Urban logistics collaboration: Insights from the UK online food retail sector

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Abstract

The aim of this paper is to investigate efficiency gains from collaborative logistics in grocery last mile distribution. Using simulation and mathematical modelling we estimate the demand for home deliveries of groceries purchased online and investigate collaboration in the stem mile without and with four-hour time windows as well as the last mile distribution with one-hour time windows. Distance reduction owing to collaboration is 9% for the stem mile, 11% for the stem mile with four-hour time windows, and 23% for the last mile. We present detailed results on two scenarios: collaboration among two and three retailers.

Keywords: Logistics collaboration, grocery retail, UK

Introduction

Managing urban areas has become one of the most significant development challenges of the 21st century with an urban population having grown from 746 million in 1950 to 3.9 billion in 2014. Considering that the world's population in 2050 is projected to be 66% urban (UN, 2015) with 41 mega-cities having more than 10 million inhabitants by 2030, urgent attention on urban planning is required for easy access to education, healthcare, infrastructure and services. Transport is a key aspect of the smooth functioning of city life; especially urban freight transport with a significant impact on the quality of life in urban environments through traffic congestion, vehicle emissions, and noise pollution (Nathanail, Adamos, & Gogas, 2017).

Increased urbanisation has led to more people living in cities and therefore an increased demand for not only food products but also all goods to be transported to and distributed inside urban areas. The developments in information and communication technologies and the Internet have enabled new convenience services such as online shopping, using desktop computers and more recently mobile devices. Books, fashion items, flight tickets, and hotel bookings are the most frequently purchased goods and services over the Internet and the food sector have also benefited from increasing ecommerce. Retailers in many countries have made grocery purchase a service available to consumers online, at their convenience. Especially cash-rich, time-poor city dwellers have demonstrated a growing preference for shopping their groceries online and demanding their groceries to be delivered to their homes on their preferred day and time.

UK online grocery sector has seen a growth of 14.7% in 2016 reaching a market size of £9.992 billion (Mintel, 2017). Major retailers such as Tesco, Sainsbury's, Ocado, or Asda operate their own vehicle fleets to fulfil the home delivery demand from consumers. Due to the nature of the service, multiple and uncoordinated vehicles visit the same location at around the same time, increasing last mile distribution costs as well as the negative impact on the environment. An increased number of delivery vans also pose a societal challenge in terms of increasing traffic congestion and noise pollution as well as increasing likelihood of road accidents. The aim of this paper is to investigate efficiency gains from collaborative logistics in grocery last mile distribution under plausible collaboration scenarios.

To address this demand, retailers have developed their own logistics operation and have avoided collaborating with other retailers despite possible benefits such as cost savings from consolidating freight (Lozano, Moreno, Adenso-Díaz, & Algaba, 2013).

A co-opetition model in the Austrian grocery industry shows that all parties improve their profitability by sharing information and setting up business with value-adding partnerships proving that competition and collaboration can occur at the same time, even in the very competition-intense atmosphere of the grocery industry (Kotzab & Teller, 2003).

To extend our current knowledge of grocery logistics, we focus our work on the UK online grocery retail market and analyse existing urban distribution models. Due to its competitive nature, there is little logistics collaboration in this market, missing an opportunity to realise financial, operational, environmental or social benefits. The purpose of this paper is to propose collaborative logistics models for stem mile and last mile grocery distribution illustrating benefits in distance reduction across multiple scenarios.

Literature Review

The grocery retail sector in the UK is known for its severe competition (Hackney, Grant, & Birtwistle, 2006) where major retailers invest large sums in the online channel more than they did two decades ago. On the other hand, the sustainability of distribution operation is yet to be established for home deliveries of groceries bought via the online channel. This is mainly due to the high impact of the online channel on the physical network that fulfils the service demand together with stringent service parameters such as one-hour delivery windows and booking of deliveries in advance. Like other online retail services, online grocery purchase and the subsequent home delivery service change consumers' shopping habits. Convenience comes at an economic, environmental, and social cost in the form of higher prices, increasing CO_2 emissions, and additional congestion on the roads. This new way of shopping groceries affects online grocery retail revenue models as well as carbon emissions in the last mile distribution due to increased convenience through two dominant models in the market: pay-per-order and subscription-based delivery service (Belavina, Girotra, & Kabra, 2017).

Numerous factors such as drop density, distance, and vehicle type affect the emissions from home delivery services. Emissions from the average shopping trip of a consumer, particularly by private car, can be greater than emissions from all upstream logistical activities (Edwards, McKinnon, & Cullinane, 2010). On the other hand, emissions from delivery vans can be reduced if it is possible to combine the deliveries over spatially and temporally comparable grocery orders. In that respect, a classic combinatorial optimisation problem, vehicle routing, has become a key aspect of managing distribution operations (Wei, Zhang, Zhang, & Leung, 2017).

The vehicle routing problem (VRP) domain is rich with many extensions including but not limited to capacitated VRP, VRP with time windows, or VRP with pickup and deliveries. VRP is a generalisation of the travelling salesperson problem (TSP) where the number of destinations visited is also a function of the vehicle capacity (Dantzig & Ramser, 1959). On the other hand, TSP determines the shortest route that passes n locations, only once. When each pair of locations are linked, the total number of routes through n locations is $1/2 \times n!$; a number that grows very large and very fast: the total number of possible routes for 10 locations is 1,814,400. TSP is generalised to VRP by imposing capacity constraints that are smaller than the total demand of all locations to be visited. In that case, multiple vehicles are needed to satisfy the total demand in the service area.

In fact, the retailer's physical network characterised by the density, size, and location of stores affects not only operating costs but also environmental costs (Cachon, 2014). It has been a long debate whether consumers' travelling to stores causes higher carbon emissions than retailers' delivering orders to consumers' homes. The answer is not straightforward as it is affected by not only the store network, but also the shopping preferences and the shopping frequency of consumers. The store network could comprise *few and far away* stores where the journey to the store takes a significant travel distance and time or *many and nearby* stores where the shopping trips are shorter. Consumers may perceive shopping as a leisure time activity and allocate several hours of travel and shopping time on a regular basis or as a chore that has to be done quickly and at minimum cost.

Currently online grocery retail firms do not actively engage in anticipating, experimenting, or determining which consumer expectations might result in a competitive advantage (de Kervenoael, Yanık, Bozkaya, Palmer, & Hallsworth, 2016), consequently preventing them from considering logistics service as an integral element of their value-added service. This is the gap we are addressing in this paper by showing theoretical gains from logistics sharing whilst competing in other core parts of the business.

Methodology

We present the conceptualisation of the online grocery distribution in Figure 1 with three collaborative logistics models:

i) <u>*Business Model 1:*</u> shared vehicles for last mile (i.e. the distance travelled from a local hub to a consumer's residence),

ii) <u>*Business Model 2:*</u> shared vehicles for stem mile (i.e. the distance travelled from a picking location to a local hub),

iii) <u>*Business Model 3:*</u> shared vehicles for stem mile based on time windows (four time intervals: A) 8:00-11:59, B) 12:00-15:59, C) 16:00-19:59 and D) 20:00-23:59). Based on the primary data set and a survey, we generated the demand for grocery deliveries using the following ratios: 19.7% for time window A, 20.6% for time window B, 36.8% for time window C and 22.8% for time window D.

We propose using micro hubs located in residential areas as a cross-docking facility for the last mile distribution or as a short-term (maximum four hours) storage facility for click and collect services. Large flows from picking locations of retailers are transported to micro-hubs in residential areas, and then the last mile distribution is performed in line with promised time windows. Three flows conceptualised in the UK Pilot are: 1) large flows from picking locations to micro-hubs, 2) small flows from micro-hubs to consumers' addresses with time window constraints, and 3) small flows with space and time window constraints where consumers collect their orders.

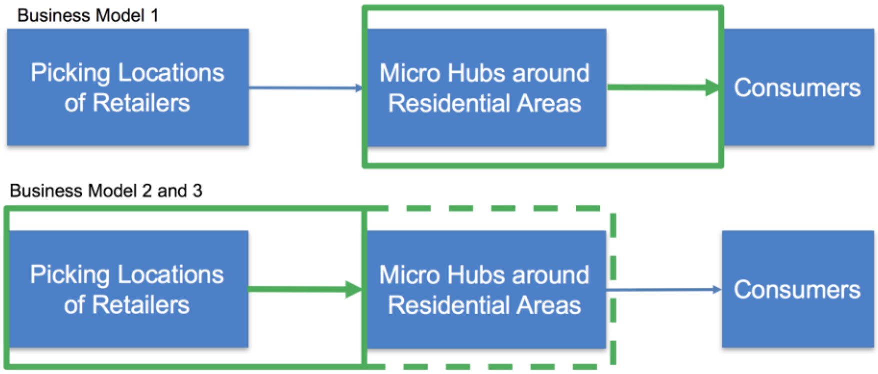

Figure 1 – Logistics Flows in Home Deliveries of Groceries

In modelling the grocery last mile distribution, we have an integrated two stage methodology to test the potential benefits of collaboration: demand estimation and capacitated vehicle routing problem. In the demand estimation stage, we generate daily grocery orders to be delivered in postcode sectors of London. In the second stage with the capacitated vehicle routing problem, we solve the daily grocery order delivery problem with the minimum distance in the objective function. We design experiments based on vehicle capacity (four capacities tested) and picking location (two locations tested) and logistics operation (independent and collaborative) among two or three hypothetical retailers, the data of which are informed by both primary and secondary data.

Our work is informed by primary data from an online grocery retailer (Retailer R) operating in London. The data is a summary of the average number of orders per postcode over one year. Specifically, it includes 346,745 transactions from 01/06/2014 to 31/05/2015 and shows the daily distribution of grocery orders and peaks on Fridays and Mondays. Since this is the only primary data, we use secondary data from publications, reports, and websites of retailers as explained in Table 1 to design an analysis framework with the same spatiotemporal data from more than one retailer that can demonstrate the likely benefits such as distance and delivery time reduction owing to logistics collaboration.

Table 1 – Data and Sources Used in This Paper

Data	**Source**
UK Online Grocery Market Size and Share	Mintel
Average basket size	Retailers' reports and industry knowledge
UK Population	ONS
Retailer store footprint	Websites of retailers
Demand seasonality	Primary data of Retailer R1
Postcode sectors	Primary data of Retailer R1

We ran Monte Carlo simulation for home delivery demand estimation and solved vehicle routing problems to estimate gains from logistics collaboration in the stem mile and the last mile distribution of groceries.

We simplify the UK online grocery market to:

a) central picking locations of retailers (stores, dark stores, distribution centres, dedicated online fulfilment centres),

b) micro hubs near consumers (one micro hub per postcode sector where 12,381 postcode sectors exist in the UK with 6,979 residents on average in 2011), and

c) consumers' locations (postcodes in the postcode sector).

We also use the latitude and longitude of postcode sectors in our distance calculations for the vehicle routing problem. Postcodes in the UK are alphanumeric references comprising an outward code of 2-4 characters and an inward code of three characters. The postcode is structured hierarchically, supporting four levels of geographic unit: postcode area (124), postcode district (3,114), postcode sector (12,381), and building postcode (approximately 1.75 million). We limit our area of analysis to 265 postcode sectors in London, for which we have primary data (Figure 2).

Figure 2 – Map of London; Study Area Shaded in Grey

To evaluate the three flows identified in the Introduction section, ideally, we need grocery demand and distribution data from multiple retailers operating in the same geography over the same period. It proved to be extremely difficult to retrieve this primary data from retailers operating in our pilot city: London. Hence, we revert to secondary data sources and apply a demand estimation methodology that takes as input the total annual demand for grocery orders and produces the output of daily grocery orders per postcode sector for home delivery. This demand estimation methodology comprises six steps as follows:

1. Estimate the UK online grocery market size from published sector reports.
2. Apportion market size in line with the market share of retailers that offer online grocery service.
3. Calculate number of orders per capita considering the UK population.
4. Assess store footprint of each retailer by postcode area.
5. For each postcode sector generate the number of online orders based on population and store footprint (e.g. size of store, consideration of industrial / residential mix per postcode).

6. Run a Monte Carlo simulation to distribute the annual number of orders to days of the year based on the seasonality distribution of Retailer R1.

In *Step 1*, we find from Mintel that the total grocery market size of the UK is £8.65B in 2015, which is the year comparable to the primary data from Retailer R1.

In *Step 2*, we apportion the grocery sales to six major retailers (Tesco, Sainsbury's, Asda, Ocado, Waitrose, and Morrisons) that comprise 85% of the online grocery market in the UK in 2015.

In *Step 3*, we identify the average basket size for each retailer from their annual reports and other publicly available data to estimate the number of grocery home delivery orders / year. With an average basket size of £101.37, the total number of grocery orders / year in the UK is 85,321,786. To estimate the annual grocery orders / postcode sector we use the UK census in 2011 and the population projection for 2015. This then informs the population per postcode sector to estimate the annual grocery home delivery orders / postcode sector.

A novelty of our approach is to incorporate the store footprint of retailers as an estimator of home delivery orders of groceries in *Step 4*. We assess the store footprint of retailers based on the types of stores and the distribution of stores in the postcode sector. The types we consider are large, standard, small, convenience, and filling stations stores (smallest store format in gas stations). We set the sales of a standard store to 1 and assume a large store sells 75% more than the standard store, whereas a small store sells 50% less than the standard store. The corresponding indices for convenience and filling station stores are 7% and 5%, respectively.

In *Step 5* we take a weighted contribution of population and store footprint per postcode sector to estimate the annual grocery home delivery orders. We assign the weights of population and store footprint to minimise the estimation error with the primary data of Retailer R1. The optimum weights for population and store footprint are 50% and 50%, respectively, with a mean absolute percentage error of 47.8%.

As the *Step 6* implies, we use Monte Carlo simulation to incorporate the uncertainty in grocery orders into our analysis framework. The simulation model is deterministic (Kleijnen, 2015) in the sense that the total number of grocery orders / year is fixed, but the exact values of its inputs (when the orders will be placed across the year – the daily grocery delivery demand) are uncertain so these values are sampled from a prior input distribution (empirical seasonality distribution from primary data of Retailer R1) through Monte Carlo methods run on MATLAB. Monte Carlo simulation is a commonly used technique to assess the impact of uncertainty in input parameters on the variability of the outputs from the system. In this case, the demand is the most critical uncertain element that governs the grocery distribution operation.

The output of this model is the annual online grocery demand for each of the six major retailers based on postcode sector. We assess the performance of our demand generation model based on the primary data set to minimise the estimation error. We also developed a consumer survey to examine the preferences for days of the week and times of the day to receive the grocery delivery. We conclude that it is realistic to use the demand distribution from the primary retailer for our collaboration scenario.

In a capacitated vehicle routing problem, the main inputs are customers, a depot, the distances between all locations, demand, and vehicle capacity. Let N be the set of customers, $N = \{1, 2, \dots, n\}$ and let 0 denote the depot. Then the set of all locations is denoted by P, where $P = N \cup 0 = \{0, 1, \dots, n\}$. An undirected graph $G(P, E)$ denotes the edges between the set of all points in P. For each edge, an associated travel cost c_{ij} is defined, and it can correspond to the distance from point i to point j, $\forall\, i, j \in$

P. K denotes the fixed number of identical vehicles (size of fleet) in the depot 0, each with a capacity C, measured in the same unit as the demand d_i of customer i. The binary decision variables x_{ij} take the value 1 if the vehicle travels from point i to point j, otherwise zero. The continuous decision variables u_i are used to eliminate subtours and bounded between the demand of the customer and the capacity of the vehicle. Then, the capacitated vehicle routing problem can be formulated as follows:

$$\min Z = \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij} \qquad i \neq j \tag{1}$$
$$\sum_{i=0}^{n} x_{ij} = 1 \qquad \forall j \in N \tag{2}$$
$$\sum_{j=0}^{n} x_{ij} = 1 \qquad \forall i \in N \tag{3}$$
$$\sum_{j=1}^{n} x_{0j} \leq K \tag{4}$$
$$u_j - u_i + C * x_{ij} \leq C - d_i \qquad \forall i \in N, \forall j \in N, i \neq j \tag{5}$$
$$d_i \leq u_i \leq C \qquad \forall i \in N \tag{6}$$

Equation (1) is the objective function, which minimises the cost of deliveries depending on the distance. Equations (2) and (3) ensure each customer is visited once, each vehicle visiting a customer also leaves the customer. Equation (4) is the bound on the total number of vehicles to be used (or it is the minimum possible number of routes (Uchoa et al., 2017)). Equation (5) is the subtour elimination to achieve a single connected tour from the depot location to the customers on the route. In other words, the inequalities involving u_i eliminate tours that do not begin and end at depot 0 (Miller, Tucker, & Zemlin, 1960). Finally, Equation (6) sets lower and upper bounds on the subtour elimination variable u_i. We run the above capacitated vehicle routing model for Business Models 2 and 3, and a modified version of this model which incorporates time windows for grocery deliveries to analyse the benefits from collaboration in Business Model 1.

We used the design of experiments to derive valid statistical inferences from our experimental observations. In these experiments, we made purposeful changes to the input variables of the grocery home delivery system and observed their impact on the benefits from logistics collaboration. We follow the factorial design where each complete trial of the experiment investigates all possible combinations of the levels of the factors (Montgomery, 2013). We consider picking locations, vehicle capacity, and logistics operation as the factors that affect the distance travelled to fulfil home deliveries of groceries purchased online. Table 2 shows the levels of each factor.

Table 2 – Design of Experiments

Business Model	Picking Locations	Vehicle Capacity (orders)	Postcode Sectors	Time Windows	Logistics Operation
Business Model 1	West, North, Centre-West, Centre-East (4)	15 and 20	2	18	Independent (As-Is) (3 retailers) and Collaborative (3 scenarios)
Business Model 2	West and North (2)	10, 15, 20, and 25 orders (4)	265	1	Independent (As-Is) (2 retailers) and Collaborative (1 scenario)

Business Model	Picking Locations	Vehicle Capacity (orders)	Postcode Sectors	Time Windows	Logistics Operation
Business Model 3	West and North (2)	15 and 20	265	4	Independent (As-Is) (2 retailers) and Collaborative (1 scenario)

We ran the mathematical models explained in the Methodology section for each picking location, for each capacity, for each logistics operation, and for each day. We identify three scenarios for four hypothetical retailers:

1. Scenario A: Retailers 1 and 2 collaborate (total market share of 16%).
2. Scenario B: Retailers 3 and 4 collaborate (total market share of 19%).
3. Scenario C: Retailers 1, 2, and 4 collaborate (total market share 20%).

In Business Model 1, we focus on two postcode sectors: N19 3 covering the areas of Upper Holloway, Archway, Tufnell Park, Hornsey, Islington with approximately 5,827 households and a population of about 13,309 (2011 census) and N17 6 covering the areas of Tottenham, South Tottenham, Haringey with approximately 7,568 households and a population of about 19,968 (2011 census). In Business Models 2 and 3 we consider 265 postcode sectors for which we have primary and secondary data for demand estimation. The number of vehicle routing problem instances we ran for each business model is given in Figure 3 totalling to 40,768.

Instances	Scenario A (R1 & R2):	Scenario B (R3 & R4):	Scenario C (R1 & R2 & R4):
Business Model 1	364*3*2*2 = 4,368	364*3*2* = 4,368	364*4*2*2 = 5,824
Business Model 2	364*3*4*2 = 8,736		
Business Model 3	364*3*2*2*4 = 17,472		

Figure 3 – Problem Instances Based on the Design of Experiments

Findings

We evaluated our models based on total distance covered by the retailer, first under the base case where retailers work independently (As-Is situation) and then under the proposed collaboration models (To-Be). When all scenarios are considered together, the total distance savings are 23% for Business Model 1, 9% for Business Model 2, and 11% for Business Model 3. Table 3 presents distance savings in both postcode sectors under the three scenarios investigated with an average distance reduction of 24% for a vehicle capacity large enough to fit 10 orders per route. The savings average 22% for a vehicle with 15 orders per route.

Table 3 – Business Model 1 Distance Savings

	Two Retailers (16%)		Two Retailers (19%)		Three Retailers (20%)	
	Islington	Tottenham	Islington	Tottenham	Islington	Tottenham
Capacity = 10	13%	19%	19%	23%	37%	33%
Capacity = 15	8%	19%	23%	23%	21%	35%

The results for Business Model 2 are given in Figure 4. The difference between the two picking locations is evident for small vehicles whereas it tends to diminish with increasing vehicle size (25 orders).

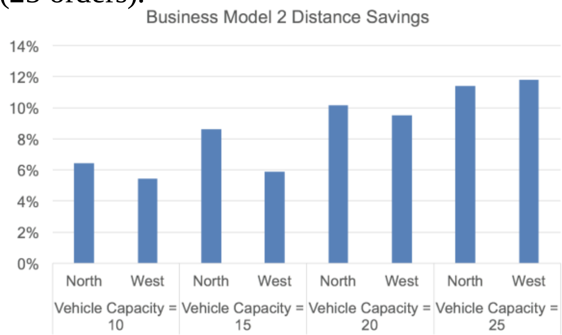

Figure 4 Distance Savings in Business Model 3

Distance savings in the case of Business Model 3 are captured in Figure 5. The North Picking Location is serving 198 postcode sectors whereas the West Picking Location is serving 67 postcode sectors. The impact of size is reflected on all time windows with an average reduction of 16%.

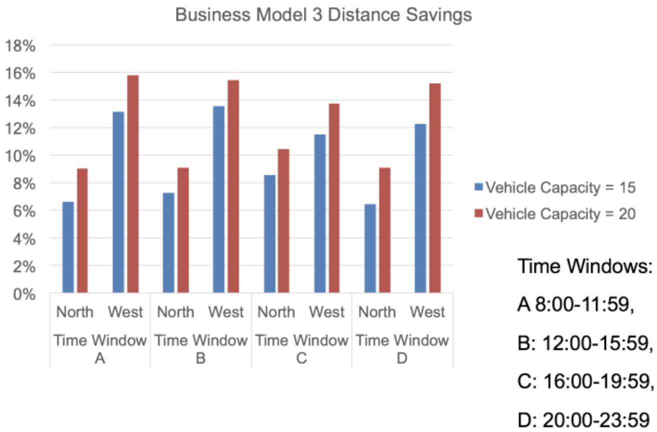

Figure 5 - Business Model 3 Distance Savings

Conclusion

Emerging convenience services such as online shopping enable people to shop online almost anything, including groceries. Online grocery purchase and delivery services are recognised as a key offering by major retailers in the UK. Unfortunately, the fierce competition and the constant requirement to 'delight the customers' has resulted in retailers' having their own fleets to satisfy the consumers' home delivery demand with inevitable inefficiencies in the distribution operation.

In this paper, we focus on the last mile delivery of groceries purchased online and investigate the benefits of logistics collaboration among retailers. Our methods comprise grocery demand estimation based on Monte Carlo Simulation and Mathematical Modelling recognised as the capacitated vehicle routing problem (with time windows) in the literature. Our approach is comparing the base case where each retailer operates their own fleet with a theoretical case where retailers collaborate.

We considered the UK online grocery market and how the online retailers could improve their operational efficiency in logistics if they collaborate with their competitors. Our results suggest that it is theoretically possible for the online UK retailers to reduce logistics costs through collaboration. To our knowledge, this is a unique contribution in relation to logistics collaboration for the UK online grocery market. However, implementation of a collaborative model still poses several challenges due to the extremely competitive nature of the food retail market. Potential extensions of our work are to define the ideal locations for the hubs, and examine cost, energy, and emission savings for different groups of collaborating retailers.

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