



# Intervention schedule optimization with travel time minimization for a Value-Added Reseller by solving the Capacitated Vehicle Routing Problem

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## ARTICLE INFO

### Keywords:

Cleaner logistics  
The capacitated vehicle routing problem  
Optimal routes  
Scheduling interventions  
Travel time minimization and labor optimization

## ABSTRACT

With the significant increase of service providing companies and the option of in home installation or maintenance, the importance of finding the optimal planning for the workers has risen accordingly. Global warming, high fuel prices, and important labor costs call for the need to minimize travel and working time and reduce the impact on the environment. In this paper, the CVRP is solved to establish a planning of interventions, being installation and maintenance, at customers of a value-added reseller (VAR). The goal is to minimize total travel time, maximize labor time per day, combine jobs that need two workers in the same van, and to reduce emissions. In contrast to previous research on routing optimization, limits are set to both the working time and the sum of the working time plus the travel time. In addition, it centralizes installations that need two workers on the same route, further minimizing the use of vans. As a result, scheduling becomes faster, more accurate, and scalable, leading to a significant reduction in overall asset and labor cost, and to less CO<sub>2</sub> emission, thus cleaner logistics. This intervention planning is compared with the random planning and planning proposed by an expert planner. Applying our algorithm on various configurations of 16 to 82 customers led – in a time span of seconds – to a relative gain of 3% for the smallest application and up to 38.6% for the largest one, compared to the time-consuming planning made by the expert human planner. Moreover, to visit 82 customers 3 less vehicles are needed (21 instead of 24), in comparison to the human made schedule.

## 1. Introduction

Private companies around the world can be classified on the basis of their structure, size, or activity (Economy-Pedia, 2021). In this paper, the latter classification is applied. First in this category, there are companies that focus on the production of goods, ranging from discrete Taylor-made products (Helu et al., 2020) such as cars to mass-produced items, e.g. fast-moving consumer goods (FMCG). These production facilities can apply different production methods, such as job production, flow production, or batch production (Online Learning College, 2022; Kurosz and Milecki, 2019). Other companies are service-oriented, such as banks that offer financial services and information technology companies that provide IT consulting. A special type of these service-oriented businesses are value-added resellers (VAR), defined as companies reselling software, hardware, discrete products, or services that deliver value on top of the original order fulfillment (Gillis, 2022). The subject of our research is the intervention planning of two of these

VAR's, being (i) a company that buys, sells, installs, and maintains window decoration products and (ii) a business that sells, installs, and maintains building alarm systems. Both venues order (taylormade) products from production facilities and store them in one or more local warehouses. When all orders arrive at the depots, the end customer is contacted to plan the installation of these products. However, this planning is ad hoc and although some effort is made to group installations in the same regions, there is still a significant amount of optimization possible. The designed schedule must also contain maintenance interventions, demanded by customers when service on the window decoration or alarm installation is necessary to correct for flawless operation.

The planning of the installation of window decoration or alarm products is proactive in nature. Hence, the list of interventions is known upfront, making it possible to organize the planning so that labor cost is reduced. Maintenance, however, is reactive of nature, must be scheduled between, and is thus more difficult to plan (Scarponi and

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Paltrinieri, 2016). In typical VAR operations, a mix of both types of interventions must be planned, resulting in a complex task to determine the optimal work schedule. To optimize the route of one van so that the total distance traveled is minimized, the Traveling Salesman Problem (TSP) can be solved (Laporte, 1992). Since there are several vehicles that go out simultaneously to perform a number of installations, with varying amounts of intervention time, the schedule is calculated by solving the Vehicle Routing Problem (VRP) (Kopfer and Kopfer, 2013). The constraints on total working time and total travel plus working time make the use of a CVRP solving method mandatory. In a standard CVRP, the maximum capacity can be defined as the number of packages in a full van or the total weight of all packages in the delivery truck. However, in this paper, the load of each van is defined as the sum of the intervention time at each customer, carried out by the worker(s) driving the vehicle. The capacity of each truck is then the maximum number of work hours to be performed. Furthermore, the sum of the intervention time and the travel time must not exceed a total working day. As an extra constraint, all interventions that need two workers to execute the tasks must be centralized in the same van to reduce the number of vans and round trips.

As a result, our solution method presents a planning per vehicle in which working time is maximized, travel time, and the number of vans are minimized, and interventions requiring more workers are concentrated in the same van. This limitation of the distance traveled also reduces the amount of CO<sub>2</sub> emitted by the vans, reducing the impact of pollution on the environment. This is the first paper to use the CVRP to plan the interventions of a VAR taking into account all constraints mentioned, according to the author's knowledge. The novelties of this paper are: (i) the use of the required working hours of each intervention as a capacity of a van and the maximum tour length as the limit to the sum of travel time and the interventions time of the worker(s) in the van, (ii) the grouping of all the interventions that need to be carried out by two workers in the same van to further reduce pollution and finally, (iii) solving a multi-depot, heterogeneous fleet vehicle routing problem with grouped workers to determine an optimal planning for the interventions with minimal travel time and within the limits of a working day.

## 2. Related work

The vehicle routing problem (VRP) is one of the most extensively studied combinatorial optimization problems (Braekers et al., 2015a), both for classical route distance minimization and for secondary problems such as allocation of resources in an electric power distribution system (Zapata et al., 2019). In the last decade, VRP has attracted the attention of a large group of operational researchers, due to the industrial significance of the problem, the aim of cleaner logistics (Fernando et al., 2024; Stamadianos et al., 2023; Pak and Mun, 2024), and the scientific challenges it poses (Laporte et al., 2013; Braekers et al., 2015b). Hence, package delivery problems are becoming increasingly complex and require appropriate planning so that costs can be minimized and efficiency can be increased. Furthermore, results obtained by solving the VRP are rarely robust, meaning that when an ad hoc change occurs in the planned route, if a customer is not home or traffic is jammed, for example, the whole calculation needs to be initiated again from scratch, which can be a lengthy process, certainly for longer routes.

Apart from the standard vehicle routing problem, several variants are well known and extensively studied, such as the Capacitated Vehicle Routing Problem (CVRP), the Vehicle Routing Problem with Time Windows (VRPTW), the Multi-depot Vehicle Routing Problem (MDVRP) and a combination of the described derivatives (Han and Wang, 2018). To meet the growing demands of the package delivery industry, more recent models have been investigated, such as, among others, the Heterogeneous Fleet Vehicle Routing Problem (HFVRP) and the Split Delivery Vehicle Routing Problem (Elatar and Riffi, 2023; Zhang et al., 2021). In this paper, the focus is on CVRP, which has a central position

in the VRP landscape (Ibrahim et al., 2019). Solving the CVRP results in a set of routes, starting and ending at the depot, in which every customer is visited exactly once, with the additional constraint that the sum of the demands – goods or packages – of the customers of each route does not exceed the vehicle capacity. The main objective is to find a solution with a minimal total route distance (Uchoa et al., 2017). Danzig and Ramser were the first to describe the CVRP application to determine the optimal routes for gasoline delivery trucks between a group of gas stations and a large terminal (Danzig and Ramser, 1959). Since then, it has been the subject of many research papers (Gounaris et al., 2013; Zhao et al., 2016; Borčinová, 2022), most recently for the still growing business of package distribution and delivery, with or without time constraints (Sangeetha et al., 2013; Cokyasar et al., 2022). The previously cited papers focus on minimization of distance alone, where all interventions are of the same duration or very limited in time. In our paper, the duration of all interventions can differ, limits are set to the working time and the sum of working time and travel time, and installations needing two workers are grouped into the same van.

Further research coupled the Capacitated Vehicle Routing Problem with driver scheduling, taking into account that the vehicles used can differ in such a way that they can carry a different amount of packages or loads, resulting in a heterogeneous fleet (Panggabean et al., 2018; Staes, 2011). This makes the CVRP more complex, with the additional constraint that the capacity of each vehicle can be set to a different value. Again, this type of problem is not only linked to the well-known package delivery business, but can even be solved for the distribution of liquid products using tank trucks, for example, liquefied petroleum gas (LPG) (Onut et al., 2014; Panicker and Mohammed, 2018). Second, several researchers worked on the Multi-depot Vehicle Routing Problem, a variant of the VRP in which trucks can depart from different depots without specific visiting time windows (Bae and Moon, 2016) or with them (Orivalde Soares da Silva Junior and Bergmann, 2011). Finally, Salhi et al. and Hanum et al. optimized the routes for a distribution company with a multi-depot organization and a heterogeneous fleet, making it a multi-depot heterogeneous fleet vehicle routing problem (MDHFVRP) in which not all vehicles thus have a similar capacity (F. Hanum and Bakhtiar, 2018; Salhi et al., 2014). They have thus investigated the same optimization problem that is the subject of this paper. However, while their solution method focuses on package delivery, our algorithm goes a step further and offers an intervention planning that takes into account limitations like total daily work time and multiple workers per job.

To solve the Capacitated Vehicle Routing Problem, several solvers can be used, such as Pulp (Kim, 2020) or OR Tools Solver (OR-Tools, 2002-2022) in combination with the Google Maps API. In the latter, the API is used to calculate the travel time between the depots and the different customers, taking into account maximum speeds and possible detours, while the solver is used to determine the optimal routes. Another group of solution methods are described as metaheuristics. A metaheuristic algorithm is a search method developed to find a good solution to an optimization problem that is complex and difficult to solve. Typical examples are the use of a Genetic Algorithm (GA) (Ren, 2012; Awad et al., 2018) or the Ant Colony Optimization Algorithm as described by Wan Othman and Wong (2018). As a final example of metaheuristic methods, Akhand et al. solved the route optimization problem by using Swarm Intelligence (Akhand et al., 2015).

Although OR Tools has been studied to solve CVRP (Salsabila et al., 2023) and VRPTW (Wang et al., 2021) separately, this study aims to solve CVRP with a heterogeneous fleet, workforce constraints – combining jobs that need two workers – and multiple depots to obtain robust planning for the installations and maintenance visits done by a VAR. It is thus the first to extend the OR Tools solver with additional, challenging job constraints. This enables its applicability to real-life use cases of the capacitated vehicle routing problem and shows that its use can be extended to the setup of a planning, rather than just the minimization of the route distance.

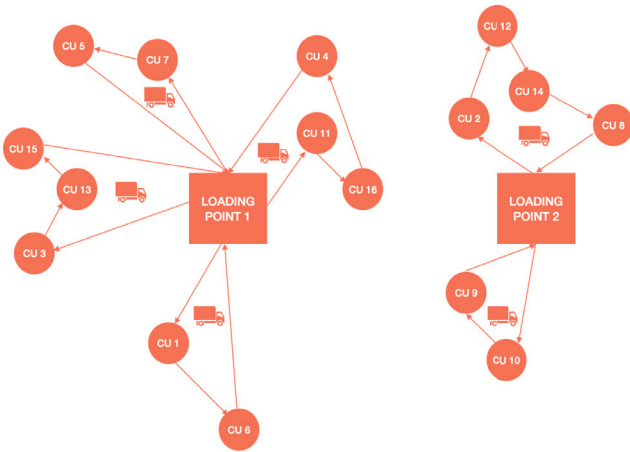


Fig. 1. Multi-Depot Configuration after solving the VRP for 16 Customers, 6 Vans and 2 Warehouses.

### 3. Method

#### 3.1. Configuration

Fig. 1 shows a configuration of 16 customers that need to be serviced in one day – for installation or maintenance – by a group of 6 vans, loading at two separate warehouses, after solving the Capacitated Vehicle Routing Problem for a one-day planning. Each customer is represented as *CU XX* (XX ranging from 1 to 16), while the warehouses are indicated as *Loading Point*. Four of the vans are starting from and returning to warehouse one, the other two have the second warehouse as loading point. In this setup, at each customer, work needs to be done, which sometimes takes between half an hour and several hours. This makes it impossible for one truck to visit each customer and for every worker to perform all necessary work at all locations. Therefore, the Vehicle Routing Problem is solved to make a planning for one day allowing all the work and travel to be done within a time span of 8 h, starting from and returning to the point of origin. In order to set a limit on the working time per day, the Capacitated VRP is solved, in which the normal capacity limit, being the number of packages to be loaded or the total weight of the truck, is replaced by the working time, also expressed in minutes. Once tested, the configuration will be extended to 50 customers, and the planning will be extended over a number of five days.

Although both investigated data sets show some similarity, the interventions done by the alarm installation company are generally much shorter and more regionally concentrated around the depot. Consequently, more interventions can be made in a single day, and less travel time is needed to visit customers, resulting in a higher level of optimization. It shows the general applicability of our solution.

#### 3.2. Outcomes of the algorithm

The outcomes of our CVRP solution algorithm are threefold, namely the optimal number of vans, the optimal route for all trucks with a minimal travel time in minutes, and a planning of all customers to be serviced, spread over a total week, with an optimal schedule per day. These are compared with a random planning, obtained by putting every intervention randomly one after the other until the total working time is reached for all vans and this over a period of 5 days. Furthermore, they are weighed against man-made planning, created by the intervention planner of the company.

To determine the feasibility of the solution, a first relative gain in time ( $\Delta G_t$ ) is calculated by dividing the total time – the sum of travel and working time – for a randomly chosen work schedule ( $ST_t|Random$ ) minus the total time obtained after optimization ( $ST_t$ )

by the randomly chosen total time of the schedule (see Eq. (1)). As a result of this equation, a percentage is calculated that expresses how much better the optimized schedule is than the random planning.

$$\Delta G_t = 100 \cdot \frac{ST_t|Random - ST_t}{ST_t|Random} \quad (1)$$

A second relative gain ( $\Delta G_p$ ) is calculated by dividing the total time – the sum of travel and working time – for a man-made work schedule ( $ST_t|Plan$ ) minus the total time obtained after optimization ( $ST_t$ ) by the man-made total schedule time (see Eq.(2)). Eq. (2) results in a percentage that indicates how much better the optimized schedule is than man-made planning.

$$\Delta G_p = 100 \cdot \frac{ST_t|Plan - ST_t}{ST_t|Plan} \quad (2)$$

#### 3.3. CVRP - problem formulation

As indicated, the vehicle routing problem is a well-known NP hard problem that is often used in the distribution sector to minimize the total distance traveled for all the transport vessels used. Since all packages need to be dropped off instantaneously, the time lost per customer is minimal, and the VRP thus leads to an optimal travel time. If there were only a limited number of packages to be delivered, one truck would be sufficient to visit every customer in one day, as all packages can be placed in one van. However, in the value-added reseller use case, there is no immediate delivery, but the trucks need to stay at a customer location to give the workers the opportunity to carry out the installation or maintenance. The time per intervention can vary from half an hour for a simple repair to several hours for a large installation. Sometimes, one worker is not enough to complete a repair or installation, and therefore an additional worker should be in the same van. The planning must thus take into account that all interventions carried out by two workers are visited by the same van, to avoid pick-up of an additional person in between interventions and thereby an augmentation of the travel time.

#### 3.4. CVRP - model

Solving the standard Capacitated Vehicle Routing Problem results in the routing of a set of  $A$  vehicles, each with capacity  $C$  to visit and service a group of customers, at minimal cost. Each customer has a specific demand that must be fulfilled by a single van.  $N$  represents a group of demand nodes – customers in need of service – and one warehouse (loading point in Fig. 1), identified as node 0, while  $d_i$  is the demand at each node  $i$ , expressed in minutes. In the description of the CVRP model used in this paper, we assume that the demand  $d_i$  can be different at all nodes – except in the warehouse where it is always zero – and is calculated taking into account the number of workers needed. This means that the demand for a job will be lower when this is done by two workers, compared to when it is executed by one worker, but not automatically by a factor 2. The variable  $c_{ij}$  equals the travel time between nodes  $i$  and  $j$ , while we consider that every customer is visited exactly once.

Different models can be found in the literature to describe the Capacitated Vehicle Routing Problem (Ordóñez et al., 2006). In the CVRP three-index formulation model hereunder, Eq. (3) describes the objective of the problem, being the minimization of the total travel time by calculating the optimal route. In this Arc-based model integer, binary variables  $x_{ij}$  indicate whether or not a vehicle goes from customer  $i$  to customer  $j$ . It also includes continuous variables  $u_i$  for every  $i \in N \setminus \{0\}$  that represents the flow in the vehicle after visiting the customer  $i$ . If a vehicle drives from node  $i$  to node  $j$ , the value of  $u_j$  must then be higher than the value of  $u_i$ . Finally, an integer variable  $y_{i,a}$  is defined, indicating whether van  $a$  services customer  $i$  or not. Arc-based routing problems (Faiz et al., 2019) are defined in a network that includes nodes and connections between nodes. These connections

are called arcs when they are directed (one-way) from one node to the other.

$$\min(\sum_{i \in N} \sum_{j \in N} c_{ij} \sum_{a=1}^A x_{ija}) \quad (3)$$

Where:

$$\sum_{a=1}^A y_{ia} = 1 \quad (i \in N \setminus \{0\}) \quad (4)$$

$$\sum_{a=1}^A y_{0a} = A \quad (5)$$

$$\sum_{j \in N} x_{ija} = \sum_{j \in N} x_{jia} = y_{ia} \quad (i \in N, \quad a \in 1 \dots A) \quad (6)$$

$$\sum_{i \in N} d_i y_{ia} \leq C \quad (a \in 1 \dots A) \quad (7)$$

$$u_{ia} - u_{ja} + Cx_{ija} \leq C - d_j \quad s.t. \quad d_i + d_j \leq C \quad (i, j \in N \setminus \{0\}, i \neq j, a \in 1 \dots A) \quad (8)$$

$$d_i \leq u_{ia} \leq C \quad (i \in N \setminus \{0\}, \quad a \in 1 \dots A) \quad (9)$$

$$x_{ija} \in \{0, 1\} \quad (i, j \in N, \quad a \in 1 \dots A) \quad (10)$$

$$y_{ia} \in \{0, 1\} \quad (i \in N, \quad a \in 1 \dots A) \quad (11)$$

The constraints represented by Eqs. (4) and (5) make sure that exactly one van services each customer  $i \in N \setminus \{0\}$  and that A vans leave the warehouse. Constraint 6 ensures that a vehicle reaches and leaves the customer  $i$  only if it services that customer, while constraint 7 enforces the capacity restriction for all vehicles  $a$ . The two last constraints 8 and 9 make sure that subtours are eliminated. A subtour is a round trip that returns to where you started but does not visit all the customers and has a start and end that can differ from the depot. Finally, Eqs. (10) and (11) denote that  $x_{ija}$  and  $y_{ia}$  can only have the value 0 or 1.

### 3.5. CVRP - solution method

Several solution methods have been developed and can be found online. There are tools like VRPy, using a column generation approach, and Google Operational Research (OR) Tools (OR-Tools, 2002-2022). Genetic Algorithms (GA) (Ren, 2012; Awad et al., 2018) and Ant Colony Optimization (ACO) algorithms (Wan Othman and Wong, 2018), described as a metaheuristic solution method, have also been used to solve the Vehicle Routing Problem. Previous research has shown that of the three investigated methods, i.e. VRPy, ACO, and OR Tools, the latter led to results comparable to the two other ones for solving the VRP with Time Windows, but much faster. Fig. 2 shows the general solution model for the CVRP. In the first step, the data that will be fed to the defined model are set, such as the location of the customer and the depot, the capacity of the vehicle, and the size of the fleet. Based on these data, an initial acceptable solution is created using heuristics and then checked whether these routes respect the capacity constraints. If not, the routes must be adjusted. After applying the optimization technique, an improved solution is generated and checked to see if these routes still meet the constraints. Finally, the stopping conditions (iterations, convergence) are evaluated: if not met, the optimization process will be repeated; if met, the model returns the best solution, and the flow ends.

This OR solver is used to unravel the capacitive vehicle routing problem, applied to the curtain shop and the alarm shop customer install base. In this paper, the capacity in the CVRP problem solved is not linked to a load quantity but rather to a total work-time limit for each worker on board of the vehicle, carrying out the installation or the maintenance at every customer visited. In addition to the maximum working time as a condition, we also set a limit on the sum of the travel time and the working time per day for each van.

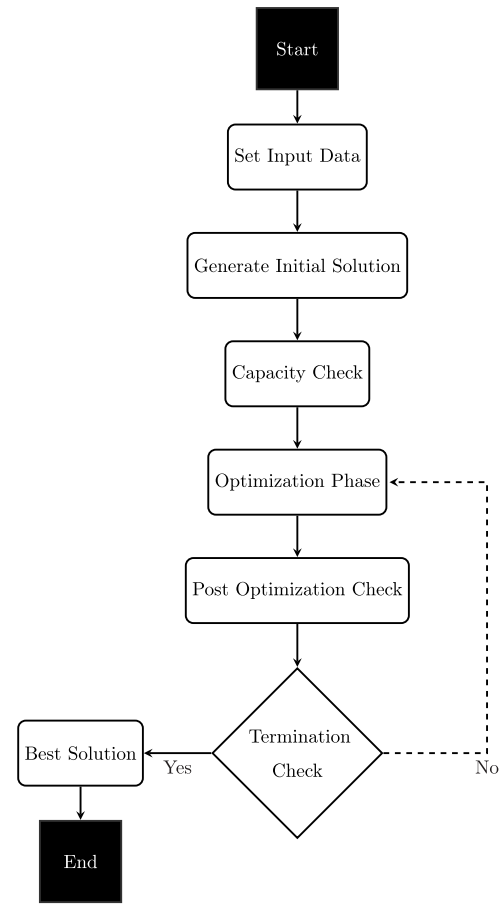


Fig. 2. Flowchart of the CVRP solution model.

In the standard capacitated vehicle routing problem (CVRP), vehicles with limited carrying capacity need to drop off or deliver items to multiple locations. The products that need to be distributed have a weight or volume, and each of the vehicles has a limited capacity to carry and transport. Solving CVRP results in minimization of the costs associated with the pick-up or delivery of the products, while never exceeding the capacity of the vehicles. Each intervention in a customer can take from half an hour up to several hours of work, while the total amount of work to be done by one worker cannot exceed 8 h per day, travel time not included. This is thus a second condition set, one that is supplementary to the standard CVRP. Hence, solving the normal CVRP has as goal the minimization of the total travel time of all vehicles while not exceeding the capacity of the vehicle. However, we describe a CVRP in which the same objective is aimed, while neither the total working-time limit nor the total sum of travel time and working time can be outran.

In addition to the conditions described above, the solver used in this paper has to take into account the fact that some of the interventions need to be carried out by two workers, instead of one. As an additional objective, the algorithm is designed to group as much as possible all installations that require two workers into the same van on the same day. In this way, only one van is needed to transport two workers who will do all the installations, requiring two people to be together. Hence, if no grouping is done, then both workers need to drive their own van and the amount of kilometers, and thus the travel time could be doubled. No other limitations are taken into account, nor the weight of the van, nor the load when calculating the optimal number of vessels and the minimal travel time necessary to service all customers. As more depots are available to start from, minimization of travel time will

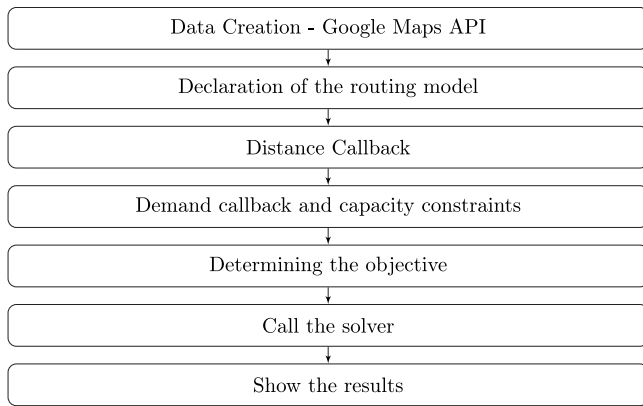


Fig. 3. Schematic overview of the OR Tools solution method for the CVRP.

consequently lead to centralization of the routes around the closest depot.

The algorithm – schematically shown in Fig. 3 – used to solve the VRP starts with the creation of input data. To calculate the travel time matrix grouping the travel time between all destinations, the google maps API is used. When sending the latitude and longitude of origin and destination to this tool, it returns the time that is needed to travel from one location to the other. This travel time is assumed to be symmetrical, meaning that the travel time from customer  $i$  to customer  $j$  is the same as the travel time from customer  $j$  to customer  $i$ . Under real-time conditions, the travel time can differ slightly with the direction of the route – from customer  $i$  to  $j$  or from customer  $j$  to  $i$  – leading to an asymmetric travel time matrix. After defining the routing model by using the Python `pywrapcp` package, the data is offered to the distance call back function, returning the distance between any two locations, expressed in minutes. This is not just the travel time, but the sum of the transit time and the intervention time at each customer, also called the demand. In addition, two time limitations are set, being first that the total work time cannot exceed a threshold and second that travel time plus working time cannot be larger than 510 min (a working day of 8 h plus a break of 30 min). Before the routing library python wrapper (solver) can be launched to calculate a new set of optimal routes, an additional constraint is added to group the interventions that need two workers to complete the job, and the objective is set. Besides travel time and demand, the data also contains the maximum number of vessels, the index of the customers serviced by two workers and the locations that can serve as depot. The latter makes it possible to plan optimal routes starting from and returning to multiple depots. The algorithm then results in grouping of vehicle runs around the indicated loading points. The tests are fully automated in such a way that the customers data are exported from the company’s database as a JSON file. This file contains the address of the customer, the needed installation or maintenance time and the number of workers needed for all interventions that have to be planned. By using the Google API, the travel time between all the customers and between the depots and the customers is calculated, resulting in a time matrix. This time matrix is then used to determine the optimal route between all customers with a minimum number of vans. In the result section, we will discuss the use of OR tools – open source software for combinatorial optimization – to solve the capacitated vehicle routing problem. The objective thereby is to obtain the shortest total travel time of the vans out of a vast set of possible solutions. The algorithm used is built around a specialized library to identify the best van routes including constraints. The solution method is based on the constraint-solver.

### 3.6. Parameters

The parameters used in this paper can be divided into three groups: (i) the input parameters are all the data known before solving the

problem, such as the location of each customer, the demands (working time), the number of workers for a job, the starting and ending point of each route, and (ii) the decision variables are defined as the outcome of each run of the calculation loop in the used solution methods. These iterations stop when the objectives are met and (iii) these objectives are described in the last group.

#### Input parameters.

$N$ , number of maintenance jobs

$B$ , number of workers for each intervention (1 or 2)

$LL = ((lat_1, lon_1), (lat_2, lon_2) \dots (lat_k, lon_k))$ , set of coordinates of each customers

$D = (d_1, d_2, \dots, d_n)$ , demand or working time at each customer

$W = (w_1, w_2, \dots, w_n)$ , loading and unloading warehouses

$t_{ij}$ , travel time between two customers or between customer and warehouse

#### Decision variables.

$A$ , number of vans

$M_S$ , a sequence of customer interventions, spread over different vans

$C_T$ , Total travel time of all the vessels

#### Objectives.

Min  $C_T$

### 3.7. Robust scheduling

By robustness we mean the ability to execute the interventions according to planning, even in situations that deviate significantly from the regular conditions. The robustness of the planning can be increased by a certain spare capacity to execute the planning, often referred to as redundancy. Resilience is the ability of the transport system to adapt itself, over and over again and preferably as quickly as possible, to recover from a temporary overload. Finally, the weakest link determines the strength of the chain, a law that also applies for the robustness of a network: The trajectory or intervention with the least spare capacity will often cause problems first, and therefore, compartmentalization is applied.

The solution method as discussed in this paper aims to set up a planning or intervention schedule for the upcoming week and is thus created upfront. Changes to this planning can occur, for example, when an urgent repair needs to be carried out and, therefore, added to the planning, or when an intervention is canceled by the customer and thus needs to be postponed. To cope with urgent repairs or installations, we will foresee gaps within the planning, which can then be filled by these critical interventions. Thus, we increase the resilience of planning. To handle the last-minute cancellations, we keep a few non-urgent interventions on hand – typically around 10% of all interventions – to fill the gaps that are created in the planning due to these abolition. This action thus helps to improve the redundancy of the planning. Both strategies help to make the customer intervention schedule of a VAR more robust and secure against sudden, unforeseen changes. By grouping interventions around different depot areas, the third option to improve robustness, namely compartmentalization, has already been built into the planning.

### 3.8. Routing, scheduling and asset management

At value-added resellers the planning of interventions and the scheduling of workers is carried out by a planner in an almost random way. This implies that this worker has the dedicated job of calling all customers who need service and offering them one or more time slots for the intervention. However, there is no predefined schedule that can be used as a guide for an optimal scheme, and thus no

optimization is done. There are just two minimal constraints that are taken into account, namely: (i) the aim to group as much as possible the interventions that are to be done by two workers and (ii) to keep one of the vans in a dedicated region, since the second depot is situated in that vicinity. As a result, the proposed scheme is rather arbitrary and does not aim to minimize costs, group installations per region, or optimize labor time. Hence, in the example planning, we see that workers are sent to the east of a region in the morning, to the west at noon, and back to the east in the afternoon. This results not only in an increase in the total travel time of the van but also in a reduction in the interventions and thus the total work at the customer. As a direct result of our solution method, the amount of working time in a day can increase, as well as the total number of interventions per week. The planner can then use the resulting schedule to impose the interventions in a correct way to the customers to minimize total costs.

Transport vehicles can be seen as important assets of the company, and the better they are managed, the less they wear down and the lower the attached costs. Therefore, reducing the number of kilometers to drive can be seen as a type of asset management. Furthermore, in the optimized schedule, time slots can and will be planned to perform maintenance on the vehicles, again resulting in a longer life cycle of the vans and in a reduction in maintenance time. We can conclude this section by stating that solving CVRP with the presented algorithm leads to three important advantages for the service-oriented company. First, the total travel time is reduced to a minimum by sending vans to customers in the same region, thereby reducing the distance between different customers. Second, since travel time is reduced, the schedule is optimized in such a way that more interventions per week are possible and installations to be done by two workers are grouped per van and per day. Finally, minimization of mileage and optimal planning of vehicle maintenance leads to better asset management.

## 4. Results

### 4.1. CVRP results

Tables 1 and 2 summarize the results obtained by executing the Capacitated Vehicle Routing Problem algorithm, with the supplementary constraints discussed. The algorithm is run to create a planning for two weeks, each for three configurations of customers of the value-added reseller for curtain products: 16 customer, 34 customers and 50 customers for weeks 25 and 14, 28 and 40 customers for week 26, each with one intervention per customer. The solution method generates a scheme to serve customers in such a way that the total travel distance is minimal and the number of vans to be used is optimal. The first parts of Tables 1 and 2 list the results for the optimal route for the three configurations and the time traveled in a randomly generated planning. The random planning in the tests is created by using an average travel time of 45 min between all interventions and by adding travel time and installation time until the maximum of 8 h is reached, thereby not grouping the interventions that need two workers. Furthermore, the relative gain (rel gain R) is calculated as an indicator of how the method used improves the total travel time of the optimal number of vehicles in relation to random planning. Finally, the number of vans needed to carry out all interventions is added for random planning (vans R) and optimal planning (Vans O).

The second part of Tables 1 and 2 compares optimal planning with the schedule made by the company planner (actual planning) and the linked travel time. Again, the relative gain in comparison to the actual planning (rel gain A) and the number of vans for both methods is added (Vans A and Vans O).

The results in Table 1 show that solving the CVRP problem with the method discussed leads to a relative gain of 33% for the small customer configuration up to 40% for the 50 customer configuration. In addition, the number of vans needed to complete the planning is reduced from 21 for the largest group of customers to 19 for the optimal route. As

**Table 1**

Optimization results for different plannings versus random and actual — Week 25.				
Random (min)	Vans R	Optimal (min)	Vans O	Rel gain R (%)
16 Customers				
1181	6	791	6	33%
34 Customers				
2226	14	1398	13	37%
50 Customers				
3184	21	1913	19	40%
Actual (min)	Vans A	Optimal (min)	Vans O	Rel gain A (%)
16 Customers				
815	6	791	6	3.0%
34 Customers				
1601	13	1398	13	12.7%
50 Customers				
2310	20	1913	19	17.2%

**Table 2**

Optimization results for different Plannings versus Random and Actual — Week 26.				
Random (min)	Vans R	Optimal (min)	Vans O	Rel gain R (%)
14 Customers				
1334	5	675	5	49.4%
28 Customers				
2393	12	1570	11	34.4%
40 Customers				
3212	17	2087	16	35.0%
Actual (min)	Vans A	Optimal (min)	Vans O	Rel gain A (%)
14 Customers				
699	5	675	5	3.5%
28 Customers				
1707	12	1570	11	8.0%
40 Customers				
2655	18	2087	16	21.4%

stated, in both cases the installations that need to be done by two workers are grouped in the same vans, both in the random planning as in the optimal one. Furthermore, Table 1 indicates that the actual planning – created by the company planner – is much closer to the optimal schedule. The results obtained by solving the CVRP are only 3% better than the actual planning for the smallest configuration of 16 customers, but increase to 17.2% for the largest group of customers. The amount of vans needed is reduced by one for the largest number of interventions, while it remains the same for the smaller groups of customers. Table 1 thus shows that, overall, we can state that the proposed CVRP solution method not only leads to a reduction of the total necessary time to complete all assignments, but also reduces the number of vans needed and this in a much shorter time. Hence, whilst the planner makes the schedule as it comes, hereby trying to group as much as possible the interventions per region and grouping them around the different depots, our method generates an optimal working and driving schedule in just a few seconds taking into account the same constraints.

Table 2 lists the same data as the ones in Table 1, but now for week 26 and a configuration of 14, 28 and 40 customers. It shows that the relative gain compared to the random and actual planning is lower than in week 25, at least for the middle configuration. This is due to the fact that in this configuration there are more interventions with larger duration, allowing fewer installations per day, and thus less maneuverability in the planning. For the smallest configuration

**Table 3**

Optimization results after solving VRPTW for a set of 82 Customers versus a randomly generated planning and a planning made by an expert planner.

Random	Vans R	Optimal	Vans O	Rel gain R (%)
3341 min	26	1786 min	21	46.5%
Actual	Vans A	Optimal	Vans O	Rel gain A (%)
2911 min	24	1786 min	21	38.6%
Random	CO <sub>2</sub> Random	Optimal	CO <sub>2</sub> Optimal	CO <sub>2</sub> reduction
3341 min	634.5 kg	1786 min	339.2 kg	295.3 kg
Actual	CO <sub>2</sub> Actual	Optimal	CO <sub>2</sub> Optimal	CO <sub>2</sub> reduction
2911 min	552.8 kg	1786 min	339.2 kg	213.6 kg

(14 customers), the value remains more or less equal (3.0% versus 3.5%), for the largest, however, the relative gain with respect to actual planning is higher due to shorter interventions (17.2% versus 21.4%). The global conclusion that can be drawn is that the higher the amount of short installations or repairs, the more gain can be obtained in comparison to the random and actual planning.

To confirm these conclusions, the same algorithm was run on a different dataset belonging to another VAR. The company specializes in the installation and maintenance of alarm installations. Compared to the interventions performed by the window decoration company, the visits performed by this VAR are generally shorter, allowing more customers to be served per day or week. In this use case, all technicians are considered leaving and returning to the same depot. Table 3 lists the results of the tests performed on a group of 82 customers to be served, dispersed around the depot. Due to the larger number of short interventions and the larger number of customers, the relative gain compared to the random route is greater than 46% and greater than 38% compared to the actual planning. The results finally show that the difference between random and actual planning is only 12.9% caused by the fact that there are more people who can put appointments on the agenda and only based on timing, not grouping per region.

As a benchmark, our CVRP model was used to find an optimal solution for the data set P-n45-k5 of Augerat (1995). This data set contains 1 depot, 44 customers, and has an optimal total route time of 510 min for 5 vehicles. The CVRP solution method in this paper led to a minimal route length of 516 min, which is 1.2% less efficient than the benchmark. However, it must be highlighted that the CVRP studied has additional constraints in comparison to the standard CVRP.

#### 4.2. Impact on the environment

The targets for the average emission CO<sub>2</sub> of a van for the years 2020–2024 are set at 189.9 grams per kilometer (European Environment Agency, 2024). In addition, a van also emits fine dust and generates ozone. For a standard diesel-operated van, the emission of fine dust is around 0.00025 kg PM10 per kilometer, and the creation of ozone is 0.00075 kg NMVOC per kilometer, where PM10 is particulate matter of 10 micrometers or less in diameter and NMVOC is defined as non-methane volatile organic compounds (Vlaanderen.be, 2024). Table 3 shows a CO<sub>2</sub> reduction of 295.3 kg when comparing a random route with an optimized route, and 213.6 kg compared to the schedule of an expert planner. Extrapolation to a whole year implies that CO<sub>2</sub> emission is reduced by 15.36 tons compared to a random route and by 11.11 tons compared to actual existing planning.

Applying the same calculations to the fine dust and ozone parameters leads to a reduction 20.215 kg PM10 of fine dust and 60.645 kg NMVOC of ozone production per year, when comparing the randomly chosen routes with the optimized schedule. Compared to the planning made by an expert planner, the reductions are, respectively, 14.625 kg PM10 and 43.875 kg NMVOC.

**Table 4**

Cost reduction after solving VRPTW for a set of 82 Customers versus a randomly generated planning and a planning made by an expert planner.

Costs	Random route	Actual route	Optimal route
Diesel cost	401 €	349 €	214 €
Labor cost	8320 €	7680 €	6720 €
Total cost	<b>8721 €</b>	<b>8029 €</b>	<b>6934 €</b>

The total CO<sub>2</sub> footprint of a gasoline-operated vehicle is estimated to be 52 tons throughout its lifecycle (Ricardo Energy & Environment, 2020). This includes not only the emissions generated while driving, but also the amount of CO<sub>2</sub> emitted during vehicle production and destruction. The reduction in the number of vans needed from 26 to 21 in the optimal schedule (see Table 3), therefore, results in an additional savings of 260 tons of CO<sub>2</sub> emission, compared to a randomly generated planning. The difference between the number of vans needed for actual and optimal planning is limited to 3, but this still reduces the total emission of CO<sub>2</sub> of the fleet by 156 tons. In conclusion, we can therefore state that both the reduction in distance traveled and the number of vans needed result in a lower total emission of CO<sub>2</sub> by the VAR fleet.

#### 4.3. Research limitation and managerial implication

The algorithm offers an optimized weekly intervention schedule for a value-added reseller. As a result, the company can not only reduce the amount of distance to be covered moving from customer to customer, but can also lower the number of van tours, and thus reduce the amount of working hours. Hence, if less vans are needed to visit all customers in the same week and each van covers 1 working day in the planning, the reduction of the number of vans results in a corresponding reduction of working time by 8 h. If the labor cost is set at 40 € per hour, the consumption of the van at 6 liters per 100 km, and the price of 1 liter diesel at 2€, we can calculate the total amount of money a manager can save by optimizing the planning, using our solution method. Table 4 shows that the cost reduction per week by optimizing planning is 1786 € or 20.5% compared to random planning and 1095 € or 13.6% compared to planning by an expert planner. The calculations are based on the distances from the route and the number of vans used in Table 3. In addition, our solution method generates a planning almost instantaneously, while an expert planner needs 2 days per week to set up the planning.

Although the use of CVRP leads to a significant cost reduction and has an important impact on the environment, there are still limitations to this solution method. Hence, planning is done upfront for a whole week and thus last-minute cancellations or urgent interventions can only be tackled by recalculating the whole schedule. We kept open slots for critical visits and some interventions in place to deal with late annulments. However, this can negatively influence the optimized schedule as detours might be necessary. Furthermore, no consideration was taken with the wishes of the customers and the planning was set up, bearing in mind only the advantages for the company.

#### 5. Conclusions and future work

To find the optimal planning for the interventions of a value-added reseller, in order to minimize travel time, to maximize the number of installations per week and to optimize the number of vehicles to be used, we have solved the Capacitated Vehicle Routing Problem. Therefore, we used the OR Tools solver, to which we added additional constraints, such as the use of a heterogeneous fleet, the option of multiple loading points and the grouping of the interventions that need two workers to the same van(s). In addition, time limits on total working time and the total sum of travel and working time are set, which means that the capacities in the CVRP are not loads, but intervention times. The total capacity of the vehicle can therefore not

exceed a predefined amount of working time, while every truck must be returned within a total time frame of a single working day. We further integrated redundancy, and this led to a relative gain of 40% compared to a random planning travel time and of 17.2% versus a man-made planning for a configuration of 50 customers, and this was almost instantaneously. The same tests for a second week and for 40 customers resulted in a relative gain of 35% compared to a random planning travel time and of 21.4% versus man-made planning. Furthermore, the number of vans needed is hereby reduced respectively by one (19 instead of 20) and two units (19 instead of 21), and interventions are organized around the two strategically placed depots of the company. Finally, all installations that need two workers are grouped in the same vans as a result of the planning algorithm. Finally, similar results are obtained for another data set of 82 customers, linked to a different value-added reseller: 21 vans needed instead of 26 for the random case and 21 instead of 24 for the actual case.

In future research and with other data sets, the solution method could be expanded to other industries, such as home nursing, for example. In this industry, the CVRP can be used in the same way to set up the ideal schedule, but then with different constraints, like: time windows in which clients need to be visited (CVRPTW) or avoiding some nurse-patient combinations due to lack of experience. Another example to discuss would be the delivery of goods, in which the intervention time is very limited and where the load of the delivery truck is the main limiting factor. These delivery plans are in themselves more robust since delivery can always take place, whether the customer is at home or not. This paper can be used as a basis for further research on the use of CVRP to plan interventions with various working times. Using two or more depots, compartmentalization leads to more robust planning, while additional actions are taken to improve both resilience and redundancy of planning, for example, by using not assigned *empty* intervention slots. However, more research is necessary to improve robustness in such a way that planning can easily be adapted without having to repeat all distance calculations and scheduling can be done around already planned interventions.

In this paper we created a planning by using a static travel time calculation, meaning that no traffic jams, accidents or road works are taken into account. These could have an effect on the total travel time and thus the planning. In future work, a dynamic travel time calculation can be implemented as an extra step to make planning more robust. The algorithm could be further adapted in such a way that foreseen holes in the planning could be filled automatically with urgent interventions, once they occur, and already planned interventions are being considered when planning unplanned interventions. For the latter, the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) can be solved, where time frames are set for interventions that have already been planned. Preliminary tests have shown that setting these boundaries for predetermined customer visits does have an impact on the order of the interventions, but no significant effect on the total travel time.

#### CRediT authorship contribution statement

**E. De Kuyffer:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **W. Joseph:** Writing – review & editing, Validation, Supervision. **L. Martens:** Supervision. **T. De Pessemier:** Writing – review & editing, Validation, Supervision.

#### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Erik De Kuyffer reports administrative support and writing assistance were provided by imec-WAVES-UGent. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Data availability

Data will be made available on request.

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