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AGENT-BASED SIMULATION IMPROVES E-GROCERY DELIVERIES USING HORIZONTAL COOPERATION

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ABSTRACT

E-commerce has increased tremendously in recent decades because of improvements in the information and telecommunications technology along with changes in societal lifestyles. More recently, e-grocery (groceries purchased online) including fresh vegetables and fruit, is gaining importance as the most-efficient delivery system in terms of cost and time. In this respect, we evaluate the effect of cooperation-based policies on service quality among different supermarkets in Pamplona, Spain. Concerning the methodology, we deploy, firstly, a detailed survey in Pamplona in order to model e-grocery demand patterns. Secondly, we develop an agent-based simulation model for generating scenarios in cooperative and non-cooperative settings, considering the real data obtained from the survey analysis. Thus, a Vehicle Routing Problem is dynamically generated and solved within the simulation framework using a biased-randomization algorithm. Finally, the results show significant reductions in lead times and better customer satisfaction when employing horizontal cooperation in e-grocery distribution.

1 INTRODUCTION

In recent years, consumer shopping habits have radically changed, mainly due to massive mobile phone adoption, Internet broadband penetration, and time pressures. One of the main changes is related to the increase in demand for e-groceries (e.g., the online purchase of groceries, including fresh vegetables and fruit) as a consequence of an exceptional development of e-commerce. Similarly, the implementation of new business models has reaped important benefits by offering more flexibility and an alternative shopping experience for consumers. However, studies on operations related to this topic, in consonance with the increment in demand, are still scarce, especially those related to the logistics field. The logistics challenges cover a wide range of food-safety-related issues or differences in the storage temperatures to perishability over time (Fredriksson and Liljestrand 2015). In fact, the consumers' requirements differ from the sellers' desires. While consumers usually prefer products with a longer perishability (Teller et al. 2018), sellers most likely benefit from shipping first items with shorter shelf lives in order to reduce food waste (Fikar 2018).

Considering the aforementioned problems, horizontal cooperation may be one of the key elements for improving the efficiency in logistics while maintaining seller competitiveness in their main activity.

Actually, horizontal cooperation may be defined as "any agreement, tacit or not, which involves more than one company without vertical relationship between them, i.e., no supplier-customer relationship, based on trust and mutual commitment to identify and exploit win-win situations with the goal of sharing benefits (or risks) that would be higher (or lower) than each company would obtain if they acted completely independently" (Serrano-Hernandez et al. 2017). This idea is not new; some authors, like Cruijssen et al. (2007) have highlighted the potential benefits of cooperation as *(i)* reducing transportation cost; *(ii)* improving service quality; *(iii)* diminishing environmental impact; *(iv)* mitigating risk; and *(v)* enhancing market share. Hence, horizontal cooperation might be particularly interesting for e-grocery, where customers are geographically widespread (e.g., in rural areas), generating long empty backhauls after deliveries. These load factors can be easily improved by cooperating to reduce empty backhauls when supermarkets share their logistics operations. Accordingly, the main contributions of this work can be stated as follows: *(i)* the modeling of the demand patterns about e-grocery (including ordering frequency, preference of supermarket, and delivery windows); *(ii)* an agent-based simulation model for generating scenarios in cooperative and non-cooperative settings, considering the real data obtained from the survey analysis, and *(iii)* the integration of Vehicle Routing Problems (VRP) and Multi Depot VRP within the simulation framework.

The remainder of the paper is organized as follows: Section 2 reviews concepts related to e-groceries, horizontal cooperation, and Agent-based Simulation. Section 3 provides a more detailed description of the survey and the simulation model. Section 4 summarizes the main results of our simulation model. Finally, Section 5 summarizes the main findings of this paper and points out future research lines.

2 RELATED LITERATURE

This section presents an analysis of the literature regarding the three main novelties that the proposed methodology presents: e-groceries, horizontal cooperation, and agent-based Simulation.

2.1 E-grocery

Electronic commerce (e-commerce) is the process of trading goods, information, or services via computer networks including the Internet (Fraser et al. 2000). This concept is included within a broader concept (e-business), that alludes to any business operation conducted through information networks (e.g., customer services and knowledge sharing). According to da Silveira (2003), the introduction of e-commerce channels in traditional companies has changed their operations and business strategy, where the main issues that arise are those related to the integration of this new paradigm: the customization in order to be competitive as well as company internationalization. This integration needs to be accompanied by procedures and methodologies that help to *(i)* reduce the transaction costs, *(ii)* facilitate just-in-time production strategies, *(iii)* boost short delivery-times, and *(iv)* improve information gathering and processing. Specific for e-groceries, it refers to the purchase or acquisition of products through the Internet (Emeç et al. 2016).

Moreover, online shopping has turned into an indispensable tool for our society. This is the reason behind the necessity of developing procedures that guarantee the optimum provision and delivery of goods. Therefore, some authors, like Fikar et al. (2019), designed and implemented a simulation- and optimization-based Decision Support System (DSS), which can help decision-makers in building e-grocery operations and corresponding service offers (e.g., perishability management or safety-related issues). In the same line, Wilson-Jeanselme and Reynolds (2006), by studying the consumers' preferences, found that ordering, product quality, time, and reliability in the delivery process are the most important attributes to know when a customer conducts a purchase. Considering the aforementioned information, the design of a competitive e-grocery service involves the consideration of its multiple-attribute nature, and based on knowledge about the customers' preferences, we need to be able to segment the market and to develop a precise service offer in which the key point is focused on the punctual product delivery.

During the last decades, some researchers like Ellinger et al. (2006) have highlighted the importance of collaboration between logistics and marketing. Moreover, Seidel et al. (2016) and Boyer et al. (2009)

state that balancing the desires for short delivery time windows – which are more attractive to consumers (marketing desire) – with longer delivery windows – which produce more efficient routes (logistics desire) – can improve the outcome performance of the e-grocery service. To address this topic, the most common mathematical model to solve this kind of scenario is the Vehicle Routing Problem (VRP) and its variations, e.g., the Capacity Routing Problem (CRP) or the Delivery Routing Problem (DRP). For example, Emeç et al. (2016) designed a mathematical program for efficient delivery services of online groceries to fulfill diverse consumer demands without raising additional inventory costs. The model is based on a distribution network, in which the goods are acquired from an external set of vendors at multiple locations within the supply network, and delivered to consumers in a single visit when we consider an e-grocery environment. Finally, it is important to say that the popularity of e-grocery has helped to reduce the carbon footprint in the urban areas (Figliozzi et al. 2020). This is one of the reasons of its success along with its excellent results when it is managed by means of horizontal cooperation.

2.2 Horizontal Cooperation

Nowadays, cooperation in a horizontal way inside the supply chain is critical to achieving meaningful results in terms of costs and environmental impacts. Collaboration and coordination among partners are necessary due to the fact that supply chains feature inter-organizational and inter-functional stages (Calleja et al. 2018). According to Soosay and Hyland (2015), this collaborative process usually involves multiple companies or autonomous business entities engaging in strategic relationships to share improved outcomes and benefits. Reinforcing the same idea, Nooteboom (2004) pointed out that some of the expected results of the collaborative process are *(i)* efficiency in the exploitation of resources; *(ii)* development of new competencies; and *(iii)* better positioning in markets. From a practical point of view, Serrano-Hernandez et al. (2017) describe horizontal cooperation policies for any coalition depending on the involved organizational level, e.g., consolidation centers at strategic level, conjoint routes at tactical level, and load factor improvement at operational level. Each of theses practices requires a certain 'level of trust' or 'commitment'.

Hence, the introduced statements call for a certain level of trust, where all stakeholders can feel comfortable and share critical information about the decision-making protocol as well as the integrated supply chain processes. Chen et al. (2011) state that collaborative-sharing relationships, based on trust and commitment are critical to achieve efficiency, flexibility, and a sustainable competitive advantage. Furthermore, Bahinipati et al. (2009) refer to horizontal cooperation as a set of joint actions developed by several companies working at the same supply chain level and oriented to obtain an enhanced outcome in economic and sustainable terms. Others, such as Lambert et al. (1999) depicted horizontal cooperation as a tailored relationship that is based on mutual trust, commitment, and openness, where the main objective is to secure a competitive advantage (i.e., the assumption that the conjoint outcome would be greater than the one achieved independently). Through close cooperation, the partnering aim at increasing the productivity, e.g., optimizing vehicle capacity utilization, reducing empty mileage, and cutting costs of non-core or supporting activities to increase the competitiveness of logistics networks (Wang and Kopfer 2014).

However, some conflicts are expected to arise. Tidström (2009) states that there is a higher potential for the emergence of opportunism and dysfunctional conflicts, due to the fact that partnering firms are competing for the same customers. Nevertheless, the aforementioned interdependencies can be supposed to be lower in intensity, since companies usually do not rely on the output of partners as input for their own operations (Serrano-Hernandez et al. 2018; Rindfleisch 2000). Nevertheless, it is possible to minimize expected conflicts by means of an integrated management that emphasizes a conflict-oriented governance of horizontal cooperation (Arlbjørn et al. 2011).

2.3 Agent-based Simulation

Agent-based models (ABMs) are computational algorithms in which artificial entities interact within customized environments (Jackson et al. 2017). They offer an unprecedented control and some statistical power by allowing researchers to precisely specify the behavior of any number of agents and observe their interactions over time. An agent is considered an actor who interacts with the environment and who functions independently in its interactions with other agents (e.g., settlements, people, political entities, or companies, among others). For this purpose, agents have protocols or mechanisms that describe how they interact with other agents, having themselves their own characteristic comportments. Moreover, an agent is an identifiable, discrete individual with a set of characteristics or attributes, behaviors, and decision-making capability (Macal and North 2009). Also, agents are adaptive in that they respond to their environment through learning and evolution and are autonomous in that they control their own goals, states, and conducts (Macy and Flache 2002).

Similarly, ABMs bring a framework for social simulation that helps to specify causal mechanisms, e.g., models that simulate not only individual behavior but also social interaction that characterizes a society's behavior (Macal 2016)). This is the reason why ABMs are present in the literature in a wide variety of fields, such as economics (Tesfatsion and Judd 2006), sociology (Bruch and Atwell 2015), political science (Cederman 2005), or artificial intelligence (Wooldridge 2003). According to Macal and North (2011), the main reasons for using agent-based modeling are:

1. The current systems that need to be analyzed and modeled are becoming more complex in terms of interdependencies. Therefore, conventional modeling tools may not be as suitable as before;
2. Some systems have always been too complex for other kinds of models (e.g., economic models);
3. Data are being collected and organized into databases at more granular levels (e.g., individual-based simulations), and
4. The computational power is advancing rapidly.

Nowadays, it is possible to compute large-scale micro-simulation models that would not have been manageable just a few years ago.

3 METHODOLOGICAL ANALYSIS

This section describes the proposed methodology to develop the study of the improvement of e-grocery deliveries with horizontal cooperation assumptions. First of all, we briefly present the survey that we have carried out to obtain the required data. Afterwards, we describe the agent-based simulation model.

3.1 The Survey

In order to obtain the input data for the simulation model, we deployed an online survey in the city of Pamplona, Spain. This survey was released on February 15th, 2020 and closed one month later on March 15th, 2020. A simple random sampling was promoted using the mailing distribution lists at the Public University of Navarre, sited in Pamplona. We also presented the online survey to some local authorities. All in all, the sample size is 182 observations, which is sufficient for the study that we develop here. The survey contents and their results after its implementation in Pamplona are at the reader's disposal if requested by email from the authors.

3.2 The Simulation Model

The simulation model is partly inspired by the work done by Serrano-Hernandez et al. (2018) in the city of Vienna in 2017-18. In that paper, a simulation model was proposed to investigate some trust-related issues in forming a coalition for the implementation of several horizontal cooperation policies in logistics operations. Therefore, we took the backbone of that model and adapted it to the requirements of this research.

The geographical scope of our model is the Pamplona metropolitan area in Spain (Figure 1), where the online survey has been deployed. The area includes a population of about 250,000 inhabitants. In our scenario, the *customer* places orders in a *supermarket* choosing the time to receive his or her bought products inside a *time window* previously selected, i.e., we assume the *customer* as the agent. One of the hypotheses that we assume is that supermarkets may cooperate to fulfill orders. In Figure 1, green dots stand for demand locations and red stars stand for supermarkets selected for the experiment. The modeling details on customers and supermarkets are provided in the next subsections.

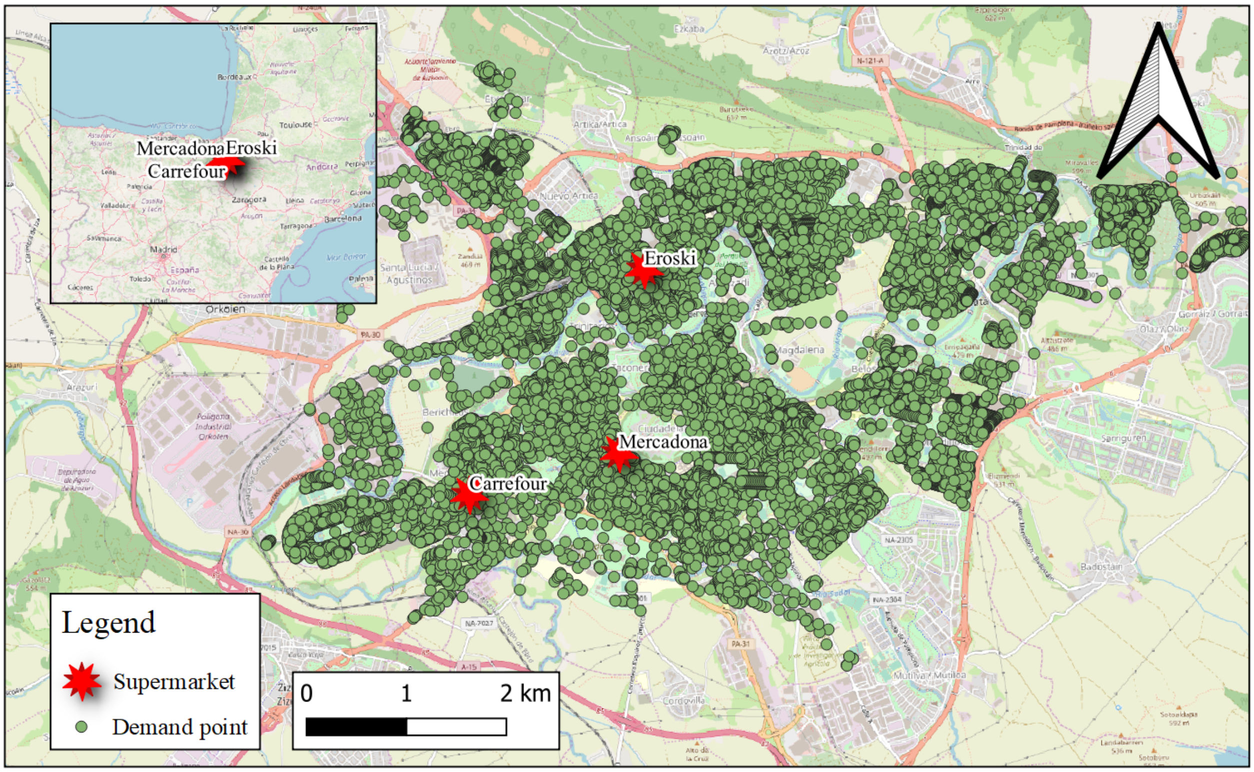

Figure 1: Pamplona region in Spain and geographical scope of the survey.

We use a regular week as a base scenario for our simulation model. This scenario is composed by typical weekdays and typical weekend days. The key performance indicators of the simulation model are based on service quality.

1. First, the lead time, which is defined as the temporal distance between the minimum value of the time window and the time when the customer received his or her order. This lead time has to be included inside a fixed time window decided beforehand.
2. Second, the rate of customers who received their orders on time, that is, within the selected time window.

3.2.1 Customer Analysis

As representation of the customers, we use the cadastre information from the metropolitan area of Pamplona. That cadastre accounts for approximately 12,000 points that identify a building number. In this area, the population is about $250,000$ inhabitants and the average number of people per household is about 2.5 (Spanish Institute of Statistics 2019). Thus, there are approximately $100,000$ households in the metropolitan area of Pamplona. Because there are $12,000$ points, each one representing a different building, which may include several households, each customer point is represented eight times in the simulation. This accounts for the fact that the majority of the Pamplona population is living in apartments or flats.

Furthermore, demand patterns are modeled using the results from the conducted survey as well as from external studies (ISDI 2017). The key factors of those studies are summarized in Tables 1 and 2. Table 1 shows the demand distribution for time windows and weekdays. Table 2 describes the online order rate for different order frequencies. Additionally, a binary indicator has been employed for each customer, in order to measure the satisfaction, which is based on the service quality in terms of on-time delivery. If the delivery is made outside the scheduled time window associated to a customer, that customer is unsatisfied for that particular delivery. Conversely, if the delivery is performed within the associated time window for that costumer, he or she is satisfied.

Table 1: Demand patterns for time windows and weekdays.

	7-10h	10-13h	13-16h	16-19h	19-22h
Weekdays	4.0 %	6.3 %	8.7 %	15.4 %	35.6 %
Weekends	5.5 %	14.2 %	5.9 %	2.4 %	2.0 %

Table 2: Rate of online ordering for some frequencies.

Frequency	Rate
Once a week	4.87 %
Once every two weeks	8.70 %
Once a month	12.53 %
Once every 2 months	4.18 %
Once every 3 months	4.52 %
Do not usually order online	65.2 %

3.2.2 Supermarket Analysis

Concerning the field analysis, we selected three supermarkets for our investigation. The chains to which they belong are very popular in Spain (Eroski, Mercadona, and Carrefour). Currently, they offer a wide range of online products, including fresh fruits and vegetables. Table 3 shows relevant information about these supermarkets. The first and second row in Table 3 show the supermarket chains and their webpages. The third row shows the supermarket preference on behalf of the customers according to the survey results. These preference percentages refer to the whole sample. The remaining 65.8 % represent the amount that is not counted in the preference description, due to other buying options or due to customers not buying online. The fourth row shows the expected weekly demand given in number of orders. This expected weekly demand is computed using the probability distribution functions related to the supermarket preference and the frequency of ordering online (being 1 for buying once a week, $1/2$ for buying once every two weeks, $1/3$ for buying once every three weeks, and so on). For these computations, we assume that there are $100,000$ households as the potential demand as explained in the previous subsections. The fifth row, which is composed of different sub-rows, shows the expected number of orders for combinations of day and time window (each sub-row shows a combination). These values are estimated using the information shown in Tables 1 and 2. Similarly, the sixth row shows the ed number of orders – considering all time windows – and per supermarket chain. The last (seventh) row in Table 3, which is again composed of sub-rows, shows the logistics capacity for each supermarket. Likewise, it is assumed that a vehicle may carry up to 20 orders. For our experiments, therefore, we assume three different scenarios related to vehicle capacity depending on the number of vehicles available for servicing. This capacity is set in terms of the coverage

Table 3: Supermarket information: preference, expected demand, and logistic capacity.

	Eroski	Mercadona	Carrefour
Webpage	www.eroski.es	www.mercadona.es	www.carrefour.es
Preference	17.60 %	9.10 %	7.50 %
Expected weekly demand (# orders)	2,332.53	1,206.02	993.98
Weekdays (7-10h)	93.30	48.24	39.76
Weekdays (10-13h)	146.95	75.98	62.62
Weekdays (13-16h)	202.93	104.92	86.48
Weekdays (16-19h)	359.21	185.73	153.07
Weekdays (19-21h)	830.38	429.34	353.86
Weekend (7-10h)	128.29	66.33	54.67
Weekend (10-13h)	331.22	171.26	141.14
Weekend (13-16h)	137.62	71.16	58.64
Weekend (16-19h)	55.98	28.94	23.86
Weekend (19-21h)	46.65	24.12	19.88
Expected Time Windows Demand	446.06	230.64	190.08
Fleet setting 25 %	6	3	2
Fleet setting 50 %	11	6	5
Fleet setting 75 %	17	9	7

of the expected time window demands as 25 % (low capacity), 50 % (medium capacity), and 75 % (high capacity). These percentages are calculated having the expected time windows as the 100 % reference value.

3.2.3 The Cooperative Behavior and the Routing Algorithms

Studying the interest in cooperation on behalf of the supermarkets is a good way to understand their future outlook and their insight in optimizing decisions. If cooperation is not enabled, each supermarket has to serve their customers independently, i.e., each supermarket has to solve as many Vehicle Routing Problems (VRP) (Mor and Speranza 2020) as time window slots it has in order to design the orders to distribution plans. Therefore, we have implemented a heuristic VRP, which is based on a biased randomization solution procedure of the well-known Clarke and Wrights savings algorithm (Juan et al. 2010). We have followed the recommendations given by Grasas et al. (2017) and Juan et al. (2010) in order to build our VRP algorithm. For the driving times, we are using real data, because the shortest paths are computed with data taken from OpenStreetMap (OpenStreetMap 2020), which is integrated in the simulation software package Anylogic 8.5.2 (AnyLogic 2020) used to develop our model. We are not going to provide a detailed description of the routing algorithms because they are out of the scope of this paper and can be obtained from the aforementioned papers in this paragraph, mainly Grasas et al. (2017).

If cooperation is enabled, all supermarkets jointly serve all their customers. The three supermarket chains establish a coalition, which defines a delivery problem for the demanded orders that has to be solved considering a number of Multi Depot Vehicle Routing Problems (MDVRP) according to the time window slots. Consequently, we implemented a heuristic MDVRP following the ideas described in Juan et al. (2015). The solution procedure starts by sorting the supermarkets based on the time distances to the customers. Then, each customer is randomly assigned to a supermarket using a biased randomization procedure (Juan et al. 2015). Supermarkets more close to the customers have a greater probability to be chosen. Once all customers are assigned, the same biased-randomization procedure previously described in the VRP is applied to obtain a complete solution. Finally, this solution is saved and a percentage of customers (50% in our experiment) are de-assigned from their supermarkets and re-assigned using the biased-randomized assignment procedure. Then, the MDVRPs are solved again. This process is repeated for a number of iterations (250 in our case study) and the best obtained solution is reported, analyzed, and put into practice.

3.2.4 Experimental Design

After having carried out the algorithm's implementation to solve our routing problems, our experiments aim at demonstrating the positive impacts of horizontal cooperation on e-grocery deliveries. Additionally, as previously stated, the supermarket capacity for meeting online orders is tested by three fleet size scenarios: 25 % (low capacity), 50 % (medium capacity) and 75 % (high capacity) coverage of the expected daily demand. To sum up, there are six different scenarios as shown in Table 4.

Table 4: Scenario descriptions.

	Low capacity	Medium Capacity	High Capacity
Horizontal Cooperation not allowed	$SC1$	$SC2$	$SC3$
Horizontal Cooperation allowed	$SC4$	$SC5$	$SC6$

3.2.5 Dynamics of the Simulation

The simulation starts at time zero for a given random number generator seed and the parameters related to the first scenario ($SC1$). Then, all data related to customers are set, i.e., for each customer the following parameters are assigned: *(i)* whether it is an online shopper, *(ii)*, if online shopper, whether it is ordering from one of the three introduced supermarkets, *(iii)* if it is ordering from one of them, at which time the customer would like to receive the order, i.e., weekday or weekend and the specific time window, and, lastly, *(iv)* a service time defined from a uniform distribution of $U[3,7]$ minutes.

Hence, at time 1, weekday orders are delivered following a sequential policy according to the time windows. All the supermarkets start their deliveries at 7 a.m., using the solution reported by the aforementioned VRP algorithm. The routes finish once all customers have been served, which implies that violating a time window will delay the starting time for the deliveries in the following time windows. Similarly, at time 2 orders for the weekend are served using the same procedure. At the end of time 2, the key performance indicators are reported and everything is restarted for testing the next scenario. Note that customer data are kept unchanged over time. Therefore, once all the scenarios are tested, the process starts again by selecting a new random number generator seed. We have run 100 replications in our simulation model.

3.2.6 Model Assumptions and Limitations

During the modeling process, we have considered several assumptions that involve the following limitations:

1. The way in which the demand is modeled could be improved with more and better data in both directions: the preference of the respondents and the cadastral information that has been only accounted for building identification. It is doubtless that a richer information related to the population socioeconomic status and the places they live would allow for a much better demand simulation.
2. We assume all orders are dispatched from the same supermarket at any chain. Actually, each supermarket has a vast network of retailers from which they can serve the orders. Therefore, here we are assuming that the supermarkets are acting as consolidation centers from where all the online orders are served.
3. We are considering a delivery process with a homogeneous fleet, i.e., all vehicles have the same capacity. This is not always the case in most of the retail chains as different vehicle types may coexist.

4. All products must be available in all supermarkets for the cooperation process to make sense, which is not always the case. Consequently, we are in fact assuming that customers order products that are identical in the different supermarkets in the coalition, such as fresh fruit, vegetables, and top brands.
5. Finally, we also assume that supermarkets can accept as many orders as they receive, or in other words, there are no limitations for serving any order for any time window.

4 EXPERIMENTAL RESULTS

The simulation model was implemented in the AnyLogic 8.5.2 (AnyLogic 2020) software and run on a standard desktop with an Intel® Core$^{\text{TM}}$ i5- 3570 CPU @3.40 GHz and 8GB RAM. The preliminary results of our experiment are shown in Tables 5 and 6. Table 5 provides the average lead times and the average satisfaction indices per scenario. The first column shows the scenarios and the second one displays whether horizontal cooperation (HC) policy has been considered. Similarly, the third column shows the level of capacity (LC) per scenario, while the fourth column shows the average lead time in minutes for the 100 replications of the simulation. The fifth one presents the standard deviation for the average lead time, with the sixth column showing the average satisfaction index, again, for the 100 replications, being the last one its standard deviation. Recall that, the lead time is the time a customer has to wait for receiving an order once the time window has been open, while the satisfaction index computes the ratio of customers who receive their orders on time.

Likewise, Table 6 shows the impacts of horizontal cooperation on lead times and on satisfaction indices. It compares the results for the two studied scenarios with and withouthorizontal cooperation policy. The first column shows the capacity level, while the second one shows the percental variation of lead times for the horizontal cooperation scenario with respect to the non-horizontal cooperation scenario. Moreover, the last column depicts the percental variation of the satisfaction index for the horizontal cooperation scenario with respect to the non-horizontal cooperation scenario. It is important to highlight that the establishment of cooperative protocols significantly improves the service quality. In fact, depending on the logistics capacity of the coalition, this improvement may reach a 39.28 % reduction of average lead times. Additionally, more efficient delivery plans also boost customer satisfaction. In average, the last row of Table 6 shows an expected reduction of a 28.57 % in average lead times and an increase of a 25.15 % in the satisfaction index.

Table 5: Average lead times and average satisfaction indices per 100 replications.

Scenario	HC	LC	Av Lead Time (min.)	Sd	Av Sat Index(%)	Sd
1	No	L	156.45	114.20	57	12
2	No	M	131.42	95.18	64	10
3	No	H	90.74	80.12	71	10
4	Yes	L	123.59	60.29	68	8
5	Yes	M	98.00	55.52	81	7
6	Yes	H	55.10	45.10	92	7

Table 6: Impacts of horizontal cooperation on lead times and satisfaction indices.

	Lead times	Satisfaction Index
L	-21.00 %	19.30 %
M	-25.43 %	26.56 %
H	-39.28 %	29.58 %
Average	-28.57 %	25.15 %

5 CONCLUSIONS AND FURTHER RESEARCH

This work proposes the use of horizontal cooperation as a way to gain competitiveness in the e-grocery delivery sector. For this purpose, we developed an agent-based simulation model to track the service quality of the logistics operations of different scenarios, which consider goods distribution for online demand from supermarkets. Some of these scenarios considered the use of horizontal cooperation for performing the deliveries, whose delivery implementation was done using a biased randomization algorithm. As a result, the use of horizontal cooperation improves the service quality of the e-grocery distribution up to 29 % and reduces the customer lead times up to 39 %.

Furthermore, there are a number of future directions related to the work presented here. Firstly, more insights could be obtained from the presented results, e.g., a better understanding of the time window length as an attribute as well as some other real-time driving uncertainties. Moreover, some assumptions may be relaxed in order to establish a more sophisticated problem setting, such as the involvement of more companies and the consideration of a constellation of coalitions running at the same time. Additionally, supplier-related metrics, such as costs or fleet utilization, can be implemented in our model. Finally, there is room for investigating the effects of particular cooperation policies. To this respect, a mechanism to share the benefits coming from the horizontal cooperation should be explicitly implemented.

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