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Using an integrated order picking-vehicle routing problem to study the impact of delivery time windows in e-commerce

Katrien Ramaekers*, An Caris, Stef Moons and Teun van Gils

Abstract

European e-commerce sales are increasing every year. Nowadays, customers buy more frequently online in smaller quantities. Handling this large amount of customer orders puts the logistic activities of the supply chain under pressure. At the same time, customers have high expectations concerning the delivery of their online purchase. In order to meet these expectations at low cost, B2C e-commerce companies have to reconsider their logistic activities. Instead of optimizing every single process of the supply chain, related problems need to be tackled simultaneously. In the integrated order picking-vehicle routing problem(I-OP-VRP), picking lists and vehicle routes are determined simultaneously. One possibility to meet the high expectations of customers is to allow customers to choose the time window in which they want to be delivered. However, the more customers select a time window during the purchasing process, the higher the total costs for the B2C e-commerce company since the company has less flexibility to construct their delivery routes. To cover the cost increase, e-commerce companies often only provide this service at an additional cost. The objective of this paper is to estimate the additional cost of allowing customers to choose a preferred delivery time window using the integrated order picking-vehicle routing problem. An experimental design is set up to investigate this service cost under varying circumstances depending on customer characteristics, time window characteristics and operator size. Based on the results of the ANOVA it can be concluded that the investigated factors have a significant influence on the additional cost of allowing customers to select a delivery time window.

Keywords: Order picking, Vehicle routing, E-commerce, Delivery time windows, Pricing

1 Introduction

In the last decades, the economic landscape in (Western) Europe has undergone a makeover. Many companies moved their manufacturing plants from Europe to low cost countries to remain competitive [1, 2]. This offshoring led to a loss of approximately 3.5 million jobs in the manufacturing industry in the European Union since 2008 [2]. At the same time, many multinational companies built a distribution centre (DC) in Europe. These DCs are generally responsible for the deliveries of goods produced outside Europe to European customers, often within the context of business-to-consumer (B2C) e-commerce transactions [3]. Since 2010, European B2C e-commerce sales have been growing annually with approximately 17% on average. More specically, in 2016, the B2C e-commerce sales grew with 15.43% in Europe, resulting in a sales figure of 530 billion euro in 2016 [4]. The share of internet users in the EU which made online purchases increased with 16 percentage points since 2007 up to approximately 65% [5].

In an e-commerce context, customers order more frequently in smaller quantities. As a consequence, the number of consignments increases [3]. In Europe, approximately 4.2 billion B2C parcels are sent to customers annually [6]. This large number of smaller quantities makes it more challenging to consolidate customer orders in an efficient way. Customers want to be able to choose the moment and location of the delivery of their parcel. The large majority of people expect their parcel to be delivered at home. Compared to traditional shopping behaviour where goods only need to be

* Correspondence: katrien.ramaekers@uhasselt.be
Hasselt University, Research Group Logistics , Agoralaan – building D, 3590 Diepenbeek, Belgium

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delivered to a limited number of stores, B2C e-commerce with home-delivery leads to a large increase in the number of possible delivery locations [3].

Furthermore, online shoppers expect a fast and accurate delivery within tight time windows at low cost or even free [7]. Often same day or next day delivery is promised to customers. The promise of faster deliveries implies a double logistic challenge: (1) dealing with an increasing pressure on the warehouse operations due to later cut-off times; and, (2) creating an efficient distribution network for parcel delivery. Accordingly, handling a large number of orders and parcels in an efficient way puts the logistic activities of the supply chain under pressure. B2C e-commerce companies have to thoroughly rethink and redesign their way of operating. Excellent logistics performance is indispensable in order to fulfil the customer expectations at low cost and to be successful in an e-commerce environment [3]. In order to achieve such a high performing overall system, extensive coordination among the different stages of the supply chain is necessary.

When considering e-commerce supply chains, the warehousing and delivery operations need to be optimised. After (e-commerce) orders are picked in a warehouse, the goods need to be delivered to the preferred delivery location of the customer. Accordingly, order picking and distribution are interrelated. Disruptions in the order picking operations will impact the deliveries. Extensive research has already been done on the optimization of warehouse operations [8]. However, to obtain more efficient schedules, the order picking and delivery decisions need to be taken at the same time. Such an integrated planning approach leads lower operational costs and/or faster deliveries in comparison with solving both problems separately and sequentially [9]. In the integrated order picking-vehicle routing problem(I-OP-VRP), picking lists and vehicle routes are determined simultaneously. Requirements and constraints of both the order picking problem and the vehicle routing problem are considered at the same time. For example, delivery time windows are taken into account when picking lists are established.

In this paper, the impact of delivery time windows in planning e-commerce operations is studied. To give a higher service to their customers, B2C e-commerce companies often allow customers to choose the time window in which they want to be delivered. This avoids unnecessary waiting at home for the customer but also leads to less failed deliveries for the company. However, the more customers select a time window during the purchasing process, the higher the total costs for the B2C e-commerce company. When customers specify when they want to be delivered, the company has less flexibility to construct delivery routes. Consequently, the average total route length and the average total distance travelled increase with the time window density. Similarly, more vehicles need to be used to deliver all orders within their time window. To cover this cost increase, e-commerce companies often only provide this service at an additional cost. However, companies should carefully determine the amount of the additional charge since the price of the delivery is a main determinant for customers in online purchases. This research is the first to use the integrated order picking-vehicle routing model formulation to estimate the additional cost of allowing customers to choose a preferred delivery time window. An experimental design is set up to investigate this service cost under varying circumstances depending on customer characteristics (clustered in an urban region or dispersed in a rural setting), time window characteristics (allowed time window width) and operator size (number of orders to schedule). Section 2 discusses related literature on the role of transportation in e-commerce operations. The modelling approach as an integrated order picking-vehicle routing problem and solution methodology to calculate total operational costs are explained in section 3. Section 4 describes the experimental set up and results. Finally, section 5 presents the main findings and reflects on these results.

2 Related literature

The shift towards online shopping in consumer behaviour has an impact on personal travel as well as freight transport. According to Suel and Polak [10], despite the recent rapid growth of digital retailing and online shopping, the impact on travel behaviour remains poorly understood. The authors provide a literature review of how online activity can be incorporated into operational transport demand models. Online shopping may replace individual trips to stores by home deliveries by retailers or third party carriers. Alternatively, ordered goods might be delivered to designated pick up locations for collection hence will generate individual trips to these collection points. Suel and Polak [10] conclude that efforts are necessary to continue to develop modelling frameworks that successfully can combine urban logistics and individual travel demand models. Such capability will also serve to answer some of the emerging and pressing questions from the business side. For example, understanding preferences for delivery slots and how their availability influences physical trip decisions is important to manage peaks in demand both for efficient logistics operations and reducing trucks on urban roads. Demand side effects of online shopping leading to a shift in personal travel has already been studied by multiple authors. We refer to Crocco et al. [11] for a literature review and analysis of aspects mostly affecting consumer choices of purchasing goods by web or in-store.

However, supply side effects concerning the possible delivery time slots offered by retailers or logistics service providers is only limited.

Current literature on managing the delivery time slots offered to customers only considers the effect on distribution costs. Agatz et al. [12] model the problem of selecting the set of time slots to offer in each of the zip codes in a service region, with the objective to facilitate cost-effective delivery routes and to ensure an acceptable level of customer service. Yang et al. [13] propose dynamic pricing policies based on a multinomial logit customer choice model to determine which and how much incentive to offer for each time slot in order to enable cost-effective delivery routes. Klein et al. [14] present a mixed-integer linear programming formulation for the tactical problem of differentiated time slot pricing in attended home delivery. All these articles assume that logistics costs are mainly due to routing costs of service vehicles. Little is known on the effect of offering time slots on total order picking and distribution costs.

The integration of order picking and delivery processes is a relatively new research direction, and hence literature is rather scarce. Moons et al. [9, 15] are the first to study an I-OP-VRP in a B2C e-commerce context and propose a local search based record-to-record travel algorithm as solution approach. Closely related, Schubert et al. [16] develop an iterated local search algorithm for an I-OP-VRP with due dates for the supply of perishable goods to supermarkets. Zhang et al. [17, 18] also examine the integration of order picking and distribution operations in a B2C ecommerce context. However, delivery is assumed to be outsourced to 3PL service providers. As such, the order picking problem is only integrated with simple distribution operations. As the work of Moons et al. [9, 15] most closely resembles the real-life context, we choose to adopt this methodology as further explained in the next section.

3 Methodology

In order to estimate the cost of allowing customers to choose certain delivery time windows, we use the modelling approach of Moons et al. [9]. The authors propose an integrated planning approach for order picking and vehicle routing. Traditionally order picking and delivery decisions are decided in an uncoordinated way. B2C e-commerce companies often outsource their delivery operations to a 3PL service operator. Every day, the 3PL operator picks up the goods at the DC at a fixed time, mostly in the evening. Based on the pickup time, the e-commerce company determines a cut-off time. All goods ordered before this cut-off time are picked before the 3PL service provider arrives at the DC. In an integrated approach, the e-commerce company executes the delivery operations itself, or there is coordination between the e-commerce company and the 3PL service provider. No fixed pickup times are implied anymore. By coordinating the order picking and distribution process and exchanging information, a vehicle can leave the DC whenever a sufficient number of orders to conduct a delivery route have been picked. As such, the start of the distribution process is more flexible. The picking and delivery operations overlap in time.

For the mathematical problem formulation and an experimental study on the value of integration, the reader is referred to Moons et al. [9]. A mixed integer linear programming formulation for an I-OP-VRP with time windows to minimize both the order picking and delivery costs is presented. Comparing an uncoordinated and integrated approach for small-size instances indicates that integration can result in both cost savings of 14% on average and higher service levels. Customers can order their goods later in time while still being delivered within the same time windows.

The following assumptions are made concerning the order picking process. A picker-to-product approach, in which manual order pickers travel along the picking locations, is used. Each order, consisting of one or more order lines, is picked individually without interruption in a single tour, i.e., single order picking policy. Pickers work in parallel in a single zone. Additional temporary order pickers can be hired in case of a high customer demand. The labour cost of a temporary order picker is higher due to the uncertainty they have about their work and to value their flexibility. Furthermore, a maximum number of pickers can work simultaneously to avoid congestion in the aisles of the warehouse. Each order picker can work for a maximum amount of time during one shift.

The delivery operations are executed with a homogeneous fleet of vehicles. Both an hour coefficient cost incurred per time unit of the tour length, which includes the labor cost of the driver, and a kilometer coefficient cost incurred per kilometer traveled are incorporated in the calculation of delivery costs. The maximum vehicle route length is restricted (due to strict regulations on the drivers working hours). Service times, which are the loading times at the DC and the unloading times at the customer locations, are explicitly taken into account. Each customer has specified a delivery time window in which the delivery of the order should start. It indicates the time period in which the customer is available to accept the parcel. Thus, early and tardy deliveries are not allowed. When a vehicle arrives early, it has to wait until the start of the time window.

This integrated planning approach enables the calculation of total operational costs in the various experimental settings in section 3. The total costs thus represent the sum of the labour cost of both the regular and temporary order pickers, the labour cost of the drivers (represented by the hour coefficient cost), and the total kilometre cost. To tackle problems of realistic size, a record-to-record travel algorithm is developed to find near-optimal solutions. First, an initial solution is generated. Next, to improve the quality of this solution, five local search operators are used in an iterative way in a record-to-record travel framework for a maximum number of iterations. A detailed description and performance analysis of this solution approach is presented in Moons et al. [15].

Mangiaracina et al. [19] identify the need for a quantitative evaluation of the environmental impact of e-commerce activities. The authors state that the relevant literature does not suggest a general consensus regarding the environmental impact of transportation activities related to B2C e-commerce. On the one hand, some negative effects have been detected, such as an increase in the number of inefficient deliveries. On the other hand, under specific assumptions – e.g. high-population density, usage of low-carbon-emission vehicles – the environmental impacts can be positive, e.g. in terms of CO_2 emissions reduction. Although our research only considers the internal costs of a company offering e-commerce activities, the I-OP-VRP solution indicates the total number of kilometres travelled to deliver all customer orders within the specified time windows as an indicator of environmental performance.

4 Empirical study

As many factors may influence the effect of delivery time windows and the additional costs associated with allowing customers to select a time window for delivery, a full factorial experimental design is set up to investigate this additional cost under varying circumstances. Both customer characteristics and time window characteristics are taken into account. Customer characteristics include the geographical spread of customers in the service region (clustered in an urban region or dispersed in a rural setting) and the percentage of customers that selects a preferred time slot. Time window characteristics include the allowed time window width. Furthermore, the impact of the operator size is studied. In section 3.1, the experimental design is described. In section 3.2, the data generation is outlined. Section 3.3 elaborates the statistical analysis used.

4.1 Experimental design

Two separate experiments can be distinguished. The first experimental design consists of three factors: the geographical spread of the customers, the time window width and the percentage of customers selecting a preferred time window. In these experiments, the number of orders is constant (100 orders). In a second experimental design, the first design is elaborated by varying the operator size (the number of orders to schedule). However, in this design, the percentage of customers selecting a preferred time window is fixed at 100%. The two experimental designs are outlined in Tables 1 and 2. The dependent variable is in both designs the additional costs associated with allowing customers to choose a delivery time window. These additional costs are calculated by subtracting the total costs of the basic scenario from the total costs found in the experiments. The basic scenario represents the situation in which customers have no possibility to choose a time window.

In both designs, a distinction needs to be made between two sets of factors: general factors which affect an instance's structure (geographical spread of the customers), and factors which only affect time window characteristics (time window width, percentage of customers selecting a preferred time slot and number of orders). For each factor level of the general factor, 30 instances are generated. The generation of these instances is further explained in section 4.2. All these instances are then solved using the integrated algorithm for different levels of the second type of factors which only affect time window characteristics. This creates dependent observations ("repeated measures"), which results in greater statistical power. However, as observations for some of the factors are no longer independent, a mixed-model ANOVA is required to analyse the main and interaction effects of the factors (with time window width, percentage of customers selecting a time window and number of orders being examples of within-subjects factors and geographical spread of customers as between-subjects factor).

4.2 Data generation

For each number of customers (50, 100 and 150), 30 instances are generated with clustered customers and 30 instances are generated with randomly spread customers. These instances are first solved for the basic scenario in which customers do not have the possibility to choose a preferred time window for delivery. These results are the total costs of the basic scenario. To calculate the additional costs of allowing customers to choose a delivery time window, the total costs of the basic

Table 1 Experimental factor setting (design 1: percentage of customers selecting a time window)

Factor	Factor levels
Geograpical spread	(1) Clustered (2) Random
Time window width	(1) 2 h (2) 4 h
Percentage of customers selecting a TW	(1) 25% (2) 50% (3) 75% (4) 100%

Table 2 Experimental factor setting (design 2: number of orders)

Factor	Factor levels
Geograpical spread	(1) Clustered (2) Random
Time window width	(1) 2 h (2) 4 h
Number of orders	(1) 50 (2) 100 (3) 150

scenario are subtracted from the total costs found when solving the instances for the different factor levels of the two experimental designs. The data used to generate the instances is described in the next paragraphs.

The order sizes are randomly generated from TRIA(1; 2; 6), where TRIA(a; c; b) defines a triangular distribution with a the minimum value, c the mode, and b the maximum value. The average order size is 3 items, which is the same as in the studies of Ruben and Jacobs [20], Petersen [21], and Zhang et al. [17] considering a mail order or B2C e-commerce problem setting. The order processing time, expressed in minutes, is randomly generated from U(10; 27), where U(x_1; x_2) defines a uniform distribution between x_1 and x_2. This leads to an average order processing time equal to 18.5 min equivalent to Gong and de Koster [22], who consider online retailers. All orders are available for picking at the beginning of the planning horizon. The order pickers use a picking device with a capacity of 20 items, as in Lu et al. [23] and Zhang et al. [18]. Since the maximum order size is smaller than the picking device capacity, each order picker is capable to pick every single order. All pickers are allowed to work 240 min during a shift. After consulting a large international logistics service provider, the labour cost of a regular and a temporary order picker are set equal to 25 and 30 euro per hour, respectively.

A fleet of homogeneous vehicles (vans) with a capacity of 100 items is available to conduct the delivery operations. A similar vehicle fleet is used in Cardenas et al. [24] who based this value on data of a Belgian logistics carrier operating in an B2C e-commerce context. The delivery locations are located in a 100 × 100-square with the DC located in the centre. For a small van, a cost of 0.22 euro per kilometre travelled is incurred [25]. The labour cost of the driver is equal to 25 euro per hour [26]. Each driver is allowed to work at most 8 h (480 min). Loading the vehicles at the DC takes 20 min, similar as in the e-grocery problem of Punakivi and Saranen [27] and in the I-OP-VRP of Schubert et al. [16]. The average unloading time of a parcel is equal to 4 min [26]. The unloading time of an order is generated from a triangular distribution TRIA(2; 4; 6). Random numbers generated from a triangular distribution are rounded to the closest integer.

By using these instances and generating the data as described above, the results of this study are only valid within the context of these instances. References are given to justify the choice of the parameters. However, if for a specific case, the parameters are outside the ranges used to generate the instances, extra experiments are needed to be able to draw conclusions for this specific case.

4.3 Statistical analysis

In order to analyse the effect of the experimental factors on the additional costs associated with allowing customers to choose a delivery time window, an analysis of variance (ANOVA) is performed. ANOVA results are subject to independency, variance and normality assumptions [28].

The empirical study consists of two full factorial designs with a mixture of between-groups and within-groups (repeated-measures) factors. This mixed factorial design requires performing a mixed model ANOVA as observations for the factor 'geographical spread' are not independent.

The assumptions of homogeneity of variance with respect to the between-groups factors and sphericity (i.e. variances of the differences between results for a particular geographical spread are equal) with respect to repeated-measures factors are violated, based on Levene's test for homogeneity of variance and Mauchly's test for sphericity. Therefore, the Greenhouse-Geisser (G-G) correction of the degrees of freedom is used before interpreting the results [29].

Finally, the last ANOVA assumption includes normality. The F statistic controls the Type I error rate well under conditions of non-normality [30], especially when group sizes are equal. Therefore, a balanced experimental design was set up to ensure an accurate ANOVA.

5 Results

In Tables 3 and 4, the results of the ANOVA are shown for the two experimental designs. The dependent variable is in both designs the additional costs associated with allowing customers to choose a delivery time window. The first columns show the sum of squares, the G-G adjusted degrees of freedom (df) and the mean squares of the main and interaction effects. The last two columns contain the F statistic and p-value for testing the statistical significance of the experimental factors and the interaction effects. In section 4.1 the results for the first experimental design with a fixed number of orders are discussed. Section 4.2 interprets the results of the second experimental design in which the impact of the number of orders is examined.

Table 3 Mixed model ANOVA results (design 1)

	Sum of squares	*df*	Mean square	*F*	*p*-value
Main effects					
F1: Geographical spread	4,745,136	1	4,745,136	200.82	0.000
F2: Time window width	4,903,994	1	4,903,994	555.93	0.000
F3: Percentage selecting TW	128,688	2.072	62,108	87.64	0.000
Two-way interaction					
F1 X F2	1295	1	1295	0.147	0.703
F1 X F3	128,688	2.072	62,108	87.64	0.000
F2 X F3	928,893	2.041	455,162	548.45	0.000
Three-way interaction					
F1 X F2 X F3	12,757	2.041	6251	7.53	0.001
Residuals					
Between subjects	1,370,472	58	23,629		
Within F2	511,633	58	8821		
Within F3	85,165	120.18	709		
Within F2 X F3	98,234	118.37	823		
Total	12,914,955	365.78			

5.1 Impact of the geographical spread, time window width and percentage of customers selecting a time window

The results of the mixed model ANOVA in Table 3 show that all main effects are statistically significant. This means that there is a significant difference in additional costs for allowing customers to choose a delivery time window for customers with a different geographical spread, for customers choosing time windows of 2 h versus 4 h and when more customers choose a delivery time window. Furthermore, two two-way interaction effects and the three-way interaction effect are statistically significant. Thus, the additional costs are influenced by the combined effect of the three factors.

5.1.1 Main effects

The first factor, geographical spread of the customers, is statistically significant. For clustered customers, the total costs increase with 11% on average when allowing customers to select a delivery time window. The percentage of total costs increase is calculated by dividing the

Table 4 Mixed model ANOVA results (design 2)

	Sum of squares	*df*	Mean square	*F*	*p*-value
Main effects					
F1: Geographical spread	878,212	1	878,212	212.63	0.000
F2: Time window width	8,407,640	1	8,407,640	1794.96	0.000
F3: Number of orders	1,064,855	1.363	781,464	152.92	0.000
Two-way interaction					
F1 X F2	17,228	1	17,228	3.678	0.060
F1 X F3	215,138	1.363	157,883	30.896	0.000
F2 X F3	383,502	1.576	243,286	243,312	0.000
Three-way interaction					
F1 X F2 X F3	19,557	1.576	12,407	12.408	0.000
Residuals					
Between subjects	239,554	58	4130		
Within F2	271,673	58	4684		
Within F3	403,871	79.033	5110		
Within F2 X F3	91,418	91.428	1000		
Total	11,992,668	295.339			

additional costs of allowing customers to choose a delivery time window by the total costs of the basic scenario. For randomly spread customers, the total costs increase with 24% on average. When customers are clustered the increase in costs is less than when customers are randomly spread because when customers are spread more randomly probably more distance is needed to travel to another customer with a close delivery time window.

The second factor, time window width, is also statistically significant. When allowing customers to select a delivery time window of two hours, the additional costs are on average 25% compared to the situation in which no time window can be chosen. When delivery time windows of 4 h are offered to the customers, the costs increase with only 11% on average. This difference can be easily explained since it is harder to solve the I-OP-VRP when time windows are narrower. Furthermore, the probability of finding a close neighbour with a similar delivery time window is higher when time windows are wider. These results are in line with Agatz et al. (2011) whose experiments indicate an increase in delivery cost of up to 25% from using two-hour time slots instead of time slots that span an entire morning or afternoon.

Finally, the percentage of customers selecting a delivery time window influences the results significantly. The additional costs are on average 10%, 15%, 21% and 25% for respectively 25, 50, 75 and 100% of the customers choosing a delivery time window. The more customers select a time window, the more restrictions there are on the I-OP-VRP resulting in higher costs.

5.1.2 Interaction effects

Two two-way interaction effects are found to be statistically significant. There is a significant interaction effect between the geographical spread of the customers and the percentage of customers choosing a delivery time window. An interaction plot is shown in Fig. 1. On the X-axis the percentage of customers choosing a delivery time window is shown, on the Y-axis the increase in total costs is shown. Fig. 1 reveals that when the percentage of customers choosing a time window goes up, the increase in total costs is higher for randomly spread customers than for clustered customers. For randomly spread customers, the distances to cover are higher leading to higher costs. This effect becomes stronger the more customers select a time window.

A second two-way interaction effect that is found statistically significant is the interaction effect between the time window width and the percentage of customers choosing a delivery time window. The interaction plot is shown in Fig. 2, where the percentage of customers is on the X-axis and the increase in total costs is on the Y-axis. The interaction plot shows that for both time window widths the total costs increase when a higher percentage of customers chooses a delivery time window but the increase is more pronounced for time windows of 2 h.

In addition, the three-way interaction effect is statistically significant. This indicates that the two-way interaction between the time window width and the percentage of customers selecting a delivery time window previously described is different for clustered and randomly spread customers. Fig. 3 shows this two-way interaction for clustered customers and Fig. 4 shows the two-way interaction for randomly spread customers. When comparing both interaction plots, we can see that the difference between offering time windows of 2 h and of 4 h is much more pronounced when customers are clustered. For example, when all customers select a delivery time window, the additional costs increase from 87€ to 392€ for clustered customers while the increase in additional costs for randomly spread customers is from 320€ to 649€.

5.2 Impact of the operator size

The main goal of the second experimental design is examining the impact of the operator size on the

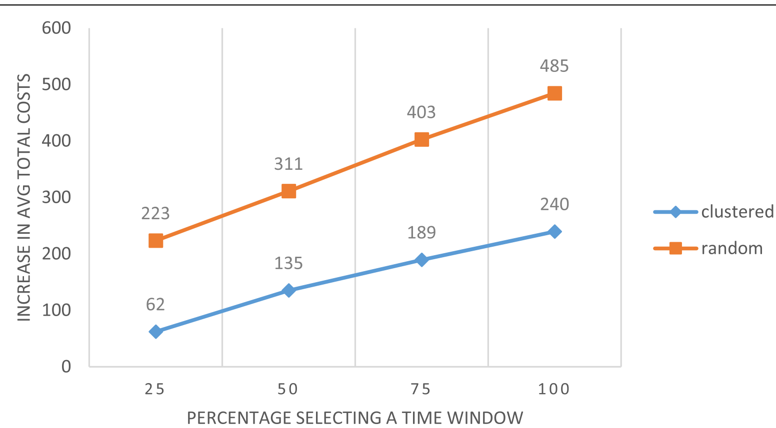

Fig. 1 Interaction plot of geographical spread X percentage selecting a time window

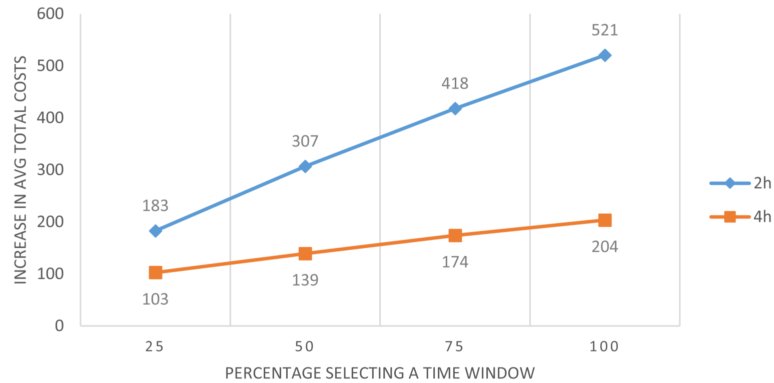

Fig. 2 Interaction plot of time window width X percentage selecting a time window

previous conclusions. Therefore, the experiments of the previous section are repeated for instances with 50 orders and instances with 150 orders. The percentage of customers selecting a delivery time window is fixed at 100% in all instances.

The results of the mixed model ANOVA in Table 4 demonstrate that all main effects are statistically significant. Furthermore, two two-way interaction effects and the three-way interaction effect are statistically significant. The number of orders is a significant factor so it can be concluded that there is a significant difference in additional costs for instances with 50, 100 and 150 customers. When only 50 customers are considered, the average increase in total costs is 4.38€ per customer. For 100 customers, the average increase is 2.97€ per customer and for 150 customers, the average increase is 2.35€ per customer. This can be explained by the fact that a small company offering customers to select a delivery time window has less possibilities to make efficient routes than companies having two or three times more customers in the same region.

In addition, the interaction effects between the number of orders and the geographical spread and between the number of orders and the time window width are both statistically significant. Interaction plots of these two two-way interactions are given in Figs. 5 and 6. On the X-axis, the number of orders is shown, on the Y-axis the average increase in total costs is given. In Table 5, the average increase in total costs per customer are shown for both interaction effects. It can be concluded that for both clustered and randomly spread customers the increase in average total costs per customer decreases when the number of orders grows. However, the decrease is less profound when customers are randomly spread. When comparing delivery time windows of 2 h and 4 h, the decrease in average total costs per customers is less pronounced when customers can select time windows of 4 h.

Finally, the three-way interaction effect is statistically significant. This can be interpreted as in the previous experiment: the two-way interaction between the time window width and the number of customers previously

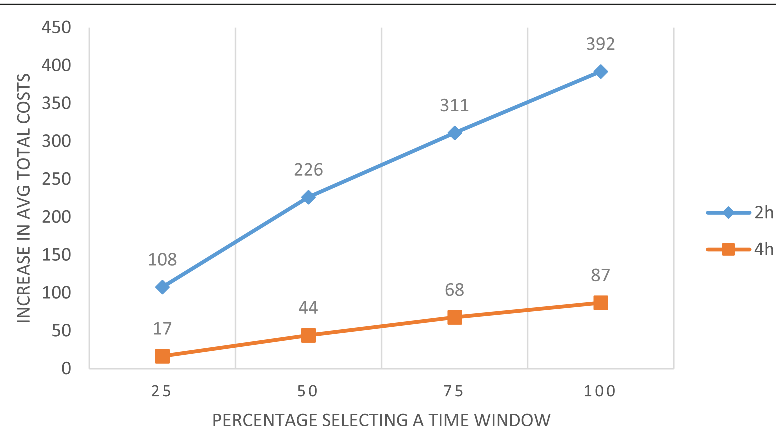

Fig. 3 Interaction plot of F2 X F3 interaction for clustered customers

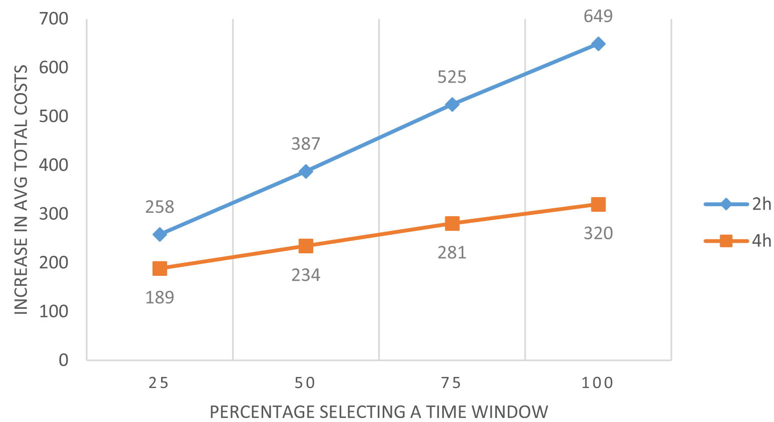

Fig. 4 Interaction plot of F2 X F3 interaction for randomly spread customers

described is different for clustered and randomly spread customers. In Table 6 the average increase in total costs per customer is shown for clustered and randomly spread customers separately. Based on the data in this table, it can be concluded that the decrease in total costs per customer for an increasing number of orders is less pronounced when customers are randomly spread.

6 Conclusions and future research

This research sheds light on the cost increase e-commerce companies incur when offering customers flexibility in selecting delivery time windows. An integrated order picking – vehicle routing problem is used to calculated this cost increase while in previous research only the vehicle routing problem is used. This integrated approach leads to efficiency gains and a higher service can be offered to customers without an increase in costs. Based on the results of the ANOVA it can be concluded that the investigated factors have a significant influence on the additional cost of allowing customers to select a delivery time window. This means that there is a significant difference in additional costs for allowing customers to choose a delivery time window for customers with a different geographical spread, for customers choosing time windows of 2 h versus 4 h and when more customers choose a delivery time window. In addition, the operator size is also a significant factor. When only 50 customers are considered, the average increase in total costs is 4.38€ per customer. For 100 customers, the average increase is 2.97€ per customer and for 150 customers, the average increase is 2.35€ per customer. However, this average increase ranges from 6.88€ per customer if customers are randomly spread and delivery time windows of 2 h are offered in case of 50 customers to 0.69€ per customer if customers are clustered and delivery time windows of 4 h are offered in case of 150 customers.

To cover the cost increase, e-commerce companies often only provide this service at an additional cost. However, companies should carefully determine the amount of the additional charge since the price of the

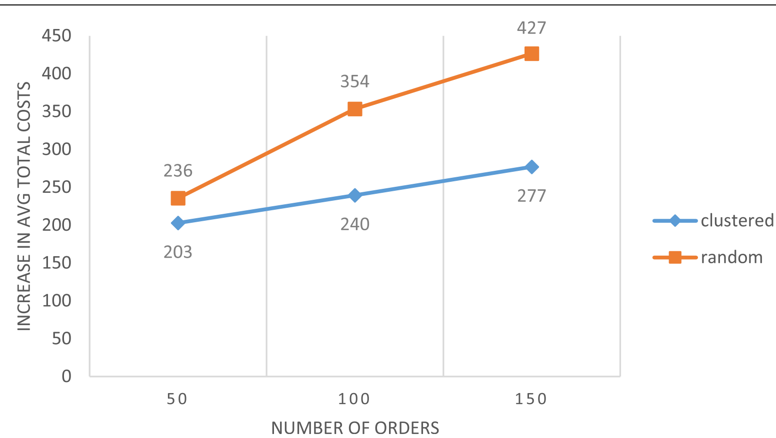

Fig. 5 Interaction plot of geographical spread X number of orders

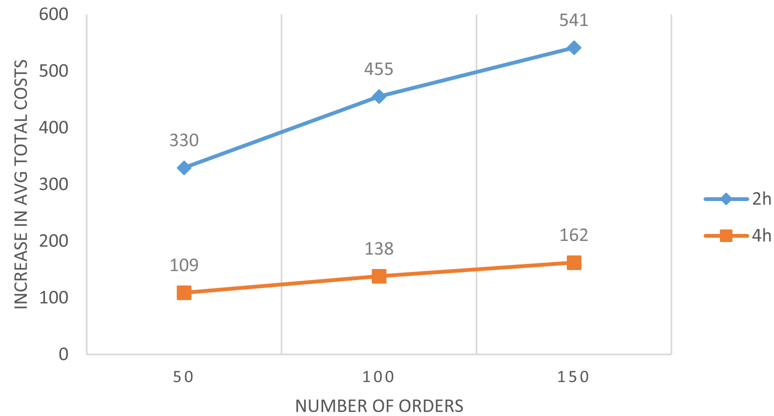

Fig. 6 Interaction plot of time window width X number of orders

delivery is a main determinant for customers in online purchases [26]. Furthermore, the willingness to pay to specify a time slot is declining over the years in the United Kingdom. While in 2009 still more than 75% was willing to pay more than 2 Pound, it declines to less than 20% in 2014. Approximately 40% of the customers is willing to pay less than 1 Pound, and another 40% between 1 and 2 Pound [31]. Similar research in Belgium indicates that customers are willing to pay not more than 4 Euro to be able to select their preferred delivery characteristic. Thus, the entire cost increase of approximately 5 Euro found in the experiments cannot totally be charged to the customers. However, it depends on the characteristics of the company whether this 4 Euro that a customer is willing to pay is achievable. For example, for companies with clustered customers, the average increase in costs by allowing customers to choose a time window is in most cases less than 4 Euro. Only if the company has only 50 customers and they allow them to choose a time window of 2 h, it costs the company more than 4 Euro. Therefore, companies need to be aware of the impact of these characteristics on the additional cost of allowing customers to choose a time window. The importance of growth can be clearly derived from the results: the more customers a company serves, the less it costs to let these customers choose a delivery time window.

In addition, the part of the cost increase above the price that customers are willing to pay, can be covered by the savings due to less failed deliveries and due to efficiency gains by using an integrated order picking – vehicle routing problem. When the service to select the preferred time window is not offered, e-commerce companies decide themselves when to deliver each customers. However, as customers will not stay home the entire day, the probability of a failed first-time home delivery is higher. In 2012, failed deliveries resulted in a cost of approximately 850 million pound for the companies and customers. Thus, when the time window selection service is offered, the costs of failed deliveries will decrease.

The results from the ANOVA can in a next phase be used to price the different time slots. For example, selecting a narrow time slot will be more expensive than choosing a wider time slot. Pricing time slots can be either done statically or dynamically. Statically would mean that pricing rules would be determined based on the ANOVA results and that these rules would apply for every customer choosing a time window. If time slots are priced dynamically, this would mean that for every customer, a specific price would be calculated taking into account the real additional cost of adding this customer to the I-OP-VRP. Another line of future research is the incorporation of the environmental impact of

Table 5 Average increase in cost per customer for selecting a delivery time window (1)

Number of customers	Geographical spread		Time window width	
	Clustered	Random	2 h	4 h
50	4.06	4.72	6.6	2.18
100	2.40	3.54	4.55	1.38
150	1.84	2.85	3.61	1.08

Table 6 Average increase in cost per customer for selecting a delivery time window (2)

Number of customers	Clustered customers		Randomly spread customers	
	2 h	4 h	2 h	4 h
50	6.3	1.82	6.88	2.54
100	3.92	0.87	5.18	1.89
150	3	0.69	4.22	1.47

e-commerce deliveries in the analysis of varying time window policies. Finally, in the future a bi-objective modelling approach can explicitly incorporate the trade-off between costs and customer service, hereby relaxing the assumption that each customer receives the same time window width.

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Availability of data and materials
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Authors' contributions
SM developed the record-to-record travel algorithm to solve the integrated order picking – vehicle routing problem. TvG participated in setting up the design of the study, the experiments and the statistical analysis. KR and AC identified the research question, positioned the research in current literature, carried out the experiments, conducted the statistical analysis and interpreted the results. All authors read and approved the final manuscript.

Competing interests
The authors declare that they have no competing interests.

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References

1. EESC (2003) Industrial change: current situation and prospects - an overall approach. In: Technical report. European economic and social committee, Brussels
2. EESC (2014) Reshoring of EU industries in the framework of reindustrialisation. In: Technical report. European economic and social committee, Brussels
3. Hultkrantz O, Lumsden K (2001) E-commerce and consequences for the logistics industry. Technical Report. Department of Transportation and Logistics. Chalmers University of Technology, Göteborg
4. Ecommerce Foundation (2017) European ecommerce report 2017. Ecommerce Foundation, Amsterdam
5. Eurostat (2016) E-commerce statistics for individuals. Technical report. In: Eurostat
6. Ecommerce Europe (2016) European B2C E-commerce report 2016. Ecommerce Europe, Brussels
7. de Koster RMBM (2003) Distribution strategies for online retailers. IEEE Trans Eng Manag 50:448{457
8. van Gils T, Ramaekers K, Caris A, de Koster RBM (2018) Designing efficient order picking systems by combining planning problems: state-of-the-art classification and review. Eur J Oper Res 267:1–15
9. Moons S, Ramaekers K, Caris A, Arda Y (2017) Integration of order picking and vehicle routing in a B2C e-commerce context. Forthcoming in Flexible Services and Manufacturing Journal. https://doi.org/10.1007/s10696-017-9287-5
10. Suel E, Polak JW (2018) Incorporating online shopping into travel demand modelling: challenges, progress, and opportunities. Transp Rev 38(5):576–601
11. Crocco F, Eboli L, Mazzulla G (2013) Individual attitudes and shopping mode characteristics affecting the use of E-shopping and related travel. Transport and Telecommunication 14(1):45–56
12. Agatz N, Campbell A, Fleischmann M, Savelsbergh M (2011) Time slot management in attended home delivery. Transp Sci 45(3):435–449
13. Yang X, Strauss AK, Currie CSM, Eglese R (2016) Choice-based demand management and vehicle routing in E-fulfillment. Transp Sci 50(2):473–488
14. Klein, R., Neugebauer, M., Ratkovitch, D., Steinhardt, C. (Published Online: 20 Jul 2017). Differentiated Time Slot Pricing Under Routing Considerations in Attended Home Delivery. Forthcoming in Transportation Science, https://doi.org/10.1287/trsc.2017.0738.
15. Moons S, Braekers K, Ramaekers K, Caris A, Arda Y (2018) The value of integrating order picking and vehicle routing decisions in a B2C e-commerce environment, submitted to international journal of production research
16. Schubert D, Scholz A, Wäscher G 2017. Integrated order picking and vehicle routing with due dates, Working paper 7/2017. Otto-von-Guericke University Magdeburg, Magdeburg
17. Zhang J, Wang X, Huang K (2016) Integrated on-line scheduling of order batching and delivery under B2C e-commerce. Comput Ind Eng 94:280–289
18. Zhang J, Wang X, Huang K (2018) On-line scheduling of order picking and delivery with multiple zones and limited vehicle capacity. Omega 79:104–115
19. Mangiaracina R, Marchet G, Perotti S, Tumino A (2015) A review of the environmental implications of B2C e-commerce: a logistics perspective. International Journal of Physical Distribution & Logistics Management 45(6): 565–591
20. Ruben RA, Jacobs FR (1999) Batch construction heuristics and storage assignment strategies for walk/ride and pick systems. Manag Sci 45:575–596. https://doi.org/10.1287/mnsc.45.4.575
21. Petersen CG (2000) An evaluation of order picking policies for mail order companies. Prod Oper Manag 9:319–335. https://doi.org/10.1111/j.1937-5956.2000.tb00461.x.
22. Gong Y, de Koster R (2008) A polling-based dynamic order picking system for online retailers. IIE Trans 40:1070–1082. https://doi.org/10.1080/07408170802167670
23. Lu W, McFarlane D, Giannikas V, Zhang Q (2016) An algorithm for dynamic order-picking in warehouse operations. Eur J Oper Res 248:107–122. https://doi.org/10.1016/j.ejor.2015.06.074
24. Cárdenas I, Beckers J, Vanelslander T (2017) E-commerce last-mile in Belgium: developing an external cost delivery index. Research in Transportation Business & Management 24:123–129. https://doi.org/10.1016/j.rtbm.2017.07.006
25. Blauwens, G., De Baere, P., Van De Voorde, E., 2016. Cost calculation in a transport firm, In: Transport economics. 6th ed. De Boeck, Berchem. Chapter 5, pp. 172–187
26. VIL (2016) E-green. Technical Report. Vlaams Instituut voor de Logistiek, Berchem
27. Punakivi M, Saranen J (2001) Identifying the success factors in e-grocery home delivery. Int J Retail Distrib Manag 29:156–163. https://doi.org/10.1108/09590550110387953
28. Altarazzi SA, Ammouri MM (2018) Concurrent manual-order-picking warehouse design: a simulation-based design of experiments approach. Int J Prod Res. https://doi.org/10.1080/00207543.2017.1421780
29. Geisser S, Greenhouse SW (1958) An extension of box' results on the use of the F distribution in multivariate analysis. The Annals of Mathematical Statistics 29(3):885–891
30. Glass GV, Peckham PD, Sanders JR (1972) Consequences of failure to meet assumptions underlying the fixed effects analyses of variance and covariance. Rev Educ Res 42(3):237–288
31. Interactive Media in Retail Group, 2014. IMRG UK Consumer Home Delivery Review.