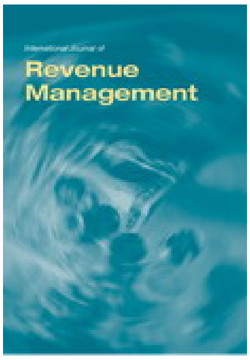

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Upselling at delivery

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Abstract: The COVID-19 pandemic has accelerated an already increasing migration from in-store to online shopping. For retailers with products conducive to upselling and cross-selling, this type of disruption can have a substantial impact on sales volume and revenue generation. One approach that has been proposed to improve a firm's resilience is to move up-/cross-selling efforts to the delivery personnel, since that is where direct contact with the customer occurs. Therefore, the purpose of this research is to formalise the 'driver becoming salesperson' strategy, and to integrate this concept with the routing of delivery vehicles for the most-efficient last-mile delivery. A mixed-integer formulation of the problem as well as bounds on the solution is provided. The resulting model is analysed with several solution procedures, a numeric experiment is conducted to illustrate the process of identifying potential upselling product to load onto the delivery vehicles, and managerial implications are presented.

Keywords: retailing; last-mile delivery; upselling; cross-selling; pantry loading; vehicle routing; time windows.

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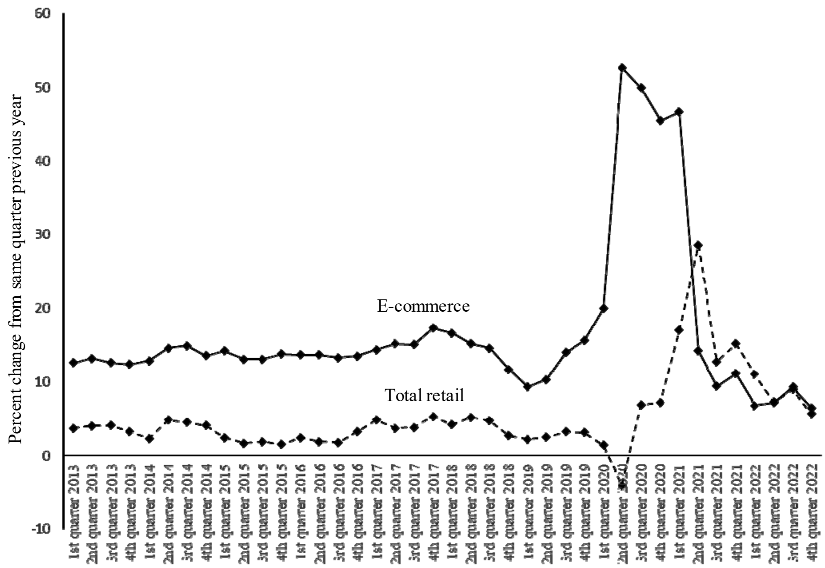
1 Introduction

Upselling and cross-selling are well-established sales tools and are considered to be some of 'the most useful tools in a salesperson's toolbox when it comes to increasing sales volume per customer' (Kamakura, 2007). Blattberg et al. (2008) note that upselling and cross-selling can increase both current and future revenue as well as increasing customer satisfaction and retention. This approach involves selling complementary product in conjunction with the item the customer is purchasing (cross-selling), upgrading the purchase of an item to a more-expensive product (upselling), or selling more units of the item being purchased (pantry loading). For example, the salesperson may recommend an adjustable bed frame to go with that mattress purchase or may suggest the customer consider a premium mattress.

The retail landscape has obviously been undergoing substantial changes with the increased adoption of online shopping (Figure 1). From 2013 through 2019, quarterly US retail sales increased (change from same quarter previous year, seasonally adjusted) an average of 3.3% while e-commerce sales grew an average of 13.7% (U.S. Census Bureau, Retail Indicators Branch, 2023). The COVID-19 crisis has further accelerated this trend. Many retailers that had not previously relied on e-commerce sales must now contend with an increase in online shopping. There was a 4.1% decrease in total retail sales for the second quarter of 2020, but a 52.7% increase in e-commerce. Total retail sales have rebounded since that time, but preliminary estimates show e-commerce sales again growing at a slightly higher rate. A survey by PricewaterhouseCoopers (Garg et al., 2020) recognised the significant increase in online shopping due to the pandemic and indicated that many consumers will continue to load their pantry at these levels.

While up-/cross-selling can be done online to some extent (e.g., suggesting items the customer may also purchase), the lack of physical contact makes it difficult for many retailers. Putting information and product in front of consumers remains the strongest way to reach shoppers and convert them into consumers (Robinson, 2019). Arora and Sahney (2018) mention that lacking the ability to touch and feel the product inhibits better product evaluations and that visits to a physical store can reduce customers' uncertainties and increase their confidence in the purchase. Dzyabura et al. (2019) find that large discrepancies can exist between customers' evaluations of products when physically examining them versus their evaluations based on online descriptions. Gauri et al. (2020) note that "some retailers have shown they can increase the conversion rate ten times and increase the average order value by 50% when an online customer directly connects with a store associate for assistance". Some online retailers have opened physical stores or showrooms 'such that customers can experience and obtain shopping advice from the salespeople' (Zhang et al., 2020). In a discussion of how the COVID-19 pandemic may change the world of retailing, Roggeveen and Sethuraman (2020) note 'consumers are also likely to become accustomed to new ways of shopping. For example, online grocery shopping with home delivery is likely to become more common place. Grocers will then need to determine how to make the online shopping more similar to in-person shopping such that it will encourage impulse purchases'.

Figure 1 US retail sales growth



Source: U.S. Census Bureau, Retail Indicators Branch (2023), fourth quarter 2022 preliminary estimate

Therefore, a number of logistics providers and practitioner-oriented publications have indicated that up-/cross-selling may move to delivery personnel for many retailers, as that is where direct contact with the customer occurs (several of these are listed in Appendix A). 'The concept of a mobile warehouse is gaining steam. The fulfiller can load non-committed inventory into delivery trucks, allowing drivers to upsell during the delivery process' (Kaplan, 2017). 'Drivers will become merchants, selling items from trucks' (Robinson, 2019). Analytics are already in place to predict upselling, cross-selling, and potential pantry loading; for example, Blattberg et al. (2008) discuss next-product-to-buy (cross-selling) models as well as models to evaluate the upselling potential of a customer. Therefore, retailers can determine which non-committed items are most likely to lead to additional revenue and load those on the delivery vehicle in addition to the originally-ordered product. This approach would be most amenable to items with fairly high value and with 'non-digital' attributes (a term coined by Lal and Sarvary, 1999) for which physical inspection of the item is necessary.

A number of retailers have already embarked on this type of strategy. Companies are currently utilising delivery drivers that can upsell products as diverse as bottled water, consumer electronics, replacement doors and windows, and even cannabis; a list of companies that have recently placed advertisements for this type of position is presented in Appendix B. Although some couriers claim to be able to upsell for their clients (Zendfast, 2021), this is likely best served by a company's own drivers, since knowledge of the product and relationship with the customers is important. Up-/cross-selling have evolved into a strategy for customer relationship management, and its effective implementation is reliant on a comprehensive customer database detailing activities of each customer (Kamakura, 2007).

The last mile of a business-to-consumer (B2C) sale is currently regarded as one of the more expensive sections of the delivery process (Gevaers et al., 2014). Thus, vehicle routing has become of ever-increasing importance with the accelerated move to e-commerce in identifying efficient delivery routes. As noted by Vidal et al. (2020), "the diversity of applications has motivated the study of a myriad of problem variants with different attributes". Despite the adoption of upselling at delivery with practitioners, incorporating upselling into the vehicle-routing (or last-mile delivery) process has yet to be examined in the research literature. There is a family of vehicle-routing models 'with profits' (Archetti et al., 2014) including the capacitated prize-collecting vehicle-routing problem; however, these models assume that not all customers have to be served.

Therefore, the purpose of this research is to investigate the new normal of retailing by formalising the 'driver becoming salesperson' strategy, and integrating this concept with the routing of delivery vehicles for the most efficient last-mile delivery. The need for a resilient logistics system is vital for online retailers to be able to respond quickly to ongoing disruptions to their operations. We present a mixed-integer formulation of the proposed problem and provide bounds on the solution. A variety of solution methodologies are discussed, and a numeric experiment is conducted to illustrate the process of identifying product to load onto the delivery vehicles for potential upselling/cross-selling/pantry loading. An extension to incorporate time windows is then analysed, which may be particularly relevant to the upselling process. Managerial implications of putting this concept into practice are also presented. We close the paper with a summary as well as various directions for future research.

2 Literature review

Despite the persistent calls for the 'driver becoming salesperson' retail strategy (again, see Appendices A and B), there is no academic research that directly investigates it. A comparable 'bring service near your home' strategy has been proposed by Choi (2020) for the service-operations industry (a private music school), but does not address the retail issues under consideration. Thus, this is not a traditional literature review that extensively summarises and critiques what has already been done in the area, but more of a review of recent research that conveys the evolution toward and justification of such a strategy. We then close this section with a review of the vehicle-routing problem in online retailing, particularly as it relates to last-mile logistics.

The move to online retailing, particularly since the onset of the COVID-19 pandemic, has likely affected the vast majority of retailers, even those with products that are not amenable to online sales. Bell et al. (2014) provide a framework for retailers concerning how the customers get their information to facilitate their purchase decisions (offline vs. online) and how the transaction will be fulfilled (at the store or delivered), ranging from traditional retail (offline/at the store) to pure-play e-commerce (online/delivered). They note that providing information to their customers online is most suited to products containing few, if any, non-digital attributes which can only be evaluated through physical inspection. Traditional brick-and-mortar retailing – providing information and fulfilling orders inside the store – works well for products with non-digital attributes; however, in an omnichannel retail environment, customers may choose to obtain their information remotely and/or to have the items delivered, simply for convenience or for social-distancing purposes during a pandemic.

One approach that some traditional retailers have adopted is the 'buy online, pickup in store' (BOPS) initiative, in which the customer places the order online, but gets the item at the store rather than have it delivered. Zhang et al. (2019) indicate that a retailer should choose this approach for products with high value and a low degree of customer acceptance of the online channel. Gallino and Moreno (2014) note that BOPS orders result in additional foot traffic to the store with increased brick-and-mortar sales due, to some extent, to cross-selling opportunities. On the other hand, Gao and Su (2017) state that customers initiating an online order but finding that the item is out of stock may result in the customers not visiting the store, thereby reducing foot traffic and cross-selling opportunities. Song et al. (2020) indicate positive effects of BOPS usage were found on the frequency of offline purchases and on the amount of online purchases. Recent studies have investigated the effect of BOPS on price and quality decisions (Lin et al., 2021), on inventory decisions (Saha and Bhattacharya, 2020), and on the decision to ship from stores instead of warehouses (Bayram and Cesaret, 2021).

One approach that some online-first retailers have adopted is to establish an offline showroom, (i.e., a physical location) where customers can visit to experience the product and place the order, yet still have the items delivered to their homes. Bell et al. (2018a, 2020) find that this may help with demand generation as well as operational efficiency for the retailer. Park et al. (2021) provide "a framework to measure and maximize the expected showcasing utility for a retail store". Fan et al. (2021) utilise a game-theoretical model to evaluate whether the physical channel should be a pure showroom or a selling store. Li et al. (2020a) evaluate the impact on pricing and information service provision from the deployment of a showroom. Li et al. (2020b, 2022) investigate various strategies within a supply chain with asymmetric information. Bell et al. (2018b) note that some traditional retailers are taking notice and replacing large stores with smaller showrooms. Some retailers have extended the concept of a showroom to a temporary store, or pop-up shop (see for example, Henkel and Toporowski, 2021).

Where the difficulty comes in – from an up-/cross-selling perspective – is that both of those approaches (buy-online-pickup-in-store and offline showrooms) require the customer to physically visit the store or showroom. For convenience and for physical distancing during a pandemic, customers are increasingly choosing the pure-play e-commerce transaction (online purchase with delivery). As mentioned previously, though, this is not conducive to the purchase of products with non-digital attributes. Consequently, the driver-becoming-salesperson approach has been identified as a method of maintaining customer convenience by allowing the customer to experience the entire purchase process at home – with online ordering and delivery to the home – while still experiencing the product before finalising the purchase.

Another issue with pure-play e-commerce is that of product returns. The online shopping channel has a 'higher likelihood of costly product returns when customers' ability to 'touch and feel' products is important in determining fit' (Ofek et al., 2011). Bijmolt et al. (2021) note that product returns is a 'key decision area that benefits from an integrated marketing-operations perspective'. They indicate that online retailers invest heavily in the management of product returns, specifically in return prevention (the likelihood of incurring returns) and return processing (the efficiency of dealing with the actual returns). The driver-becoming-salesperson approach can reduce the likelihood of returns by allowing the customer to experience the product before purchase. This approach may also be utilised for return processing (rather than have the customer simply mail back the return) which would provide additional opportunities for up-/cross-selling.

Although the traditional vehicle-routing problem (VRP) can be used in various retail situations, it has recently been generalised to account for the characteristics inherent in online retailing. Abdulkader et al. (2018) analyse an omnichannel retailer where customers can purchase in store or online, coordinating two distribution systems – one from the warehouses to the retail stores and another from the stores to the customers – using the same set of vehicles. Jiang and Li (2021) further integrate the two distribution systems such that the retailer must decide which warehouse should be assigned to each customer order, how to consolidate orders to stores, and how to route customers' orders while meeting their service time window promises. Janjevic et al. (2021) extend this to a three-echelon system 'incorporating multiple delivery services, product exchange options, and last-mile transportation'.

Paul et al. (2019) consider the 'buy online, pickup in store' approach where the pick-up point for the online orders is in the same store where customers shop; they apply the VRP to jointly plan the supply of the pick-up points and the store's inventory replenishment. Some retail deliveries require products to be maintained at different temperatures – for example, grocery deliveries may have frozen, chilled, and room-temperature requirements – so the VRP has been generalised to utilise multi-compartment vehicles (Hübner and Ostermeier, 2019). Due to the inefficiencies in retail deliveries, such as low asset utilisation and repeated trips to nearby neighbourhoods, Aktas et al. (2021) use the VRP to measure potential benefits when online retailers collaborate in the last-mile delivery services.

Another application of the VRP to retail logistics is the routing of unmanned aerial vehicles (UAVs, or drones) in the last-mile delivery to the customer. Macrina et al. (2020) provide a review of the travelling salesperson problem and the vehicle routing problem in this context, and further classify the literature into models where only drones perform the deliveries or where synchronised vehicles and drones both do so. Additional reviews are provided by Madani and Ndiaye (2022) and Zhang et al. (2023) which classify the literature by problem formulation and solution methods. Rather than having the drone deliver directly to the customer, Dayarian et al. (2020) present a model in which drones resupply the vehicles that, in turn, deliver to the customer.

As noted above, however, none of these studies address the 'driver becoming salesperson' strategy. Thus, we now turn our attention to the design of the last-mile logistics operations to incorporate upselling at delivery.

3 Model

The model under consideration is an extension of the classic capacitated vehicle routing problem which identifies the most-efficient routes for delivering product to customers. The generalisation we consider is to decide whether additional, non-committed inventory should be delivered to the customer. The driver would then be responsible for up-/

cross-selling this product to the customer. Due to the fallout from the COVID-19 pandemic, we include the possibility of pantry loading in addition to upselling and cross-selling. From a supply-chain perspective, pantry loading is generally considered detrimental because of the resulting bullwhip effect, but may now be beneficial as it may result in fewer trips that would need to go to the customer.

3.1 Formulation

There are several approaches to the formulation of vehicle-routing problems, including set-partitioning, vehicle-flow, and commodity-flow formulations (Laporte, 2009). The basis of our model is the capacitated vehicle-routing problem (CVRP) as presented by Toth and Vigo (2002). This particular formulation includes a measure of the load of the vehicle, which is necessary when deciding on which additional, non-committed inventory to load onto the vehicle for potential upselling/cross-selling/pantry loading.

In this formulation, an undirected graph $G = (V, E)$ is given, where $V = \{1, 2, \ldots, n, n + 1\}$ is the set of nodes representing the customers (nodes 1, 2, …, n) and the depot (node $n + 1$), and E is the set of edges with non-negative costs, c_{ij} (i.e., the variable delivery cost, likely based on distance, to travel from node i to node j, $\{i, j\} \in E$). Each of the n customers has placed an order requiring q_i units of vehicle capacity, and m identical vehicles are available, each with Q units of capacity. The objective is to minimise the delivery cost to all customers, $\Sigma_{i\in V}\Sigma_{j\in V}c_{ij}x_{ij}$, where $x_{ij} = 1$ if a route includes the edge from node i to node j, $x_{ij} = 0$ otherwise, and y_i represents the load of the vehicle after visiting customer i. The CVRP formulation is as follows:

$$\text{Minimise} \sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij} \tag{1}$$

$$\text{Subject to:} \sum_{j\in V} x_{n+1,j} = m \tag{2}$$

$$\sum_{j\in V} x_{i,n+1} = m \tag{3}$$

$$\sum_{i\in V} x_{ij} = 1 \qquad \text{for all } j \in V \setminus \{n+1\} \tag{4}$$

$$\sum_{j\in V} x_{ij} = 1 \qquad \text{for all } i \in V \setminus \{n+1\} \tag{5}$$

$$y_i - y_j + Qx_{ij} \le Q - q_j \qquad \text{for all } i,\ j \in V \setminus \{n+1\},\ i \ne j; \text{ s.t. } q_i + q_j \le Q \tag{6}$$

$$y_i \ge q_i \qquad \text{for all } i \in V \setminus \{n+1\} \tag{7}$$

$$y_i \le Q \qquad \text{for all } i \in V \setminus \{n+1\} \tag{8}$$

$$x_{ij} = \{0, 1\},\ x_{ij} = 0 \qquad \text{for all } i \in V \tag{9}$$

$$y_i \ge 0 \qquad \text{for all } i \in V \setminus \{n+1\} \tag{10}$$

The objective (1) is to minimise the total delivery cost. Constraints (2) and (3) ensure that m vehicles leave from and return to the depot, respectively. Constraint sets (4) and (5) ensure that exactly one vehicle serves each customer. Constraint sets (6) through (8) are the classic Miller-Tucker-Zemlin (Miller et al., 1960) subtour elimination constraints, modified for the vehicle-routing problem, that impose the capacity requirements.

We now generalise this model to determine how much of the vehicle we should allocate for unordered inventory. Each customer has an existing order of a certain size, but some will have the potential for purchasing additional product, either purchasing a more-expensive item of that ordered (upselling), purchasing other related items (cross-selling), or purchasing additional units of the product already ordered (pantry loading). So for each customer, not only do we have the item ordered and the corresponding capacity used by it, we also have a set of options that includes all potential upselling/cross-selling/pantry loading combinations (so only one will be selected) along with the capacity of the vehicle that is used, the likelihood of making the sale, and the incremental contribution to profit of each. As mentioned in the Introduction, analytics have been developed to predict the sale probability and profit contribution for potential upselling, cross-selling, and pantry loading, so the required information will be readily available.

To illustrate, suppose a customer has placed an order from the hardware store for a corded-electric chainsaw. We assume that we will deliver that item to avoid the perception of bait-and-switch. But we could also sell the customer a 50-foot extension cord (cross-sale, with probability of sale, incremental unit profit, and vehicle capacity used) or an upgraded battery-powered chainsaw (upsale, again with probability of sale, incremental unit profit, and capacity used). If the battery-powered chainsaw is sold, we may also sell a replacement battery (with a different probability of sale, incremental unit profit, and capacity used). So the set of options would include the combinations of the upgraded chainsaw and the two accessories, each with an associated incremental expected profit contribution and vehicle capacity required:

1 50-foot extension cord

2 battery-powered chainsaw

3 battery-powered chainsaw and replacement battery

4 50-foot extension cord and battery-powered chainsaw

5 50-foot extension cord, battery-powered chainsaw, and replacement battery.

Note that there is no need to have the replacement battery without the battery-powered chainsaw, so those combinations need not be considered. Also note that, for options 4 and 5, we will not be selling everything loaded on the vehicle – in fact, we may not sell any of the five options – and we may not even sell the originally-ordered item if another item is upsold. Still, we will want to load whatever the customer may purchase as long as there is room in the vehicle. So for this customer, we have five potential up-/cross-sell options, $L_i = \{1, 2, \ldots, \ell, \ldots, |L_i|\}$, from which at most one will be selected to be placed on the delivery vehicle, each with an associated expected incremental contribution to profit, $p_{i\ell}$ and required amount of capacity, $r_{i\ell}$. Thus, we define a new set of decision variables: $z_{i\ell} = 1$ if option ℓ is loaded on the vehicle for customer i, $z_{i\ell} = 0$ otherwise.

The resulting formulation of the capacitated vehicle-routing problem with upsell (CVRP – U) would then be (for ease of discussion, we will simply use the term upsell to refer to upselling, cross-selling, and pantry loading unless a distinction must be made):

$$\begin{aligned}&\text{Minimise} \sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij} - \sum_{i\in V\setminus\{0\}}\sum_{\ell\in L_i} p_{i\ell}z_{i\ell} \\ &\text{Subject to: constraints (2), (3), (4), (5), (8), (9), and (10)}\end{aligned} \tag{11}$$

$$\begin{aligned}y_i - y_j + Qx_{ij} + \sum_{\ell\in L_j} r_{j\ell}z_{j\ell} \le Q - q_j \quad &\text{for all } i, j \in V\setminus\{n+1\}, \\ &i \ne j \text{ s.t. } q_i + q_j + \sum_{\ell\in L_i} r_{i\ell}z_{i\ell} + \sum_{\ell\in L_j} r_{j\ell}z_{j\ell} \le Q\end{aligned} \tag{12}$$

$$y_i - r_{i\ell}z_{i\ell} \ge q_i \qquad \text{for all } i\in V\setminus\{n+1\};\ \ell\in L_i \tag{13}$$

$$\sum_{\ell\in L_i} z_{i\ell} \le 1 \qquad \text{for all } i\in V\setminus\{n+1\} \tag{14}$$

$$z_{i\ell} = \{0,1\} \qquad \text{for all } i\in V\setminus\{n+1\};\ \ell\in L_i \tag{15}$$

The objective (11) is to minimise the delivery cost offset by the additional expected contribution to profit of upselling. Constraint sets (12) and (13) modify the subtour elimination constraints to incorporate the upsale possibility. Constraint set (14) allows at most one upsale option for each customer. We note that the routing and upselling decisions are interdependent as we may wish to adjust our routes to increase the likelihood of available vehicle capacity for upselling.

3.2 Other considerations

As noted above, each of the particular up-/cross-selling options under consideration has a probability of sale derived from appropriate predictive analytics. If fact, there are two probabilities associated with this sale:

1 the probability the purchaser is available for delivery (e.g., at home)

2 the conditional probability of purchasing that particular option if they are at home.

Thus, the probability of sale is the product of these two probabilities. Depending on the product being delivered, it may be possible to have an unattended delivery if the purchaser is not available (as with the chainsaw in the example above, perhaps); however, we would not realise the upsale. On the other hand, if an attended delivery is necessary, an appointment for delivery may need to be made or a time window established. For these situations, an extension of the CVRP – U formulation incorporating hard time windows on the customer deliveries is presented in Section 6.

We use the incremental profit contribution in the objective function for several reasons. First, it is not necessary to include the profit contribution of the existing order in the formulation, since it is not affected by our delivery and upsell decisions. Although this objective is less intuitive than, say, a pure profit function, the profit of the existing order is not relevant to this decision. Second, we propose using the expected value, not a service level of, say, 95%. Since we are providing the ordered units, we actually have a 100% service level; the customer was not expecting the additional purchase. Third, the expected profit contribution of cross-selling and pantry loading can directly be used, since these are purchases *in addition* to the original order. But the upsell purchase is *instead* of the original order – the customer will no longer be purchasing the original item

– so the *incremental* profit contribution (the difference between that of the upsell and the original order) is relevant.

One of our assumptions is a known number of vehicles available. This would be appropriate for a retailer with existing day-to-day vehicle availability. Here we simply have the variable cost, c_{ij}, associated with an existing vehicle, which would likely be the mileage (primarily fuel) required and, perhaps, some opportunity cost of what the driver could be doing otherwise (the fixed cost of vehicle/driver is sunk). If we can deliver everything with less than m vehicles – which can be determined by solving the CVRP without upselling – we can solve CVRP – U for any number of vehicles up to m and find the breakeven cost for the vehicle itself. On the other hand, if we wanted to directly find the optimal number of vehicles, we could alter the formulation by making this value a decision variable, including the fixed cost as part of the objective, and making constraints (2) and (3) less-than-or-equal-to constraints.

The objective as shown consists of the expected profit contribution from upselling less the delivery cost. While the profit contribution will likely include the driver/salesperson's salary, it does not explicitly reflect any incentives that may be offered. Since delivery is a large part of the job, the driver/salesperson will likely have a base salary, but may also be provided potential commissions based on sales. Simple financial incentives, such as linear (fixed rate) cash commissions, could easily be incorporated into the objective function. Other financial incentive systems – such as a nonlinear relationship between the commission rate and sales, or a bonus when a sales target is met – and/or non-financial incentives may be appropriate, but are beyond the formulation presented above.

3.3 Bounds

The objective function (11) consists of two components: the delivery cost and the incremental expected profit contribution of the upsale. The minimum delivery cost can easily be identified by solving the traditional CVRP – from (1) through (10) above-ignoring the possibility of upselling. The maximum expected profit contribution of upselling can be identified by a modified multiple-knapsack problem (see for example, Kellerer et al., 2004), as follows. Let $\xi_{ij} = 1$ if the ordered item for customer $i = 1, 2, \ldots, n$ is placed in vehicle $j = 1, 2, \ldots, m$; $\xi_{ij} = 0$ otherwise, and let $\psi_{ij\ell} = 1$ if upsell option $\ell = 1, 2, \ldots, |L_i|$ for customer i is placed in vehicle j; $\psi_{ij\ell} = 0$ otherwise. Then:

$$\text{Maximise} \sum_i \sum_j \sum_{\ell \in L_i} p_{i\ell} \psi_{ij\ell} \tag{16}$$

$$\text{Subject to} \sum_j \xi_{ij} = 1 \qquad \text{for all } i \in V \setminus \{n+1\} \tag{17}$$

$$\sum_j \sum_\ell \psi_{ij\ell} \le 1 \qquad \text{for all } i \in V \setminus \{n+1\} \tag{18}$$

$$\psi_{ij\ell} - \xi_{ij} \le 0 \qquad \text{for all } i \in V \setminus \{n+1\};\ j = 1, 2, \ldots, m;\ \ell \in L_i \tag{19}$$

$$\sum_i \left(q_i \xi_{ij} + \sum_\ell r_{i\ell} \psi_{ij\ell} \right) \le Q \qquad \text{for all } j = 1, 2, \ldots, m \tag{20}$$

$$\xi_{ij} = \{0,1\},\ \psi_{ij\ell} = \{0,1\} \qquad \text{for all } i \in V \setminus \{n+1\};\ j = 1, 2, \ldots, m;\ \ell \in L_i \tag{21}$$

The objective (16) is to maximise the value of upsale items put on vehicles (again, we assume that all of the ordered items will be delivered). Constraint set (17) ensures the ordered item for each customer will be placed in a vehicle. Constraint set (18) ensures at most one upsell option is selected for each customer and that it can only go into one vehicle. Constraint set (19) ensures the original order and the upsell option of a particular customer, if any, are on the same vehicle. Finally, Constraint set (20) ensures the capacity of each vehicle is not exceeded. A lower bound of CVRP – U is given by the difference between the minimum delivery cost and the maximum expected profit contribution.

4 Solution methodologies

The capacitated vehicle-routing problem is known to be NP-hard, so solving this more-general, mixed-integer linear program as formulated in Section 3.1 will be restricted to small problem instances. From a practical perspective, we are not faced with as large a problem as the traditional CVRP (think UPS or FedEx) due to the upselling process that takes place. On the other hand, due to customers' desire to have their orders filled quickly (see Fisher et al., 2019), we will have a limited amount of time for identifying and implementing the solution. So, optimally solving the CVRP – U may not be feasible for many applications. Thus, we turn our attention to a variety of solution methodologies to identify good solutions.

4.1 Early-termination mixed-integer programming (MIP)

While it may not be feasible to identify and guarantee the optimal solution with a linear, MIP solver for reasonably-sized problems, a good solution is frequently identified early in the branch-and-bound process. Thus, one approach that we will consider for solving the CVRP – U is the use of a commercially-available MIP solver with a specified termination criterion (optimality gap, number of iterations, time limit, etc.).

4.2 Bound extensions

Two straightforward approaches to identifying solutions to the CVRP – U are to extend the bounds discussed above:

1 The CVRP/Knapsack approach: for a given number of vehicles, solve the CVRP ignoring upselling but providing the minimum delivery cost, then solve the knapsack problem for each vehicle to fill up the remaining space with the most-profitable upsell items of those customers assigned to that route.

2 The knapsack/CVRP approach: solve the modified multiple-knapsack problem presented in Section 3.3 ignoring the delivery costs but providing the maximum expected profit contribution, then solve the capacitated vehicle-routing problem treating the upsell options identified in the multiple-knapsack solution as required delivery items.

While these will obviously perform well (optimally) on one aspect of the problem – delivery cost or expected profit contribution of upselling – they are sequential in nature and do not simultaneously consider both aspects.

4.3 Min-max vehicle load

One drawback of the CVRP/Knapsack approach in the previous subsection is that the CVRP may completely fill a vehicle with previously-ordered items, but one of those customers may be a good candidate for upselling. Furthermore, if there is a fair amount of excess vehicle capacity, the CVRP may put very few customers on a route and fill other routes entirely. We can take advantage of the fact that there are several alternate-or near-optimal solutions for the CVRP, and identify one that allows as much room in each vehicle as possible for upselling.

Recall that y_i represents the load of the vehicle after visiting customer i in the CVRP. By keeping all of these variables as small as possible, we can ensure that non-committed inventory can be loaded into all delivery vehicles, to the extent possible. So we modify the CVRP formulation to minimise the maximum y_i value:

$$\text{Minimise } w \cdot \varphi + \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} \quad (23)$$

Subject to: constraints (2) through (10)

$$y_i - \varphi \leq 0 \quad \text{for all } i \in V \setminus \{n+1\} \quad (24)$$

$$\varphi \geq 0 \quad (25)$$

where φ is the maximum y_i value, determined by constraint set (24). This value represents the load of the most-heavily loaded vehicle. The objective (23) is to minimise the weighted average of this maximum load and the delivery cost, where w is the weight. A relatively large value of w will keep the maximum vehicle load near its minimum value while giving some consideration to total delivery cost; a small positive value will maintain the focus on the delivery cost with minimising the maximum vehicle load as a secondary objective.

As with the CVRP/Knapsack approach, solving this problem assigns the customers to routes; we can then solve the knapsack problem for each vehicle to fill up the remaining space with the most profitable upsell items. While this is still somewhat sequential in the decision-making process, the aim is to allow the possibility of including the higher-profit upsell items to a greater extent.

4.4 Greedy algorithm

We now turn our attention to an intuitive solution methodology that incorporates the upselling assignment and the routing assignment/sequence at each iteration of the process. The concept is to incrementally add upselling customers based on their expected profit contribution relative to the amount of vehicle capacity that they utilise; that is, the greatest $p_{i\ell}/r_{i\ell}$ ratio. This process is continued as long as an improvement in the objective function is realised. The formal algorithm follows:

Greedy Algorithm

Let A be the set of potential, unassigned options for upselling customers.

Let B be the set of customer options that have been assigned for upselling.

Let R be the remaining vehicle capacity after the customers from set B have been assigned.

Let OV be the best objective-function value found.

STEP 0: Initialise by placing all customer options in set A and calculating the remaining vehicle capacity after including the original orders: $A = \{L_i | \; i \in V \setminus \{n+1\}\}$, $B = \emptyset$, and $R = mQ - \Sigma_i q_i$. Solve the CVRP with no upselling, save the solution as the best solution found, and set OV equal to the resulting delivery cost.

STEP 1: Remove any options from set A that have a capacity requirement, $r_{i\ell}$, greater than R.

STEP 2: If A is an empty set, stop. Otherwise, select the option from set A with the greatest $p_{i\ell}/r_{i\ell}$ ratio – arbitrarily breaking ties – and remove it from the set.

STEP 3: Solve the CVRP with the option from STEP 2 in addition to the original orders and all options from set B; then…

…if there is no feasible solution without adding a vehicle or if the expected incremental profit contribution of this option is less than or equal to the increase in delivery costs, go to STEP 2.

…if a feasible solution is identified with this option and the expected incremental profit contribution is greater than the increase in delivery costs, go to STEP 4.

STEP 4: Update the best solution by

1. including the option from STEP 2 in set B,
2. subtracting the capacity requirement of this option from R,
3. saving the solution as the best solution found and updating OV to the delivery cost of this CVRP less the expected incremental profit contribution of all options in set B (including this option), and
4. removing all options of this customer from set A. Return to STEP 1.

It is recognised that a greedy approach based on the $p_{i\ell}/r_{i\ell}$ ratio will not necessarily identify the optimal solution to the 0 – 1 knapsack problem – and, hence the CVRP – U.

An option is to provide a starting solution by replacing the solution in STEP 0 (i.e., the CVRP with no upselling) with the CVRP/Knapsack solution presented in Section 4.2. The idea behind this is to save on the number of iterations required by the algorithm, hence, the number of CVRPs to solve.

4.5 Backward elimination

Comparable to the greedy algorithm using the $p_{i\ell}/r_{i\ell}$ ratio to select the customers for upselling in a forward-selection manner, an alternative approach is to extend the knapsack/CVRP solution presented in Section 4.2 by using that ratio in a backward-elimination process. Customers that were identified for upselling in the Knapsack/CVRP solution are considered for removal based on the lowest $p_{i\ell}/r_{i\ell}$ ratio. Customers are then removed one at a time until there is no longer an improvement in the objective-function value.

5 Numerical analysis

To illustrate the capacitated vehicle-routing with upsell problem (CVRP – U) as well as the use of the proposed solution methodologies, the 21-customer dataset for the traditional CVRP from Christofides and Eilon (1969) was analysed (note, this was, in turn, taken from Gaskell (1967) and is designated as E-n22-k4 in the vehicle-routing literature). Ralphs (2003) provides the variable delivery costs (distances) between all pairs of customers, c_{ij}, capacity requirements (demand) of each customer, q_i, and vehicle capacity, Q, for these datasets. For the upselling decisions, we include one upselling option for each customer, with the expected incremental profit contribution, $p_{i\ell}$, randomly generated from a uniform distribution between \$0 and \$100, and the capacity requirements equal to the capacity requirements of the original customer order, $r_{i1} = q_i$. A fixed delivery cost of \$250 per vehicle is incurred. Finally, we include an expected profit contribution of \$100 per customer for the original orders (excluding the expected upselling profit as well as the fixed and variable delivery costs). While this will have no effect on the solution, it will provide a more intuitive objective function value; thus, we will report the net profit that is equal to the profit contribution of the original orders plus the expected incremental profit contribution of upselling minus the fixed and variable delivery costs. We also disregard the use of time windows in order to focus our attention on the basic routing decisions versus the upselling decisions, but will return to this aspect in Section 6.

IBM ILOG CPLEX Optimisation Studio was used to solve all MIPs used in these procedures. A time limit of five minutes was imposed for the CVRP – U and CVRP runs due to the likely next-day, or even same-day, delivery requirements for these types of products. All CPLEX parameter default settings were used, except the MIP emphasis feasibility setting was changed to emphasise integer feasibility over optimality, in order to find good solutions quickly despite not verifying optimality.

A minimum of four vehicles is required to deliver the originally-ordered items, but very little additional product can be loaded on the vehicles for upselling. A common measure considered in CVRP analyses is the 'tightness' of the capacity constraint; that is, the demand-to-capacity ratio: $\Sigma_i q_i/mQ$. In this instance, it is equal to 0.9375. In general, as the tightness approaches one, the feasible solution space becomes limited and finding feasible solutions becomes more difficult for most solution methodologies. For example, the 21-customer, 4-vehicle CVRP (not including upselling) can be solved using the CPLEX MIP solver (all default settings) in 4.41 seconds, for 5 vehicles (tightness of 0.75) in 1.94 seconds, and for 6 vehicles (tightness of 0.625) in 0.36 seconds. Adding product to the vehicles for upselling opportunities will generally fill them at or near capacity, so the tightness for the CVRP – U, $\left[\sum_i \left(q_i + \sum_{\ell \in L_i} r_{i\ell} z_{i\ell}\right)\right] \Big/ mQ$, will almost certainly be near unity, making it impractical to solve to optimality even for this size of problem.

The results for this example are presented in Table 1. The incremental expected profit contribution of upselling and the variable delivery cost are displayed for each solution methodology. The net profit is then the expected profit contribution of the original order ($100n$) and the incremental expected profit contribution of upselling less the fixed ($250m$) and variable delivery costs. Similarly, the upper bound is identified using the minimum delivery cost from by solving the traditional CVRP ignoring upselling and the maximum expected profit contribution of upselling by solving a modified multiple-knapsack problem as indicated in Section 3.3. Finally, the best known solution is the best solution identified from any procedure conducted, including allowing the CVRP – U MIP to run for 24 hours (note that this is solely provided as a means of comparison and not included as one of the potential solution methodologies, as it would likely not be used in a practical setting).

There is very little difference in the net-profit values of the various techniques for four vehicles. Only the min-max vehicle load MIP with w = 100 (emphasising evenly-loaded vehicles) performed particularly poorly; while it effectively evened out the excess capacity on each vehicle, there was not enough for additional product to be loaded onto the vehicle. The increase in the expected incremental profit from upselling by adding a fifth vehicle more than offsets the increased fixed and variable delivery costs; however, adding a sixth vehicle is not cost-effective. Here, though, we begin to notice a difference in the various solution methodologies. The early termination CVRP – U, the greedy algorithm, and the backward-elimination method (initialised with the knapsack/CVRP solution) tend to outperform the other techniques. The CVRP/Knapsack and the min-max vehicle load methods begin with the focus on the delivery cost before considering upselling opportunities. It appears to be advantageous to pursue the more-profitable upselling customers as a reasonably-efficient routing schedule can be identified for a given set of upselling customers.

To further illustrate the process, the 32-customer (E-n33-k4) and 50-customer (E-n51-k5) data sets of Christofides and Eilon (1969) were used – the 32-customer instance was originally in Gaskell (1967), and Ralphs (2003) provides the CVRP data for both instances. Since the CVRP and CVRP – U have O(n^2) binary variables (with one upselling option per customer), the MIP time limits were increased to ten and thirty minutes for the 32-and 50-customer instances, respectively. Tables 2 and 3 provide the results for these instances.

The results of the 32-customer instance illustrate the superiority of the greedy algorithm and the backward-elimination method, providing better solutions than any other method, including the early termination CVRP – U. For the six-vehicle problem, they even provide the best-known solution, performing as well as the 24-hour CVRP – U run. While initialising the greedy algorithm with the CVRP/Knapsack solution may save some calculations, this includes some customers for upselling that actually hinders the overall profitability. As with 21 customers, adding one vehicle above the minimum requirement is profitable, but diminishing returns are particularly apparent here as the increased profit margin barely covers the variable delivery costs let alone the fixed costs.

The 50-customer instance was found to be particularly difficult to solve for tightly-constrained problems, despite setting the MIP option to emphasise integer feasibility over optimality. In fact, for the six-and seven-vehicle knapsack/CVRP problems, a feasible CVRP solution could not be identified within the 30-minute limit; thus, a travelling-salesperson problem (TSP) was used in its place to find the solution for each vehicle. While this is effective in quickly finding solutions, it does not consider reassigning the customers to other routes as the CVRP might. Fortunately, the greedy heuristic (with no initial solution) and the backward elimination process provide the best results, even outperforming the 24-hour CVRP – U. For this instance, there are enough profitable upselling customers to go to seven vehicles.

Table 1 Comparison of solution methodologies – 21-customer instance

Delivery vehicles	*Upper bound*	*Best-known solution*	*Solution methodology*	*Incremental exp. profit of upselling (A)*	*Variable delivery cost (B)*	*Expected net profit {100n + (A) – 250m – (B)}*
4	1,948	1,909	Early termination CVRP – U	540	912	1,828
			CVRP/Knapsack	234	835	1,599
			Knapsack/CVRP	583	907	1,876
			Min-max load, $w = 1$	436	914	1,722
			Min-max load, $w = 10$	408	914	1,694
			Min-max load, $w = 100$	459	882	1,777
			Greedy, no initial solution	545	869	1,876
			Greedy, with initial solution	346	866	1,680
			Backward elimination	583	907	1,876
5	2,232	2,121	Early termination CVRP – U	481	921	1,510
			CVRP/Knapsack	1,203	1,080	2,073
			Knapsack/CVRP (TSP)	1,040	1,049	1,941
			Min-max load, $w = 1$	1,093	1,161	1,882
			Min-max load, $w = 10$	1,018	1,066	1,902
			Min-max load, $w = 100$	1,199	1,045	2,104
			Greedy, no initial solution	661	993	1,618
			Greedy, with initial solution	1,188	1,027	2,111
			Backward elimination	554	1,033	1,221
6	2,045	1,893	Early termination CVRP – U	1,353	1,172	1,881
			CVRP/Knapsack	554	1,033	1,221
			Knapsack/CVRP (TSP)	1,378	1,287	1,791
			Min-max load, $w = 1$	1,241	1,208	1,733
			Min-max load, $w = 10$	1,187	1,275	1,612
			Min-max load, $w = 100$	1,225	1,306	1,619
			Greedy, no initial solution	1,363	1,170	1,893
			Greedy, with initial solution	1,337	1,159	1,878
			Backward elimination	1,363	1,170	1,893

Table 2 Comparison of solution methodologies – 32-customer instance

Delivery vehicles	*Upper bound*	*Best-known solution*	*Solution methodology*	*Incremental exp. profit of upselling (A)*	*Variable delivery cost (B)*	*Expected net profit {100n + (A) – 250m – (B)}*
4	1,948	1,909	Early termination CVRP – U	540	912	1,828
			CVRP/Knapsack	234	835	1,599
			Knapsack/CVRP	583	907	1,876
			Min-max load, $w = 1$	436	914	1,722
			Min-max load, $w = 10$	408	914	1,694
			Min-max load, $w = 100$	459	882	1,777
			Greedy, no initial solution	545	869	1,876
			Greedy, with initial solution	346	866	1,680
			Backward elimination	583	907	1,876
5	2,232	2,121	Early termination CVRP – U	481	921	1,510
			CVRP/Knapsack	1,203	1,080	2,073
			Knapsack/CVRP (TSP)	1,040	1,049	1,941
			Min-max load, $w = 1$	1,093	1,161	1,882
			Min-max load, $w = 10$	1,018	1,066	1,902
			Min-max load, $w = 100$	1,199	1,045	2,104
			Greedy, no initial solution	661	993	1,618
			Greedy, with initial solution	1,188	1,027	2,111
			Backward elimination	554	1,033	1,221
6	2,045	1,893	Early termination CVRP – U	1,353	1,172	1,881
			CVRP/Knapsack	554	1,033	1,221
			Knapsack/CVRP (TSP)	1,378	1,287	1,791
			Min-max load, $w = 1$	1,241	1,208	1,733
			Min-max load, $w = 10$	1,187	1,275	1,612
			Min-max load, $w = 100$	1,225	1,306	1,619
			Greedy, no initial solution	1,363	1,170	1,893
			Greedy, with initial solution	1,337	1,159	1,878
			Backward elimination	1,363	1,170	1,893

Table 3 Comparison of solution methodologies – 50-customer instance

Delivery vehicles	*Upper bound*	*Best-known solution*	*Solution methodology*	*Incremental exp. profit of upselling (A)*	*Variable delivery cost (B)*	*Expected net profit {100n + (A) – 250m – (B)}*
5	3,532	3,506	Early termination CVRP – U	156	611	3,295
			CVRP/Knapsack	12	521	3,241
			Knapsack/CVRP	303	583	3,470
			Min-max load, $w = 1$	111	543	3,318
			Min-max load, $w = 10$	88	539	3,299
			Min-max load, $w = 100$	80	704	3,126
			Greedy, no initial solution	303	583	3,470
			Greedy, with initial solution	245	601	3,394
			Backward elimination	303	583	3,470
6	4,183	4,097	Early termination CVRP – U	1,122	620	4,002
			CVRP/Knapsack	394	535	3,359
			Knapsack/CVRP (TSP)	1,218	1,030	3,688
			Min-max load, $w = 1$	448	537	3,411
			Min-max load, $w = 10$	1,039	565	3,974
			Min-max load, $w = 100$	1,081	605	3,976
			Greedy, no initial solution	1,191	594	4,097
			Greedy, with initial solution	1,137	613	4,024
			Backward elimination	1,175	611	4,064
7	4,501	4,403	Early termination CVRP – U	1,742	668	4,324
			CVRP/Knapsack	669	556	3,363
			Knapsack/CVRP (TSP)	1,807	1,132	3,925
			Min-max load, $w = 1$	966	566	3,650
			Min-max load, $w = 10$	1,698	667	4,281
			Min-max load, $w = 100$	1,660	676	4,234
			Greedy, no initial solution	1,785	656	4,379
			Greedy, with initial solution	1,709	610	4,349
			Backward elimination	1,779	626	4,403

6 Extension of CVRP – U with time windows

Although many deliveries are made without the use of specific time windows (for example, ‘we’ll deliver it Thursday morning’), they may be particularly beneficial in the proposed system in order to better ensure the customer is present to allow for upselling. The capacitated vehicle-routing problem with time windows (CVRPTW) has been extensively studied in the literature. In this section, we briefly discuss how to modify the CVRP with upsell to incorporate time windows. Then we conduct a numerical analysis on several instances to evaluate the proposed solution methodologies.

6.1 Model

The capacitated vehicle-routing problem with upsell formulation can be extended to allow for hard time windows (CVRPTW – U) as follows. Let:

- τ_i be the elapsed time after visiting node i (continuous decision variable)
- $[a_i, b_i]$ be the time window at node i; that is, the earliest/latest time service can begin
- t_{ij} be the time it takes to travel from node i to node j
- T be the maximum time allowed for a route, perhaps a shift length (i.e., the time window for the depot is $[0, T]$)
- s_i be the service time at node i
- $u_{i\ell}$ be the additional service time required for upselling option ℓ at node i.

We then add the following constraints to the CVRP – U formulation of Section 3.1:

$$\tau_i - \tau_j + Tx_{ij} + \sum_{\ell \in L_i} u_{i\ell} z_{i\ell} \le T - (t_{ij} + s_j) \quad \text{for all } i \in V \setminus \{n+1\},\ j \in V \quad i \ne j;\ \text{s.t. } t_{ij} + s_i + s_j \le T \tag{26}$$

$$-\tau_j + Tx_{n+1,j} + \sum_{\ell \in L_i} u_{i\ell} z_{i\ell} \le T - (t_{n+1,j} + s_j) \quad \text{for all } j \in V \setminus \{n+1\} \tag{27}$$

$$\tau_i - \sum_{\ell \in L_i} u_{i\ell} z_{i\ell} \ge s_i \quad \text{for all } i \in V \tag{28}$$

$$\tau_i - \sum_{\ell \in L_i} u_{i\ell} z_{i\ell} \ge a_i + s_i \quad \text{for all } i \in V \tag{29}$$

$$\tau_i - \sum_{\ell \in L_i} u_{i\ell} z_{i\ell} \le b_i + s_i \quad \text{for all } i \in V \tag{30}$$

$$0 \le \tau_i \le T \quad \text{for all } i \in V \tag{31}$$

The bounds for the CVRP – U can easily be adapted to incorporate time windows. The minimum delivery cost can be identified by solving the traditional CVRPTW. The maximum expected profit contribution of upselling can be identified using the modified multiple-knapsack model of Section 3 with an additional constraint set to ensure the total service time and upselling time does not exceed the maximum time allowed for a route:

$$\sum_i \left(s_i \xi_{ij} + \sum_\ell u_{i\ell} \psi_{ij\ell} \right) \le T \quad \text{for all } j = 1, 2, ..., m \tag{32}$$

Unfortunately, this may not provide a strong bound, since this constraint set does not include the travel times. Furthermore, the modified multiple-knapsack solution may not be feasible when incorporating time windows; for example, two customers assigned to the same vehicle may have the same time window, but separated far enough such that the vehicle could not get from one to the other on time.

Finally, several solution methodologies of Section 4 can also be extended to incorporate time windows by simply substituting the solution of the CVRP and CVRP – U with the solution of the CVRPTW and CVRPTW – U, respectively. However, those utilising the modified multiple-knapsack procedure may be impractical due to the potentially infeasible solution when incorporating time windows.

6.2 Numeric results

A well-known set of CVRPTW benchmark problems have been developed by Solomon (1987). The geographic data – that is, the customer coordinates – for these instances are generated randomly (R problem sets), clustered (C problem sets), and a mix of random and clustered (RC problem sets). These are 100-customer Euclidean problems where travel times equal the corresponding distances (truncated to one decimal); however, smaller problems have been created by considering only the first 25 or 50 customers.

Four of these instances were selected to evaluate the CVRPTW – U solution methodologies. Each of these have a time horizon of just under four hours (a morning or afternoon shift), service times of 10 or 15 minutes, time-window widths ranging from 10 to 60 minutes, with 100% of the customers having time windows. Table 4 provides the detailed parameters used for each of these problem sets (note, the clustered problems use ten-second time units to provide practical parameters for an upselling scenario).

Table 4 Solomon data for the CVRPTW

	Parameters from Solomon				*Corresponding parameters*			
Problem set	*Number of customers*	*Service time*	*Width of windows*	*Time horizon*	*Assigned time unit*	*Service time*	*Width of windows*	*Time horizon*
R101	50	10	10	230	1 minute	10 min.	10 min.	3.83 hr.
R105	25	10	30	230	1 minute	10 min.	30 min.	3.83 hr.
C107	25	90	180	1,236	10 seconds	15 min.	30 min.	3.43 hr.
C109	50	90	360	1,236	10 seconds	15 min.	60 min.	3.43 hr.

The Solomon problem sets list the vehicle capacity at 200 units for each of these instances. However, due to the time-window constraints, the vehicles are loaded at 30% or less for the R105-25 and R101-50 instances at the optimal CVRPTW solution. At these capacities, we can load most of the upselling units without adding another vehicle. Thus, we set the vehicle capacity at 75 units for these two instances and keep the 200-unit capacity for the C107-25 and C109-50 instances.

Other relevant parameters – the fixed delivery cost per vehicle, the expected profit contribution for the original orders, and the expected incremental profit contribution and capacity requirements of upselling – are established as discussed in Section 5. Finally, the additional customer service time requirements for upselling are set equal to the service times provided in the Solomon data set, $u_{i1} = s_i$.

Table 5 provides the results of the early termination MIP (5 minutes for the 25-customer instances and 30 minutes for the 50-customer instances), the greedy algorithm (with no initial solution), and the backward elimination procedures. Note that the methods dependent on the multiple-knapsack solution (such as the bound extensions) were not considered due to the potentially infeasible solutions and weak bounds provided when there are binding time-window constraints. Also, the min-max vehicle load method was not considered due to the poor performance with the CVRP – U.

Table 5 Performance summary of CVRPTW – U Solution methodologies

a Mean percent deviation from optimal solution, 25-customer instances

	Problem set		*Overall mean*
Solution methodology	*R105*	*C107*	
Early termination	0.00	0.00	0.00
Greedy algorithm	0.54	1.35	0.88
Backward elimination	1.00	11.79	5.62

b Mean percent deviation from best-known solution, 50-customer instances

	Problem set		*Overall mean*
Solution methodology	*R101*	*C109*	
Early termination	0.41	1.21	0.81
Greedy algorithm	1.72	1.40	1.56
Backward elimination	9.09	2.05	5.57

The most noteworthy observation is that the optimal solution can quickly be identified for the 25-customer instances. All but one were solved and proven optimal in less than 2½ minutes. The optimal solution for the three-vehicle instance of the C107 problem set was identified in the 5-minute early termination MIP, but took nearly an hour to prove optimality. The greedy algorithm again performed quite well for the 25-customer instances, with less than a 1% mean deviation from the optimal net profit. The backward elimination procedure, on the other hand, did relatively poor on the C107 problem set with fewer vehicles – perhaps due to multiple customers with high $p_{i\ell}/r_{i\ell}$ ratios and conflicting time-window requirements – such that increasing the number of vehicles allows those customers to be separated.

For the 50-customer instances, the optimal solution was identified only once (R101 with 11 vehicles), so best-known solutions were identified using a 24-hour run for the CVRPTW – U MIP. The early termination MIP provided solutions within a 1% mean deviation from the best-known solution (gap), often benefited by the evolutionary algorithm for polishing MIP solutions (Rothberg, 2007) that is a default heuristic in the ILOG CPLEX MIP solver. The greedy algorithm also performed well, with a 1.56 percent gap. Again, the backward elimination procedure did relatively poor on one problem set (R101) with fewer vehicles.

7 Managerial implications

While important from a practical perspective, the driver-becoming-salesperson approach has received no attention in the academic literature. It effectively integrates the upselling (marketing/demand) and delivery (operations/supply) decisions for a retailer. Based on the results of the numerical analysis, it appears that we should put a relative emphasis on the upselling decision (for example, of the two bound heuristics, Knapsack/CVRP consistently outperforms CVRP/Knapsack as some routes are very small), since the CVRP can find a reasonably-good solution for a given set of upselling customers. Of course, the forward-selection, greedy heuristic and the backward-elimination procedure incorporate the upselling and the routing assignments throughout the solution procedure, but if any deviation from those solutions is necessary, the decision maker should attempt to maintain the upselling assignment as much as possible.

Table 6 Performance summary of CVRP – U solution methodologies

a Mean percent deviation from upper bound

	Number of customers			Overall mean
Solution methodology	*n = 21*	*n = 32*	*n = 50*	
Early termination CVRP – U	6.35	6.74	4.99	6.03
CVRP/Knapsack	13.56	30.19	17.74	20.49
Knapsack/CVRP	7.12	7.75	8.80	7.89
Min-max load, $w = 1$	16.66	13.30	14.47	14.81
Min-max load, $w = 10$	12.57	16.63	5.49	11.57
Min-max load, $w = 100$	18.44	14.80	7.46	13.56
Greedy, no initial solution	6.90	5.62	2.17	4.90
Greedy, with initial solution	7.30	16.48	3.70	9.16
Backward elimination	7.12	5.52	2.26	4.97

b Mean percent deviation from best-known solution

	Number of customers			Overall mean
Solution methodology	*n = 21*	*n = 32*	*n = 50*	
Early termination CVRP – U	0.85	2.00	3.38	2.08
CVRP/Knapsack	8.50	26.85	16.40	17.25
Knapsack/CVRP	1.66	3.13	7.29	4.03
Min-max load, $w = 1$	11.85	8.91	13.07	11.28
Min-max load, $w = 10$	7.49	12.46	3.89	7.95
Min-max load, $w = 100$	13.67	10.57	5.88	10.04
Greedy, no initial solution	1.43	0.84	0.52	0.93
Greedy, with initial solution	1.85	12.17	2.07	5.36
Backward elimination	1.66	0.73	0.61	1.00

Table 6 summarises the performance of the various solution methodologies for the CVRP – U, providing the mean percent deviation of the solution from the upper bound (Table 6a) and from the best-known solution (Table 6b). It is apparent that the greedy algorithm and the backward-elimination method outperform the other methodologies considered. The mean deviation from the upper bound of these two methods is less than 5%, so even sophisticated algorithms specifically designed for the CVRP – U would likely result in minimal improvement to the net profit. From a practical perspective, the upselling probabilities and expected profits are likely not that precise.

When time windows are incorporated into the formulation (CVRPTW – U), optimal solutions can be quickly identified for the 25-customer instances, perhaps due to the reduced solution space. Even after adding upselling product, the vehicles are not generally filled to capacity due to the time-window constraints, so the tightness of the capacity constraint does not appear to be as critical an issue in identifying optimality as it is with the non-time-window situation discussed in Section 5. The greedy algorithm performed admirably for all instances, providing solutions that are again likely well within the precision of estimating the upselling probabilities and expected profits.

Undoubtedly, the decision to use drivers for upselling involves more than identifying appropriate product and routes for delivery. Appropriate analytics will need to be in place to determine which customers are likely to up-/cross-buy which products (see for example, Behera et al., 2020) and to identify which customers may not be good candidates for such an approach (Shah and Kumar, 2012). Drivers will need to be trained in sales (or salespersons trained in driving) and be provided adequate incentives to do so (Kamakura, 2007). It should be noted that the US Department of Transportation has already defined the 'driver-salesperson' (U.S. Code of Federal Regulations, 2020). Since the drivers will now have two major responsibilities, delivery and upselling, a sense of role clarity – clearly communicated goals and procedures – will be important to help the driver/salesperson prioritise tasks (Zboja and Hartline, 2012), particularly since distribution and sales are traditionally distinct cost/profit centres of the organisation.

Furthermore, Van Hoek et al. (2020) present concerns regarding the lack of talent in the post-COVID-19 world. If it is difficult to identify and train appropriate talent for the driver-becoming-salesperson strategy, it may be advantageous to split the customers into two groups, those that have a reasonable likelihood of upselling (with appropriately-trained personnel and the use of the proposed model and solution methodologies) and those that do not (for which traditional delivery personnel and CVRP models are appropriate). Finally, as mentioned in the literature review, we can expect fewer product returns, since the customer can 'experience' the product before purchase.

8 Conclusions

Hübner et al. (2016) note "the growing importance of online sales means that traditional bricks-and-mortar retailers need to create new distribution systems to serve customers through multiple channels". The novel coronavirus, COVID-19, has amplified this growth in online sales and the need for new delivery practices for customer engagement. Our research addresses this need to serve the online retail consumer by designing the last-mile logistics operations to incorporate upselling strategies. The driver-becoming-salesperson approach essentially brings the showroom to the customer – without having to actually have a physical showroom – as part of a retailer's omnichannel strategy. Recent advances in predictive analytics enables retailers to identify those products a customer is likely to purchase, making this approach a potentially profitable endeavour.

This accomplishes several objectives:

1 it provides customers appropriate 'experience' for products with non-digital attributes before finalising the purchase

2 it allows retailers that rely heavily on upselling to respond quickly to disruptions and to reduce potential losses in revenue

3 it decreases the likelihood of returns, since the customer can experience the product before purchasing

4 it addresses the needs of customers who simply prefer personal service, particularly during a pandemic (and as new variants of the virus spread).

Although our focus has been on order fulfillment for retail customers (i.e., last-mile delivery), it could also be beneficial for direct store delivery (Ray, 2010).

This paper advances the retail marketing and operations research literature by formalising the driver-becoming-salesperson strategy. The resulting model is essentially a combination of the capacitated vehicle-routing problem and the multiple-knapsack problem. A variety of solution methodologies are presented and, fortunately, simple search techniques are found to be quite effective – with and without time windows – using the profit-to-capacity ratio to incrementally select the customers for upselling. We find that the focus should be on which customers to upsell first, since the vehicle-routing aspect can generally be used to find good solutions. Given the solution quality of the proposed procedures and the likely precision of the parameter estimates in practice, the development of sophisticated algorithms specifically designed for the CVRP – U would likely result in minimal improvement.

Since there has been no research conducted on the VRP in this context, there are a number of areas of future research that could be pursued from a vehicle-routing perspective (Vidal et al., 2020). Since the driver will now be interacting directly with the customer, incorporating stochastic service times into the model would be appropriate. For same-day-delivery retailers, dynamic models may also prove worthwhile. The effectiveness of upselling may be enhanced by having a customer regularly served by the same driver to establish a personal relationship, so an extension to the period VRP (Smilowitz et al., 2013) would be of value. From a theoretical perspective, tighter bounds would be helpful, particularly on the time-window extension. Generalising beyond the realm of the proposed CVRP – U model, it would be beneficial to investigate inventory models that incorporate the potential demand from upselling, and decision support systems to schedule the time slots for attended home delivery.

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Appendix A

Moving up-/cross-selling to delivery personnel

Title: Why It’s Time to Rethink Your Final Mile Logistics Plan

Author: Sean Hart

Date: 28 December 2020 (accessed 1 January 2021)

URL: https://www.thepowerscompany.com/supply-chain/why-its-time-to-rethink-your-final-mile-logistics-plan/

Excerpt: “Shippers will need to find ways to reach shoppers and convert them into product consumers. Putting the products directly in front of the customers seems to be the strongest way to encourage this conversion. Experts predict drivers will become merchants, but this will present several challenges. For example, as Susie Walker of Veriship points out, the question of who assumes the burden of risk for products that have not been paid for or the question of what will happen to products that consumers want to return after they have been purchased from drivers”.

Title: Last Mile Logistics: 8 Key Trends to Watch in 2021

Author: Jennifer Wilson

Date: 7 December 2020 (accessed 31 December 2020)

URL: https://www.sage.com/en-us/blog/last-mile-logistics/

Excerpt: “With autonomous vehicles on the horizon but security a perennial issue and drivers still required to hand over product, the driver’s future role might be as an AI-augmented salesperson. That’s according to Susie Walker, formerly of shipping expense platform Veriship and now at request proposal firm RFP360. She says: “Apparently, retailers are shipping items you haven’t ordered but believe you might want using your shopping data. The carrier has the opportunity to sell it on site. It’s taking products ordered in the past or ‘recommended items’ the consumer might like off the website and bringing it to their doorstep””.

Title: 2020 Last Mile Trends Every Retailer Must Know

Author: DispatchTrack

Date: 13 November 2020 (accessed 31 December 2020)

URL: https://www.dispatchtrack.com/blog/last-mile-trends-retailers

Excerpt: “Many online shopping platforms use consumer data to recommend related or similar goods to sell to clients after they have browsed or ordered as part of their marketing efforts. Upselling is finding its way to shippers as some are now doing door-to-door marketing. For example, the delivery driver may ask a customer who always orders skincare products each month in the last three months if he or she would be interested in related products or new variants of the same product. Likewise, a customer who bought a drill is a potential candidate for upselling other do-it-yourself tools".

Title: 8 Trends in Last Mile Delivery to Look Out for in 2020

Author: Maryland Messenger

Date: 18 May 2020 (accessed 31 December 2020)

URL: https://www.marylandmessenger.com/8-trends-in-last-mile-delivery-to-look-out-for-in-2020/

Excerpt: "One of the great benefits of consumer data is the opportunity it affords e-commerce businesses to upsell. If your analytics tells you that customers who bought a specific product are also likely to buy another specific product why not offer it to them during the buying transaction. Many e-commerce businesses already do this. The trend in last mile delivery is for the delivery driver to become part of the selling process. The delivery driver can carry additional stocks of associated products and sell them directly to the consumer." …. "These opportunities are driven by the same analytics that recommends products at the online checkout stage. They can be a feature of last mile delivery of food, apparel, and pharmaceuticals amongst other product areas".

Title: Last Mile Delivery: What It Is & Trends To Watch For

Author: Swarnendu De

Date: 18 September 2019 (accessed 31 December 2020)

URL: https://customerthink.com/last-mile-delivery-what-it-is-trends-to-watch-for/

Excerpt: "Retailers are constantly looking for new ways to make money. With the help of data collection and using AI, companies can estimate what their customers may want to buy. Drivers are stocking their vehicles up with goods and items a customer has previously ordered and might need again. Industries like food, pharmaceutical, and apparel are increasingly using this method".

Title: 7 Top Trends in Last Mile Logistics – The Revolution Is Coming

Author: Adam Robinson

Date: 30 April 2019 (accessed 1 January 2021)

URL: http://www.supplychain247.com/article/7_top_trends_in_last_mile_logistics_the_rev_is_coming

Excerpt: "Shippers need to find ways to reach more shoppers and convert them into consumers. While up to 65% of all purchases use the internet for research purposes before making a purchase, putting information and product in front of consumers remains the strongest way to encourage this conversion. In conjunction with faster, better technology, including driverless trucks, the role of the driver will evolve. Drivers will become merchants, selling items from trucks, but there are several challenges shippers face in accessing this new resource, reports Susie Walker of Veriship".

Title: 9 Trends in Last Mile E-Commerce Delivery

Author: Alfredo Gómez

Date: 8 October 2018 (accessed 31 December 2020)

URL: https://www.ecommerce-nation.com/trends-last-mile-e-commerce-delivery/

Excerpt: "Thanks to Big Data, retailers can predict what more a customer might want, even if they haven't ordered it. The mobile warehouse concept is gaining strength. The fulfiller can load inventory onto delivery trucks, allowing drivers to increase sales during the delivery process. Just as Amazon shows customers additional products they may like during the checkout process, the courier can bring items that the consumer has ordered in the past or may need or want by processing a possible additional order in person. This can work very well in the food sector, as well as the household goods sector, or even in fashion".

Title: 9 Trends in Last-Mile Delivery: How e-commerce Is Forcing Changes in How Retailers and Carriers Do Business

Author: Deborah Abrams Kaplan

Date: 22 May 2017 (accessed 1 January 2021)

URL: https://www.supplychaindive.com/news/last-mile-spotlight-trends-tech-gig-perfect/443091/

Excerpt: "Using Big Data, retailers can predict what else a customer might want, even if they didn't order it. The concept of a mobile warehouse is gaining steam. The fulfiller can load non-committed inventory into delivery trucks, allowing drivers to upsell during the delivery process. Just as Amazon shows customers additional products they might like during the checkout process, the driver can bring items the consumer has ordered in the past or might need or want, processing a potential additional order in person". "We're seeing this on the food side", said Armanious, as well as with household commodities and even apparel. On the pharmaceutical side, drivers can sell pill cutters and syringe disposal products.

Appendix B

Want ads for drivers and upselling, all accessed 6 December 2021

Product: Bottled water and related products

Company: Primo Water North America

URL: https://www.wisconsinjobnetwork.com/job/detail/61887952/Route-Sales-Representative

Excerpt: Job Responsibilities: "Deliver pre-ordered products and also to upsell our popular brands/products" "Efficiently manage customer base within established route with an average of 50+ stops per day"

Product: Uniform and garment services

Company: UniFirst

URL: https://jobs.unifirst.com/job/new-york/route-service-representative-unifirst/7729/16351532704

Excerpt: "The Route Service Representative will make daily visits delivering and picking up customer products on an assigned route". What you'll be doing: "Create opportunities to upsell and grow existing customer base."

Product: Consumer electronics

Company: Asurion

URL: https://equalopportunityhires.com/career/35120/Device-Delivery-Driver-Sales-Expert-Part-Time-New-York-Ny-Syracuse

Excerpt: What you'll be doing: "Meet with customers face-to-face at the customers' home location" "You will be expected to upsell our customers with an emphasis on serving, solving and selling."

Product: Cannabis

Company: Flower Market

URL: https://es.jobsearchi.com/California/palmsprings/sls/hiring-cannabis-delivery-driver-coachella-valley-4588613.html

Excerpt: Driver Duties: 'Drive for long periods of time around the Coachella Valley' 'Explain products to customers, upsell items'

Product: Replacement windows and doors

Company: Design Windows and Doors, Inc.

URL: https://inlandempire.craigslist.org/trd/d/ontario-retrofit-window-remeasure-tech/7415684946.html

Excerpt: "Expertly install retrofit windows, nail-fin windows, sliding doors, French doors, entry doors, and have solid finish carpentry skills" "When you install jobs, you will upsell the customer on additional product or add-ons such as jamb extensions, stool and apron for windows".

Product: Environmental products and services

Company: Safety-Kleen

URL: https://jobsearcher.com/j/class-b-driver-at-safety-kleen-in-atoka-tn-En1ZeJX

Excerpt: "As a Sales Route Driver you will visit customer locations to provide onsite service for parts washer machines, collect used solvent and upsell a variety of products and other Safety Kleen Services".

Product:	Ice cream products
Company:	Hershey’s Ice Cream
URL:	https://jobsearcher.com/j/route-sales-delivery-driver-at-hershey’s-ice-cream-in-pensacola-fl-pJKkrG
Excerpt:	“We are looking for an energetic and motivated Route Sales Delivery Driver to deliver our ice cream products to clients like convenience stores, schools, hospitals and supermarkets” “Here’s just some of what we have to offer our drivers…Opportunities to upsell products”.
Product:	Landscape lighting
Company:	Foley Pools
URL:	https://www.salary.com/job/foley-pools/landscape-lighting-installer-and-sales/a198aec2-d02b-4e14-aa28-2d704384ee02
Excerpt:	Core responsibilities: ‘Installing low voltage lines and lights’ ‘Upsell customers to add additional lights’.