that, contrary to Figures 3, 4 and 5, both performance measures show a very similar pattern. If the average size of a partner's orders is smaller than 9, the coalition's performance is lower when the partner allows its orders to be delayed. This is mainly because the ability to defer its orders enables the partner to implement a more efficient stand-alone operational plan. Therefore, the benefit from collaborating is less prominent. In contrast, if the average size of a partner's orders is greater than 9, the coalition's performance is slightly better when the partner allows its orders to be delayed. Remember that, in these scenarios, most of the trucks involved in the stand-alone plan of this partner transport a single order only. In consequence, the ability to defer orders has no direct impact on the efficiency of such plan. However, in the joint operational plan, delaying some of the partner's orders can help to use the left-over capacity of the trucks more efficiently.

5 Identifying the best partners to collaborate with

In this section, we describe a more detailed analysis of the data generated by the experiment. The goal of this analysis is to identify the promising characteristics that a company A should look for in a partner B, in order to form the most profitable coalition. To this end, we follow a case-by-case approach: we study the data from the point of view of three different companies (with different characteristics). For each company, we investigate how the characteristics of the potential partner influence the coalition profit. For that, we focus on the most important interactions (between the partner's characteristics) identified in Section 4.2. These

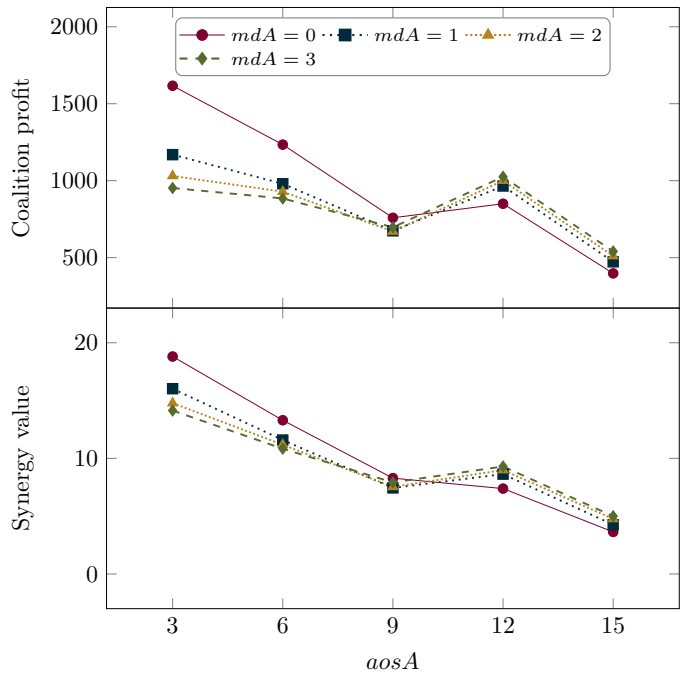

Figure 6: Average profit and average synergy value of coalitions formed when one of the partners has orders of different sizes and allows its orders to be delayed different numbers of days.

interactions are between the partner's number of orders and the partner's average order size ($noB \times aosB$) and between the partner's average order size and the number of days the partner allows its orders to be delayed ($aosB \times mdB$). Contrary to Section 4, we do not consider the synergy value in this analysis. The reason for this decision is that, in the previous section, the synergy value was shown to be a misleading measure of the coalition's performance.

5.1 Case #1 - A very flexible company with a few large orders

The first case considers a company that requires to transport a small number of orders. These orders, however, are very large. Additionally, the company is very flexible as it allows its orders to be delayed for several days. This description is typical of companies that transport large batches of products to major retailers or to intermediate distribution centres. Since these facilities usually maintain relatively large inventory levels, the company is able to delay its orders with no major impact on their operations.

A coalition involving a company with these characteristics can be represented considering the following levels: $noA = 5$, $aosA = 15$ and $mdA = 3$. Figure 7 shows the average coalition profit when this company collaborates with partners with different numbers of orders, and with orders of different sizes. In other words, it shows the average coalition profit for each value of the interaction $noB \times aosB$. Observe that the coalitions with the largest profit are achieved with a partner that requires to transport orders of very small size. In other words, it is best for the company to collaborate with a complementary partner whose orders can take full advantage of the unused capacity of the trucks. Note also that the number of orders the partner requires to transport has relatively low impact on the coalition profit.

Figure 8 shows the average coalition profit when the company collaborates with partners with orders of different sizes, and that allow their orders to be delayed different numbers of days. In other words, it shows the average coalition profit for each value of the interaction $aosB \times mdB$. Note that the coalitions with the

largest profits are formed with a partner that does not allow its orders to be delayed. In other words, it is best for the company to collaborate with an inflexible partner that can truly benefit from the added value of the coalition.

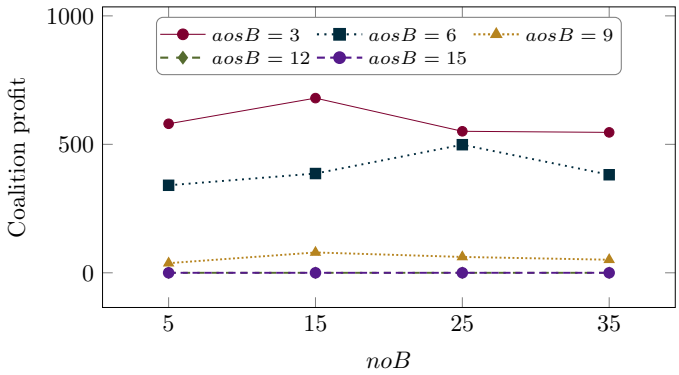

Figure 7: Average profit of coalitions formed when the company in case #1 collaborates with partners with different numbers of orders and with orders of different sizes.

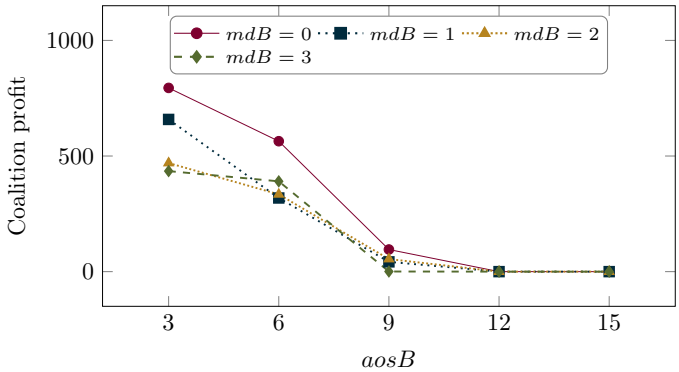

Figure 8: Average profit of coalitions formed when the company in case #1 collaborates with partners with orders of different sizes and that allow their orders to be delayed different numbers of days.

5.2 Case #2 An inflexible company with many orders of small size

The second case considers a company that requires to transport a large number of small orders. The operational plan of this company is very strict as it does not allow orders to be delayed. This description is typical of retail companies that need to serve several customers on a regular basis. For this kind of businesses, customers satisfaction is one of the top priorities and it is paramount that orders arrive right on time. A coalition involving a company with these characteristics can be therefore represented considering the following levels: $noA = 35$, $aosA = 3$ and $mdA = 0$. Figure 9 shows the average coalition profit for each value of the interaction $noB \times aosB$. Observe that the coalitions with the largest profits are formed with partners that require to transport many orders of large size. In particular, with a partner that requires to ship 35 orders of average size equal to 12. This means that it is best for the company to collaborate with a complementary partner whose stand-alone plan involves many trucks with plenty of unused capacity. The left-over capacity can be taken advantage of by the company's small orders, while the large number of trucks increases the potential to create efficient routes in the joint operational plan.

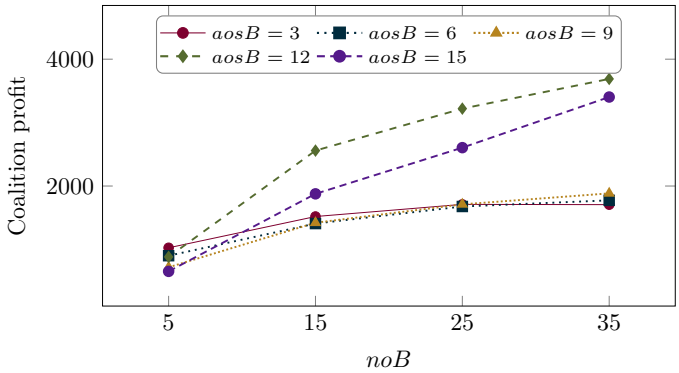

Figure 9: Average profit of coalitions formed when the company in case #2 collaborates with partners with different numbers of orders and with orders of different sizes.

Figure 10 shows the average coalition profit for each value in the interaction $aosB \times mdB$. Observe that the coalitions with the largest profit are formed with a partner that requires to transport orders of average size equal to 12, and that allows its orders to be delayed. In other words, it is best for the company to collaborate with a complementary partner that is flexible, and whose stand-alone plan involves trucks with plenty of unused capacity. In this case, the partner's flexibility is beneficial for the coalition since it allows for a more efficient use of the left-over capacity in the joint operational plan.

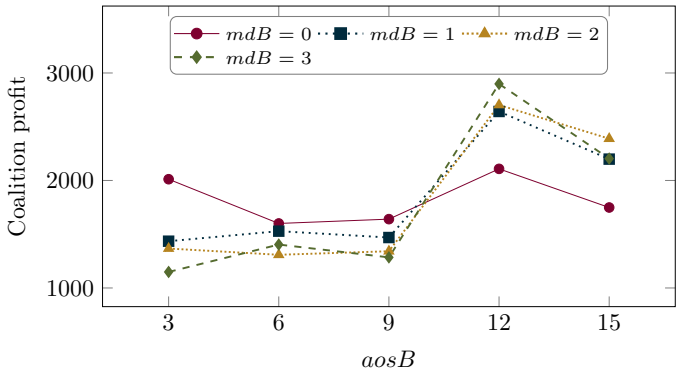

Figure 10: Average profit of coalitions formed when the company in case #2 collaborates with partners with orders of different sizes and that allow their orders to be delayed different numbers of days.

5.3 Case #3 - A flexible company with orders of medium size

The last case explores an intermediate scenario in between those studied with the previous two companies. It considers a company that requires to transport a moderate number of medium-sized orders. Moreover, these orders can be deferred for a few days, if necessary. A coalition involving this company can be represented considering middle levels such as $noA = 15$, $aosA = 9$ and $mdA = 2$. Figure 11 shows the average coalition profit for each value of the interaction $noB \times aosB$. Observe that the coalitions with the largest profit are formed with a partner that requires to transport many orders with an average size equal to 12. In other words, it is best for the company to collaborate with a partner whose trucks have plenty of unused capacity that can fit the company's orders. Note, however, that if the partner requires to transport 15 orders or less, the largest coalition profit is achieved when these orders have two different average sizes, either 3 or 12. This suggests that, when collaborating with a partner with these limited numbers of orders, it is best for

the company if the partner contributes to the joint operational plan in one out of two complementary ways: either by having small orders that can be easily shipped in the left-over capacity of the company's trucks, or by having trucks with enough capacity to fit the company's orders.

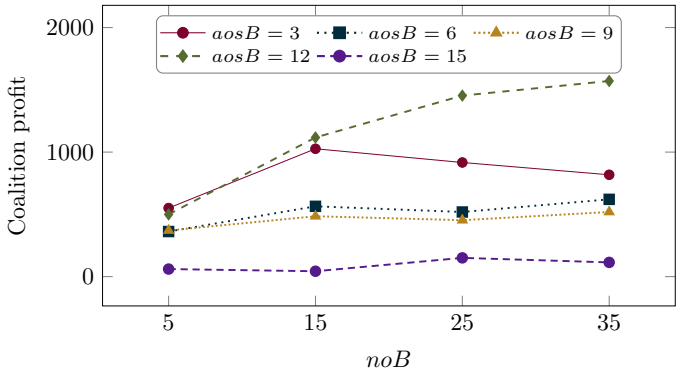

Figure 11: Average profit of coalitions formed when the company in case #3 collaborates with partners with different numbers of orders and with orders of different sizes.

Figure 12 shows the average coalition profit for each value in the interaction $aosB \times mdB$. Note that the coalitions with the largest profits are formed with two very dissimilar partners. The first partner requires to transport very small orders and does not allows its orders to be delayed. In other words, if the partner's orders are very small (and can easily fit in the company's truck), it is best for the company if the partner is inflexible and cannot carry out a very cost-effective operational plan by itself. The second partner, on the other hand, requires to transport orders with an average size equal to 12 and allows its orders to be delayed for 3 days. This is, if the partner's trucks have plenty of unused capacity that can fit the company's orders, it is best for the company if the partner is very flexible. In this way, it is possible to use the left-over capacity of the partner's trucks more efficiently in the joint-operational plan.

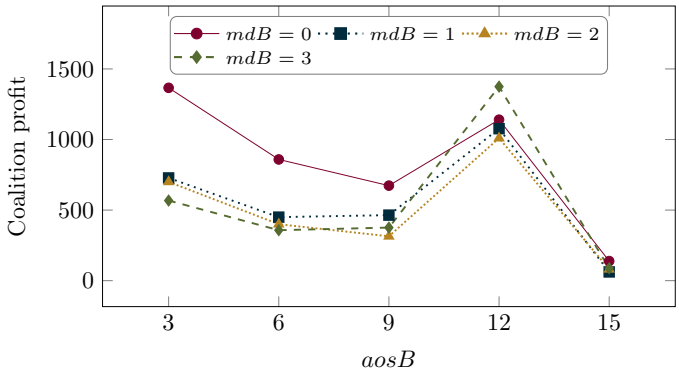

Figure 12: Average profit of coalitions formed when the company in case #3 collaborates with partners with orders of different sizes and that allow their orders to be delayed different numbers of days.

6 Conclusions

Horizontal collaboration offers a great opportunity for companies to improve their transport operations. By forming a coalition and carrying out a joint operational plan, companies are able to become more profitable and more environmentally friendly. The extent of these benefits is, however, highly dependent on the partners

that form the coalition and the characteristics of their operations. Different companies might have different requirements and could enforce different restrictions on the joint operational plan. These differences between the partners' characteristics have a large impact on the performance of the coalition. For that reason, it is important that companies take them into account when choosing the best partner(s) to collaborate with.

In this paper, we had a deeper look at the performance of two-partner coalitions formed by companies with different characteristics. We analysed the results of a simulation study carried out with two main objectives. First, to identify the partner characteristic that influence the coalition's performance the most. Second, to determine the combinations of characteristics that lead to the most profitable coalitions. The results obtained show that the interactions between the characteristics, and the way the partners complement each other, have a major influence on the coalition's performance. Choosing a partner according to very general considerations, like those suggested by Cruijssen et al. (2007a), can therefore lead to missed opportunities for very successful collaborations. The results also show that the synergy value is not an appropriate measure of a coalition's performance. At least of two-partner coalitions in which the profit generated is equally divided between the partners. Considering this measure on its own can lead to erroneous conclusions about which coalitions are the most beneficial.

The simulation study carried out led to three main insights that can help companies to make better partner choices:

1. The average order size is the most influential characteristic on the coalition's profit. The most fruitful coalitions are formed by companies that have complementary order sizes. In these coalitions, one company transports large orders that, in the company's stand-alone plan, cause the trucks to have plenty of unused capacity. The other company transports small orders that, in the joint operational plan, can take advantage of the unused capacity of the partner's trucks.

2. The number of orders a company requires to transport has also a considerable impact on the profit generated by the coalition. The larger a company's number of orders, the larger its potential to achieve a more efficient operational plan when collaborating with a partner.

3. The ability of a company to delay its orders has a much milder effect on the coalition's profit than the other characteristics. Such flexibility is beneficial for the coalition when it cannot be exploited by the company itself, but it can enhance the efficiency of the joint operational plan. This happens when, in a company's stand-alone plan, there are many trucks with a large unused capacity. In these cases, the company's flexibility allows the joint operational plan to make a better use of the left-over capacity of these trucks. On the other hand, when the company can take advantage of this flexibility to achieve a more efficient stand-alone plan, the added value of collaborating might reduce significantly.

We would like to stress that the previous insights are limited only to the collaborative scenarios investigated in this paper. These scenarios represent coalitions formed by two partners and implement an allocation method that divides the generated profit equally between the partners. Additionally, the scenarios assume that both partners carry out their operations under specific conditions: they share the same distribution centre and their customers are randomly located in the same distribution area. These operating conditions, and their impact on the insights obtained, were not explored in our analysis.

The simulation study presented in this paper can be extended in different ways. The most interesting extension, however, would involve evaluating coalitions with more than two partners. In particular, because this would allow to investigate the impact of the cost allocation method on the results of the simulation. By evaluating coalitions of larger size and dividing the profits in other ways, different opportunities for successful collaborations might be identified. Moreover, a partner that is very suitable to collaborate with considering a specific allocation method, might not be so considering a different one[4]. Identifying these cases is certainly a very promising avenue for future research.

[4]We refer the reader to the papers by Lozano et al. (2013), Guajardo et al. (2015) and Guajardo and Rönnqvist (2015b) for more information about determining the best coalitions, given a finite set of potential partners.

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