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On line shopping and logistics: a fast dynamic vehicle routing algorithm for dealing with information evolution

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Abstract

Online shopping has seen booms of orders in recent years. In online shopping, the orders are characterized by tight order-to-delivery lead times and the frequent and discrete arrival of orders.

Online shopping has recently expanded into new sectors. Due to the pandemic, online grocery shopping showed a boom and the shift from physical grocery shopping to on line shopping is not expected to disappear with the pandemic end. This increases the number of online orders that should be delivered directly to customers.

Online shopping is changing its characteristics: customers even more often pick up online orders in stores. This increases the number of online orders that need to be delivered to physical stores and places requirements on supply chains—especially in terms of speed and efficiency.

Delivery at the time and place that is convenient to the consumer is one of the main issues for increasing customer satisfaction and therefore business efficiency. This study proposes an exact algorithm for solving a multi-constrained dynamic vehicle routing problem with a short execution time. The algorithm is therefore able to satisfy customer preferences, allowing for instance last minute changes in order lists and/or delivery addresses.

Keywords: Logistics, online shopping, real time vehicle routing, business, customer satisfaction

1. Introduction

The pandemic has impacted everyone around the globe in never before seen ways, forcing governments and authorities to take drastic measures in order to control the spread of the virus, such as lockdowns, social distancing and restrictions on the movement of people and goods. Movement restrictions, long queues and closures of physical stores have pushed people to try e-commerce channels. Online grocery shopping has seen booms of orders growing by 200-300% compared to the same time period last year (Rakuten Intelligence, 2020) and in March 2020 42% of the US population purchased their groceries online at least once a week.

Orders for groceries on Amazon have increased by as many as 50 times (Mohsin, 2020). However, thanks to the e-commerce, also small shops were able to satisfy part of the emerging online grocery shopping demand, becoming dark stores, when not able to deal with pandemic restrictions. In Rome, three young startuppers joined their local shopkeepers into an online store: the order of goods is performed online, the delivery service is provided by the shops. In other cases, the order of goods is performed online but the delivery service is provided by a third part that is in charge of collecting e-orders from customers, physically buying the products from the supermarkets within a radius of 10-15 kilometers and delivering them to the customers by a refrigerated electric vehicle.

The shift from physical grocery shopping to on line shopping is not expected to disappear with the pandemic end: over half of online grocery shoppers say they're now more likely to continue to shop online even after the pandemic. On line grocery shopping is becoming an important phenomenon and the foreseen demand is high.

Traditional retailers are expanding their online offerings and introducing new models, such as in-store fulfillment of online orders. Online players such as Amazon and Zalando are opening their own physical stores. Retailer company needs to collaborate with its suppliers, in better predicting and meeting consumer demands and thus reducing shortages, overstocks, and waste, and ensuring the performance and resilience of its supply systems. Production flexibility and logistics are key issues in such a dynamic market. Advanced systems for supporting the decision process are required for retail stores (Bruzzone et al., 2010).

If button clicking online is an easy thing, delivering what is ordered will be another challenge. In online shopping, the orders are characterized by tight order-to-delivery lead times and the frequent and discrete arrival of orders. Customers expect to receive their products anytime and anywhere with excellent service and high convenience. This places requirements on supply chains—especially in terms of speed and efficiency.

1.1. The importance of delivery for online shopping

Delivery is one of the most important issue in on line shopping. Delivery impacts widely on the transport cost, then, on customer satisfaction and in turn, on the demand level. In fact, a high percentage of cart abandonments are due to costs for shipping and non-satisfactory delivery schedule topped the list of dissatisfaction with e-shopping.

Delivery options refers to the delivery location, which can be attended or not, and the time slot choice. These options are described in the following.

1.1.1. Delivery place options

Attended deliveries:

- Home deliveries: the customer has to stay at home waiting for the delivery. When the customer is not at home at the time of delivery, i.e., first time delivery failure, it causes higher operating costs for online retailers/carriers and inconveniences to customers that lead to lower satisfaction. The advantage is that the customer has not to cover any distance for collecting the products.
- Collection points like petrol stations or corner shops: the customer is free to choose his/her more convenient time for the collection but have to pass through the collection point, making a deviation in his/her daily route.

Unattended deliveries. In the pandemic period, this delivery methods become more important for safety issues since they guarantee contactless: products do not need to go directly from driver's hands to customer's hands. Unattended delivery can be simply leaving an item on someone's doorstep, or in their garden, but this brings many security concerns. Some of the secure unattended delivery methods are reported in the following.

- Lockers/reception boxes: fixed location. DHL Parcel Germany runs the Packstation service, which allows customers to self-collect parcels, 24 hours a day, seven days a week, in fixed locations. Punakivi and Tanskanen (2002) show that transportation costs using the shared reception box concept are 55-66 per cent lower in comparison with the current standard concept with attended reception and two-hour delivery time windows.
- Lockers which position is daily optimised. Molfino et al. (2015) propose, within the FURBOT EU project (FP7-SST-2011-RTD-1), a last mile delivery system based on mobile safe parcel-lockers and a small electric vehicle (the FURBOT prototype). Parcel-lockers are consolidated in the Urban Consolidation Centre with packages addressed to many customers. Each parcel-locker is addressed to a temporary unloading bay where the customers need to self-collect the parcels. The unloading bay is selected in order to minimize the distance the customers have to cover for collecting their products from the parcel-locker (Cepolina E.M. 2016). The parcel-locker is delivered to the assessed temporary unloading bay by FURBOT and is automatically unloaded (Silvestri et al., 2019; Masood et al., 2020) and left there for a given time window. Afterwards, the empty parcel-locker is automatically collected by FURBOT and moved to the Urban Consolidation Centre, for a new delivery trip.
- Lockers fixed on a van. The locker is fixed on the van and the customers collect their products directly from the van, while it is parked in a convenient place. This solution requires a narrow collection time. This service is cold, by the Udelv company, the Mobile Locker. Their autonomous delivery vans (ADVs) are filled with goods in one location. The vans drive to another 'hot spot', where it sits while, as many as 32 delivery customers, come out to retrieve

their goods. Udelv (Urban delivery vehicles) are already used as Mobile Locker for grocery delivery as well as Nuro R2 and CargoPod by Oxobotica. Draeger's Market, a San Mateo (CA) grocery store, is using the udelv ADV; the shop has an agreement with multiple office buildings, for free grocery delivery during a specific day of the week. Draeger's Market pickers load the udelv vehicle at 4:00pm. The vehicle arrives close to an office building by 4:30pm, and sits until 5:30pm. Customers retrieve their order when they exit from the office, before to take the car to go home (Udelv, 2021).

According to Xu et al. (2008), unattended reception is the optimal service concept from the perspective of cost efficiency. It allows for greater operating efficiency but requires investment in reception solutions at the consumer end. From e-shoppers' point of view, it could reduce the time in waiting for delivery.

However, unattended delivery is not always the preferred choice for the customers: according to results of a survey related to online shopping in UK (Ferrand et al. 2020), most consumers resulted against unattended safe boxes; instead, they are in favour of using a neighbouring house or collection points, so long as these collection points are within short distance and is time convenient.

1.1.2. Timed delivery options

The majority of consumers who order groceries, want goods to be delivered between 6 p.m. and 8 p.m. with Thursday to Sunday being favourites. This places large demands on the delivery fleet during busy period that is 20% of the day and leaves vans running at low capacity for 80% of the day.

From the reported information results that delivery at the time and place that is convenient to the consumer is one of the main issues in on line grocery shopping. A survey of 100 companies conducted by Consignia (2001) revealed that 58% of the respondents ranked this issue as the second most important factor influencing the market.

Delivery at the time and place that is convenient to the consumer has to cope with customer' complex and dynamic activity chains and traffic congestion. On one side customer places vary during the day according to their activities; on the other side travel times are unpredictable because of the traffic conditions in urban area, where most of deliveries take place. Therefore "delivery at the time and place that is convenient to the consumer" has to be supported by routing algorithms that run every time the data (customer position, travel times) change or a new event takes place (shopping cart updating; new shopping cart). The computation time has to be very short for enabling the design of vehicle delivery routes in an online fashion. The definition of such algorithms is the target of the presented research.

The proposed delivery system refers to online grocery shopping that is becoming so important in this pandemic period.

Customers buy on line from different shops or dark stores. An autonomous electrical vehicle (the FURBOT prototype that is improved to reach SAEL level3/4 (Masood et al., 2021 a and b) collects the products and deliver them to customers: when the autonomous vehicle stops close to a shop, the shop personnel load the required products on the locker fixed on FURBOT. When the autonomous vehicle stops in a delivery point, the customer has to unload his products while the vehicle is parked.

The designed delivery system offers contactless unattended deliveries.

The paper proposes a vehicle routing algorithm that allows the logistics service provider to readily make adjustments to meet changes in customer needs. The algorithm allows to increase flexibility, that is defined as the process of adapting things based on the customer requirement (Verma et al., 2011) that in turn increases customer satisfaction and therefore makes more competitive the service provider (Yu et al. 2015).

The agile delivery strategy is aimed at achieving flexibility and adaptability in the face of competitive environment through rapid, dynamic and continuous response (Qrunfleh and Tarafdar, 2014).

In effect, as highlighted in (Mor and Speranza, 2020), many classes and subclasses of vehicle routing problems can be defined and for each of them valid models and solution schemes have been defined under specific hypotheses valid for that type of problem, using theoretical or heuristic methodologies developed by researchers and available in the literature.

When the problem becomes complex due to the number and heterogeneity of the parameters to be taken into account, the use of standard methodologies or the adoption of well studied variants are no longer sufficient and efficient in terms of computation time.

The rest of the paper is organized as follows. Section 2 focuses on the delivery advisor, a tool born to plan product collections and deliveries. Section 3 gives an overview of the optimization method. Then the delivery advisor's algorithms are applied to a case study (Section 4); the results are reported and commented. Section 5 concludes the paper with final remarks.

2. The delivery advisor

The delivery advisor is a digital tool that can run on mobile phones or tablets (with internet connectivity).

The tool first collects the orders of the customers, then an optimization algorithm defines the vehicle routing that is passed to the autonomous delivery van.

The advisor software is an internet based distributed solution that allows mitigating problems related to software crashes or data lost.

The overall framework of the delivery advisor is described in Figure 1. On the left side there is the data input: each client orders a certain quantity of products from a product list, in specific shops. The customer specifies also his main daily schedule: in terms of the locations where he will stay for a consistent time, and the related arrival and departure time.

In the following it has been assumed that only one electric vehicle is in charge of all the deliveries.

The output is the optimized sequence of stops and the related loading/unloading activities. Stops can be shop addresses, delivery addresses or the deposit address where the charging station is. Each trip starts and ends in the deposit. An example of trip is reported in Figure 1: the van has to leave the deposit, reaches location Z: here the fish ordered by customer X is uploaded; then, the van moves to location D: here the cheese ordered by Y is uploaded; then, the van delivers the fish to customer X in location A; then, the van moves to location C for collecting the vegetables ordered by customer Y; afterwards moves to location F for collecting the meat ordered by customer Y and finally delivers to customer Y the products in location I. The van needs to know always where to drive. The delivery advisor needs to provide clear and reliable instructions.

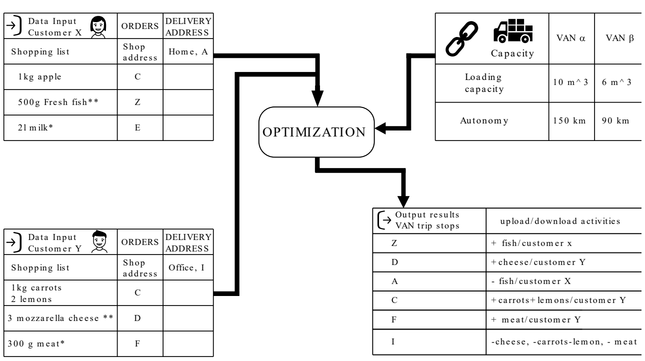

Figure 1. Delivery advisor framework

The delivery advisor main feature is the exact algorithm able to solve dynamic vehicle routing problems in a short execution time; this allows to deal with:

- Changes in the choice of the delivery point. The delivery address can be updated according to the customer needs. The customer, during the day, in general, needs to follow his activity time schedule based in different locations. In the proposed model, the customer is requested to share, with the delivery app, his current position, limited to the delivery day, or needs to specify the locations where he will be during the delivery day and the related time period: for instance, from 9 to 5pm in the office and from 6 to 8pm at home. The algorithm has the capability to meet the customers where they are, without asking them to wait the products in a place long time.
- Changes in the order lists. The proposed algorithm, gives to the customers the possibility to update online orders, in case some products have been missed. The speed of online shopping can make the customer re-think about the purchased products and he may desire to add/delete products to the already completed order before its physical delivery. Many e-commerce platforms do not allow it; normally it is only possible to open a new cart, add the new order, pay again the delivery cost and, eventually, send back the purchased products once received.
- Changes in travel times due to dynamic traffic flow conditions or unexpected events: road section blockage; road accidents etc.

Every time the data change, a new optimization problem is set, and a new run of the optimization algorithm is performed. At the end of the execution time, the autonomous van has to leave the pervious optimal routing and to start following the new one (Figure 2). Figure 2 shows the time line. At time t0, after a first optimization, the van leaves the deport and follows the optimized route. At time t1, a customer changes the delivery address: instead of home delivery (in location b) asks for a delivery at his office place: location e. At this time instance, a new optimization is run and at t2 the previous optimal route is updated to take into account the new input. The van leaves the previous route and follows the new one.

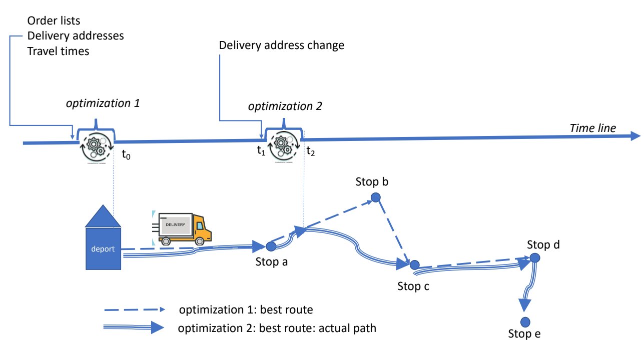

Figure 2. Time line: optimization time and delivery routes

3. Optimization strategy

Referring to the taxonomy of vehicle routing problems by information evolution and quality reported in Pillac et al. (2013), the research aims to design vehicle routes dynamically: the problem consists in designing the vehicle routes in an online fashion, communicating to the vehicle which activity to perform next. Moreover, the problem is characterized by the evolution of information, meaning that the information available to the planner may change during the execution of the routes, for example, with updated lists of orders or new customer requests. The performed analysis is deterministic.

The proposed optimization could be considered periodic, meaning that the approach uses time slices: that is, the day is divided in periods and the problem solved during a time slice only considers the requests known at its beginning. Hence, the optimization is run statically and independently during each time slice. However, in the proposed approach the time slices are not defined a priori and don't have equal duration as in Montemanni et al. (2005), Gambardella et al. (2003) and Rizzoli et al. (2007). In the proposed research, whenever the available data changes, the previous time slice ends, a new time slice starts and a new optimization is run statically with the new data. A watchdog procedure allows to identify the instant of data change. Of course, the time slice duration cannot be smaller than the optimization computation time. Therefore, the research aims to define algorithms that provide the best solution in terms of vehicle routing in a computation time that is suitable with the data input change frequency. In this sense, the proposed approach is similar to continuous re-optimization; however, continuous re-optimization maintains information on good solutions in an adaptive memory (solution pool) and these good solutions are used to generate a distinguished solution (Taillard et al., 2001; Barcelo et al., 2007; Chang et al., 2003; Attanasio et al., 2004; Beaudry et al., 2010). This solution pool is not adopted in the proposed approach because the quick computation time of the proposed algorithm allows to assess the best solution starting again ex novo each time.

In order to solve the proposed combinational problem, some exact algorithms and some heuristics have been evaluated and discussed in Cepolina et al. (2021). The presented algorithm is an exact algorithm that guarantees optimality and a suitable execution time.

The proposed optimization methodology is subdivided in 6 basic steps, each step is described in one of the following paragraphs.

3.1. Step 1: Data input

As mentioned in the simulation framework (Figure 1), the simulation tool needs the following input: delivery address, list of orders, and preferred delivery time (Figure 3). Each customer orders a certain quantity of products from a specific shop (Orders). The shop selection has to be done within a predefined choice set. The customer is allowed to dynamically update his orders and new orders will be collected and delivered instead of the previous ones.

The data input provided by the customers, plus the deposit location, give the places that should be visited by the van, for product collection, product delivery, or vehicle charging.

The data input provided by the service operator refers to the available fleet of vehicles, their loading capacity and their autonomy. In the following, we assume that the fleet is composed by only one vehicle: the FURBOT prototype.

The times/distances among all the locations are reported in a table.

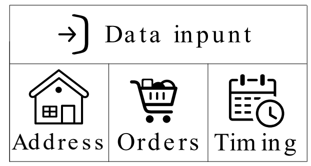

Figure 3. Data input

3.2. Step 2: Constraints

There are two groups of constraints: compulsory constraints and optional constraints.

Compulsory constraints are always active.

Optional constraints can be active or not, depending on the time at disposal for the optimization process. The active constraints define feasible solutions.

Nine examples of constraints are here down reported. Some of them are depicted in Figure 4.

1. Full collection: all the products in the order lists have to be collected
2. Full delivery: all the products collected need to be delivered
3. First collection - then delivery: it is not feasible visiting a customer without having collected at least some of the products he ordered.
4. Capacity: van has a limited capacity in weight and volume. The size/weight of the goods may impose additional physical constrains to the van "load" and unload; for example, it may be necessary to load last, and unload first, a big/heavy package.
5. Range: the FURBOT is electric and needs a "charge" after a certain mileage. The constraint "charge" states that the parameter battery level needs to be always higher than ¼.
6. Group-delivery: in case two customers ask their shopping to be delivered in the same place, the constraint "group" may be activated; it asks the van to visit each place only once, and to deliver all the shopping at the same time. It applies also where multiple deliveries for the same customer need to arrive simultaneously.
7. Timing: the customer may request a specific delivery time window, or may opt for sharing his physical position. The predictive estimated times of arrival are

critical for relaying delivery expectations to keep customer satisfied

8. Priority: there are specific classes of goods, like "fresh/frozen" food and "drugs", which may require prioritized delivery and specific handling in order to preserve the product quality (Giusti et al., 2019).
9. Traffic: the "traffic" of each road changes with the time of the day: there are specific streets that should be avoided during peak hours. Late afternoon delivery may be preferred inside crowded cities.

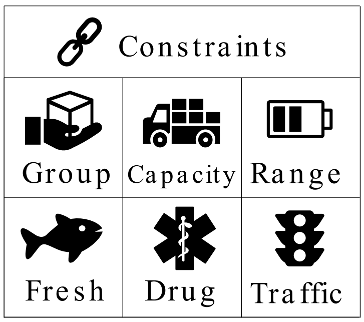

Figure 4. Some of the problem constraints

3.3. Step 3: Search space exploration

A solution is a delivery trip formed by a sequence of stops. A stop takes place in a delivery address or a shop address or the deposit address. All the locations should be visited at least once.

Each location can be visited more than once in a trip; for instance, the van may need to go twice to the charging station. Each trip starts and ends in the deposit.

The search space dimension is given by the number of permutations with repetition of n different stops.

n= customer addresses + shops to visit. A permutation is a trip: a generic sequence of steps.

Each permutation is a possible solution. Not all the solutions are feasible solutions. Feasible solutions are the ones that satisfy the active constraints.

Three approaches have been tested for the search space exploration: the first two (A1 and A2) allow the global optimization and the last one (B) a local optimization. These approaches have been described and compared in Cepolina et al. (2021). In the following only a description of approach A2 (called "pre-treated global optimization") is reported.

The "pre-treated global optimization" approach generates the solution adding one stop each time and a stop is added only if it is feasible. The feasibility of one stop depends on the active constraints and on the stops previously added to the solution. The following criteria define whether a stop is feasible or not:

I. Next stop can be a customer's delivery address only if there are still products to deliver there (constraint 2 active).
II. Next stop can be a customer's delivery address only if the customer's products have been already collected and not yet delivered (constraint 3 active).
III. Next stop can be a shop address only if the loading factor is <1 (constraint 4 active)
IV. Next stop can be a shop address only if there is still something to collect there (constraint 1 active)
V. Next stop can be different from the deposit, only if the battery level is >1/4 (constraint 5 active) and so on for the other activate constraints, for instance:
VI. Next stop can be the delivery address of a customer only if the customer is at the delivery location (constraint 7 active)

The stops that satisfy these criteria belong to the feasible set Fi:

$$F_i = \left\{ \begin{array}{c} \text{all the feasible stops P, being in } S_i \text{ and having already} \\ \text{visited } S_{i-1}, S_{i-2}, \dots, S_1 = \text{deposit} \end{array} \right\}$$

3.4. Step 4: Target function

It is possible to minimize the overall journey length or the overall time (Figure 5). In order to simplify the problem, a single variable optimization is performed.

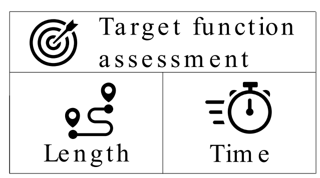

Figure 5. Target function

3.5. Step 5: Evaluation

The optimization algorithm has been improved integrating the comparison of solutions, inside the solution generation. This embedded approach evaluates the target function value of a partial solution during its generation and compares it with the target function value in the current best solution. In this way, the algorithm stops the exploration of any not finished solution, if its length is already longer than the shortest solution found. In case the length of a path is already longer than the winning path, all the sons of this tree branch do not need to be explored. Rejecting a single branch may erase even 1000 sons in one shot. This branch pruning makes the algorithm blazing fast since not necessarily all the feasible solutions are generated and evaluated.

3.6. Step 6: Output

The delivery advisor helps in selecting the higher score solution among the feasible ones.

The output, expected from of the simulation, is: the list of the optimized sequence of the van displacements and the tracking information for each customer (Figure 6). Benefits of integrating IT tracking and routing systems into last-mile distribution operations have been investigated in Salhieh et al. (2021).

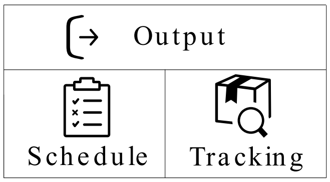

Figure 6. Outputs

4. CASE STUDY

A case study shows the performance of the proposed delivery advisor. The small size test environment allows easily judging if the solver is offering correct solutions. The van moves inside a village scenario and serves three customers.

4.1. Data input

The village has a square map (Figure 7): the area is subdivided by 8x8 small squares, each having a 1 km2 size.

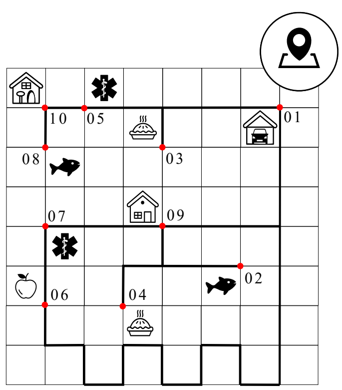

Figure 7. Case study, the road network

The roads are graphically represented by thick lines. The van can stop in each of the places shown by a small red circle. There are overall 10 places: 1 garage (place 01), 2 houses (place 09 and 10) and 7 shops. Down town there are these shops: two fish shops (place 02 and place 08), two bakeries (place 03 and place 04) two pharmacies (place 05 and place 07) and a fruit seller (place 06). The van moves inside the village scenario.

Given the road network (Figure 7), it is possible to calculate the distance between any couple of places; for example, the "place 06 – fruit seller" is 5 km away from the "place 09 – house". The solver, in order to perform its optimization tasks, needs, as an input, the distances among all the places of interest (Figure 8). It is assumed that there are no one-way traffic links: the distance A→B (A and B being two generic places) is the same as the distance from B→A.

01	02	03	04	05	06	07	08	09	10	
00	09	04	09	05	11	09	07	06	06	01
09	00	13	04	14	08	06	16	03	15	02
04	13	00	13	03	15	13	05	10	04	03
09	04	13	00	14	08	06	16	03	15	04
05	14	03	14	00	16	14	02	11	01	05
11	08	15	08	16	00	02	18	05	17	06
09	06	13	06	14	02	00	16	06	15	07
07	16	05	16	02	18	16	00	13	01	08
06	03	10	03	11	05	06	13	00	12	09
06	15	04	15	01	17	15	01	12	00	10

Figure 8. Case study, the distance matrix in km

Three customers live in the two houses; Ann and Joe live together in the house 10, while Tom lives alone in the house 09. Each customer provides a personal shopping list and a preferred delivery time (Figure 9). Each good quantity is expressed by its own specific unit of measure; kilograms, liters, units etc. For example, Tom would like to receive at 9.00 in the morning: 1 kg of fish, 2 kg of bread and 2 kg of apples.

			02	03	04	05	06	07	08
Tom	09	09:00	01 (Kg)	00	02 (Kg)	00	02 (Kg)	00	00
Ann	10	10:00	00	03 (Kg)	00	02 (--)	00	00	03 (Kg)
Joe	10	14:00	00	00	00	00	03 (Kg)	00	02 (Kg)

Figure 9. Case study, the orders expressed in units/kg

The advisor uses the following constrains (Chapter 3.2): Full collection (1), Full delivery (2), First collection – then delivery (3), Range (5). The target function refers only to journey length.

4.2. Output results

The results of the case study are now provided and discussed.

Hardware: MacBook Pro Late 2013 (processor 2,3 Ghz, Quad-Core, Intel(R) I7, 16 GB RAM).

Software: Python 3.9.0 (Oct 5 2020, 11:29:23). Code length: 114 lines

The total execution time is 0.6 seconds.

After 0.1 seconds, the first solution has been found:

Route 1) 01→02→03→04→05→06→08→09 →10 (108 km)

It is interesting to notice that the van, in order to end its delivery tour, did not need to reach the "pharmacy 07" because no customer has bought any good from this shop. The total delivery journey is 108 km long.

So far this is the best (and only) solution found: from now the delivery advisor will show additional solutions only if they are shorter than 108 km.

The program has found overall 5 solutions.

After 0.3 seconds this solution has been found.

Route 5) 01→02→04→06→09→03→05→08→10 (42 km)

Only after 0.59 seconds the program ends to explore all the remaining solutions and then it is possible to state that the route 5 (42 km long) is the overall best solution.

A graphic representation (Figure 10) shows the solution of the route 5. A dashed grey line represents the path of the van; when the van stops in a place, the grey line enters into the red circle.

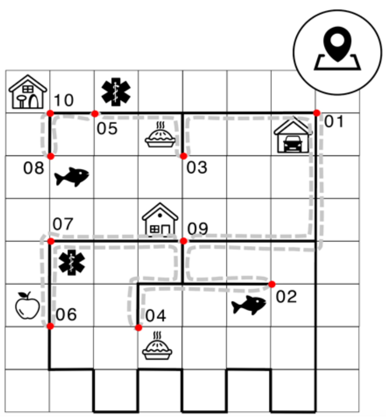

Figure 10. The best path

The final version of the Python delivery advisor is relatively fast: it needs 0.6 seconds to solve the problem.

4.3. Data input change and related updating of the delivery route

At time instant t* Tom changes his mind and decides to buy the bread from bakery 3 instead of bakery 4 (for instance he realises that there is special offer in bakery 3 in the current day).

The van starts from the deposit according to the initial orders (bread in bakery 4 for Tom). When the van reaches stop 2 and has already covered 9 Km from the deposit, the system is notified of the Tom's new request. The algorithm runs again with the new input from Tom (bakery 3 instead of bakery 4) and after 0.1s, at time t*+0.1s, provides the new optimal route that satisfies the Tom's new request. The new route results 8 km longer but Tom's satisfaction is very high.

New Route 6) 01→ 02 (t*)→ 06 →03→05→08→10→09 (50 km)

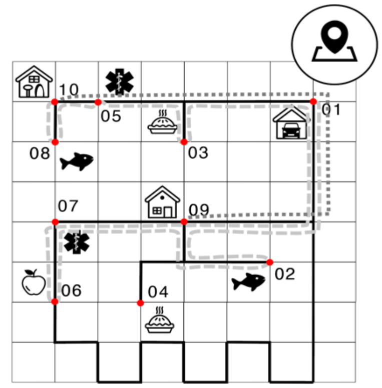

Figure 11. The modified route that satisfies Tom's new request

A graphic representation (Figure 11) shows the solution of the new route 6. The execution time can highly increase with the complexity of the problem. Every time a single problem constraint changes, it is necessary to run again the simulation. If the overall simulation time takes a few minutes, it may be advisable to wait always for the best solution. In any case the optimization process can be stopped at a time considered optimal (time/performance trade off), and the most suitable solution can be selected among the found ones.

5. Conclusions and future work

Online shopping has seen booms of orders in recent years, also pushed by pandemic. The characteristics of online orders put constraints on production and logistics that are required to be more flexible and to dynamically respond to changes in customer needs, satisfying the cornerstones for a sustainable economy and society.

Delivery is one of the key aspects either form the delivery operator point of view, either from the customer point of view. Delivery options have different travel costs and delivery time and location affect customer satisfaction. Delivery at the time and place that is convenient to the consumer is one of the main issues for increasing customer satisfaction.

The paper refers to the following on line grocery shopping: customers buy on line from different shops or dark stores. An autonomous electrical vehicle collects the products and deliver them to customers: when the autonomous vehicle stops close to a shop, the shop personnel load the required products on the locker fixed on it. When the autonomous vehicle stops in a delivery point, the customer has to unload his products while the vehicle is parked. The designed delivery system offers contactless unattended deliveries.

The proposed delivery advisor allows the logistics service provider to readily make adjustments to meet changes in customer needs. This enhanced flexibility is a very important factor for increasing customer satisfaction. The advisor is fast enough to solve almost real time vehicle routing problems, allowing customers to change their preferences about orders and delivery locations and allowing the routing to take into account the real traffic conditions.

The software, coded using the Python Language, is already fully developed, while the graphic interface and the design of the mobile phone app are still under development.

The proposed delivery advisor will be adopted in the context of grocery last mile delivery in the Trikala city center (Greece). This demonstration will be part of the SHOW EU project.

In the next future, the authors would like to improve the presented delivery advisor to complement an automated decision support system architecture including dynamic databases, decision heuristics, and dynamic process simulation, for the systematic generation of cost-effective fleet configurations, as it has been already done for fleet management in maritime logistics (Bruzzone et al., 2002).

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