Capacity Vehicle Routing Problem with Time Windows: Simulation Tool for Footprint Network Design

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Abstract. The paper focuses on a decision support system designed for logistic experts and aimed at addressing Vehicle Routing Problem that includes multi-vehicles and multi-depot with time constraints and considers the capacities of vehicles and logistic nodes too. The paper proposes a novel solution featuring a three-layer architecture and a system able to simulate the behavior of the network. Therefore, the paper proposes a tool to assess the impact of changes in volumes and capacities on overall delivery times. The integration of information about sorting nodes, delivery nodes, travel distances, and daily item demands is crucial for simulating accurate arrival times at each destination point. Computational experiments are depicted for validating the model and showing its effectiveness and its application.

Keywords: Vehicle Routing Problem · Multi-Depot · Capacity and Time Windows · Digital twin · Logistic Network

1 Introduction

Vehicle Routing Problem (VRP) introduced by George Dantzig and John Ramser in their seminal paper titled "The Truck Dispatching Problem" [1] is still relevant to industries that require efficient organization of its network aimed at guaranteeing the demanding challenges of e-Commerce, such as postal and logistics companies. The evolution of the needs is leading to different scenarios by increasing the alternative delivery endpoints as lockers, post offices, retailers' networks as supermarkets and shopping malls or delivery points at jointly owned buildings. According to a recent literature review on VRP for city logistics [2], the adoption of VRP in urban areas is driven by its ability to reduce congestion and improve the mobility of freight transportation services at minimum cost. Another significant benefit is its positive contribution to the environment and sustainable development [2]. Postal and logistic industries can benefit from novel decision support systems that can solve the problem described by considering the logistic infrastructure required for delivery operations and ensuring working time slots and customers' delivery time windows. Our aim is to model this problem in three-layer delivery architecture from

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sorting to middle-mile delivery and to propose a tool able to simulate the delivery time considering volumes, logistics nodes and related capacity being a digital twin of the entire networks. In Sect. 2 we introduce Vehicle Routing Problem (VRP), the related formulation with a review of the state-of-the-art, in Sect. 3 we discuss the foundation of our model and in Sect. 4 the proposed approach for a real-world application. Next, we describe in Sect. 5 experimentation and computational results. Finally, we present our conclusions and some future directions.

2 Literature Review

VRP is a type of transportation problem, which has many applications in real life such as logistics and transportation. This problem is an NP-hard that needs to find an optimal set of routes for serving a set of customers by a fleet of vehicles [1]. It generalizes the Travelling Salesman Problem (TSP) by including different vehicles from the departure point and aims at minimizing the total cost for all the vehicle tours with a solution that consider the shortest path ensuring that each customer is visited exactly once by a vehicle. Christofides' algorithm [3], proposed in 1976, tackle the TSP, but its insights and principles have influenced approaches to solving the VRP when it is reduced to a series of TSP instances. The algorithm consists of four steps: (i) Find a Minimum Spanning Tree (MST) of the graph, (ii) find a minimum weight perfect matching to form a multigraph, i.e., a graph where multiple edges between the same pair of vertices, are allowed, (iii) form a multigraph (a graph where multiple edges between vertices are allowed), and (iv) build a Hamiltonian circuit (a closed tour that visit each vertex once) from the multigraph by skipping repeated vertices.

The goal of Capacity VRP (CVRP) is to determine a set of routes, each starting and ending at the warehouse, while adhering to a limited capacity constraints on each vehicle. In addition, delivery points may include Time Windows (TW) requests: meaning each customer should be visited by only one vehicle during a specified time interval, i.e., CVRPTW problem.

Time Windows constraints have been studied by Solomon and Desrosiers [4] that summarized the routing problems with time windows. On the other hand, for this complex VRP variants such as the VRP with Time Windows in cases where the time windows are relatively loose, adaptations of Christofides' algorithm can be particularly useful in constructing initial feasible solutions that are then improved upon using other optimization techniques as experimented by Ufuk Dereci and Muhammed Erkan Karabekmez [7] for a case study in Turkey. Heuristics and meta-heuristics as Genetic Algorithms [5] and Tabu Search [6] have been proposed in the last decades to solve this class of NP-hard problem. Moreover, the VRP can be Single Depot (SD) or Multi Depot (MD) [8] in case of the departure is a single fixed node or different points.

The focus of this research would be on Multi Depot Capacity Vehicle Routing Problem with Time Windows (MDCVRPTW). For the sake of simplicity, we call it Capacity Vehicle Routing Problem with Time Windows (CVRPTW) with MD. The key objective of MDVRPTW is to minimize the total cost, which can include various factors such as: (i) Total distance or travel time, (ii) Number of vehicles, (iii) Penalties for time window violations, and (iv) combination of costs including operational costs.

Recent research has focused on the MDVRP and optimization of vehicles and routes among multiple depots. Among solution studied, Rapanaki et al. [9] addressed the problem by means of the Artificial Bee Colony (ABC) algorithm, a meta-heuristic approach inspired by the behavior of the real honeybee colony. They compared this approach with other meta-heuristic such as Particle Swarm Optimization and Genetic Algorithms to prove the feasibility. More recently, in December 2023, P. Stodola and J. Nohel [10] explored the adaptation of Ant Colony Optimization (ACO) with Node Clustering. The algorithm was inspired by the behavior of ants in nature when searching for food and it is adopted in conjunction with node clustering for solving the minimization of total costs in MDVRP. Node clustering enhances the algorithm's performance because it is used in the phase of creating a solution when the algorithm searches the next node to be inserted into one of the routes of vehicles (ants).

Goel et al. [11] addresses the stochastic Vehicle Routing Problem with Time Windows which involves uncertainties in customer demands and service times. The authors introduce a mathematical model to estimate potential shortages a vehicle might encounter on its route and to predict the distribution of arrival times at customer locations. They propose an ant colony system-based approach to solve the stochastic VRPTW, noting that optimal solutions for deterministic VRPTW may not be feasible when faced with stochastic variations. Finally, in a previous work [12], we proposed C2VRPTW, a model that assigns capacity to both vehicles and nodes. The variability of time spent at logistic nodes is incorporated into the model to enhance its applicability to real-world scenarios, where logistic nodes in the first mile of the delivery process serve as critical hubs for sorting activities.

Following these research directions, the contribution of this paper is the proposal of a simulation tool based on an overall architecture for first mile and middle-mile delivery tasks for the postal sector and an assessment of impacts on delivery times at varying the size and the fleet of the network.

3 Capacity Vehicle Routing Problem with Time Windows

Every day the items to be delivered are collected at the first mile depots and addressed to the first mile destinations. The connections between nodes indicate the time needed from depot to destination, and the minimization of vehicle is classified as a VRP with multi-depots. The problem falls into the domain of CVRPTW as it requires that node has a fixed time slot to be served and each vehicle has a fixed capacity. Many formulations have been proposed for the CVRPTW. In particular, we refer to the review published by Solomon et al. [4] and the research works of Ursani ed al. [5] and Baldacci et al. [13] which described the problem and its solution, focusing on the state-of-the-art of exact algorithms and meta-heuristics, respectively.

Formally, the CVRPTW with Multi Depots (MD) can be formulated as follows: Let $G = (\mathcal{N} \cup \mathcal{H}, \mathcal{A})$ be a directed graph whose node set is the union of a set $\mathcal{N}$ of customers and a set $\mathcal{H}$ of depots.

Non-negative costs $d_{i,j}$ are associated with each $arc(i, j) \in \mathcal{A}$, representing the travel cost, and $t_{i,j}$ is the travel time to reach $j \in \mathcal{N}$, starting from $i \in \mathcal{N}$, i.e., the difference between the arrival and the starting time of the route.

Each customer $i \in \mathcal{N}$ has a delivery demand q_i, a delivery time window $[a_i, b_i]$ and a vehicle must arrive at the customer before b_i. If it arrives before the time window opens, it has to wait until a_i to service the customer. Moreover, each customer i has a service time ${s_i}^k$ that expresses the arrival time in the node i, with k $\in \mathcal{K}$ that represents a set of vehicles. Each vehicle has a known capacity Q_k $\forall k \in \mathcal{K}$. In this version of the problem, we assume that all vehicles can be freely associated with any depot: this corresponds to the situation in which the location of the vehicles at the depots is a decision. The vehicles do not necessarily leave their depots at time 0: due to customer time windows, it may delay the departure time to arrive at customer locations within their time windows. According to Solomon et al. [4] formulation, the goal of this problem is the minimization of the total distance travelled by vehicles as described in Eq. (1), where x_{ij}^k expresses whether the vehicle k travelled from node i to node j and it takes the value 0 or 1.

$$\min \sum\nolimits_{k \in K} \sum\nolimits_{i \in \mathcal{N}} \sum\nolimits_{j \in \mathcal{N}, j \neq i} d_{ij} \cdot x_{ij}^k \tag{1}$$

Subject to:

$$\sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}, i \neq j} x_{ij}^k = 1 \quad \forall j \in \mathcal{N} \tag{2}$$

$$\sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} q_i \cdot x_{ij}^k \leq Q_k \quad \forall k \in \mathcal{K} \tag{3}$$

$$\sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} q_i \cdot x_{ij}^k \leq Q_k \quad \forall k \in \mathcal{K} \tag{4}$$

$$x_{ij}^k \cdot \left(s_i^k + t_{ij} - s_j^k \right) \leq 0 \tag{5}$$

$$a_i \leq s_i^k \leq b_i \qquad \forall \mathrm{i} \in \mathcal{N}, \qquad \forall \mathrm{k} \in \mathcal{K} \tag{6}$$

Equations (2) and (3) constrain that each customer can be visited by only one vehicle. Equation (4) ensures that the vehicle capacity is not exceeded. The Eq. (5) establishes the relationship between the vehicle departure time from a customer and its immediate successor. Moreover, constraints in Eq. (6) affirm that the time windows are observed. We assumed that the transportation cost of each vehicle depends on the travelled distance. The transportation network is considered asymmetrical, that is the time spent from node i to reach node j can be different from the time spent from node j to node i.

Capacity constraints are designed to limit the amount of goods or services a vehicle can carry or perform on a single route, ensuring that the solution is feasible in terms of real-world logistics capabilities. In this paper we adopt the formulation described by Birtolo and Torre [12] for a real-world problem where the capacity is assigned to the nodes too, i.e., C2VRPTW with MD. The main goal is to model the first mile sorting scenario, where items and goods are collected in the collection points, addressed to the national sorting centers that have the key task of routing it to destination sorting center. In this scenario the sorting centers act both as depots and customers, according to the goods flow: (i) the sorting center collects the items of its region and routes the items to the national sorting centers according to the destination of the items collected, (ii) the same sorting center receives the items from the other sorting centers for items to be delivered in its region.

4 Simulation Engine for CVRPTW Applied to Real-World Logistic Delivery Problem

4.1 Three Layer Architecture Design

The main depots are the first level of architecture and send and receive items for their networks, in other words they work as pick-up and delivery points. Transshipment nodes are intermediate depots for Delivery Centers, closer to the delivery area than the main depots. And finally, the third level is the delivery centers which are the collection points for customers.

This architecture has been applied to real-world logistic network, as shown in Table 1, where the first-level is the connection among the sorting centers which collect regional items and goods to be delivered and address it to the target sorting center, the second level is the city or the facility acting as a transshipment node for its logistic area to serve, and finally for the third level, each transshipment node address the middle-mile segment to send the item to the target delivery center, the closest to the final addressee.

Table 1. Three level architecture for multi-depot VRP where each first mile sorting centers collects items to send in Italy.

Routing level	Node	Example
Depot	Sorting Center at Origin	Bari
First mile	Sorting Center at Destination	Florence
Intermediate Logistic Node	Transshipment Node	Lucca
Middle-mile end point	Delivery Center	Viareggio

Figure 1 depicts the three layers, i.e., blue circle represents the Origin and Destination of the first level (i.e., multi-depot model), and it is called first mile of the logistic network. This level communicates with the second level of architecture (light blue nodes) in charge of regional distribution of item addressed to the target region. Each intermediate node serves its third level targets that are the delivery centers allocated to each of transshipment node. In the figure, each level relates to direct connection that is not visible in terms of number of vehicles needed for the delivery tasks, that leads to the design of nested VRP problems. In this formulation, we do not consider the time that each vehicles requires to return to the depot because the fleet is managed to avoid the movement of empty vehicles, therefore in our model, each vehicle starts from a depot and there is no need to return to the same depot.

The three-layer architecture describes the routing problem in a flexible way in order to address delivery challenges as the same-day delivery or cost optimization problem. Each layer can be modelled by means of a dedicated VRP formulation as depicted in Fig. 2 and differs for type of operations and vehicle adopted. In a national scenario, the first mile is served by trucks and the sorting machines installed in the node must route the goods and items to the target region and city, for this reason we classify this first level by means of C2VRPTW with MD which extends the capacity constraints to both nodes and nodes [12]. Additional constraints in this level is that each node acting as a depot and at the same time as a customer node, must look for a trade-off between capacity allocated to sorting activities and capacity allocated to delivering received items.

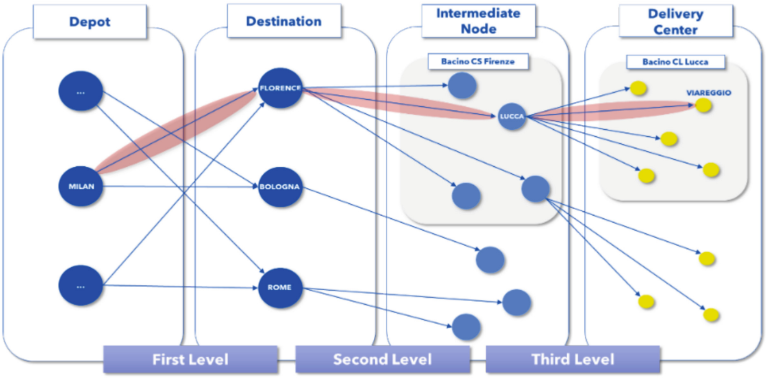

Fig. 1. Three-layer architecture highlighting the direct connections between layers for depot in Milan and destination in Viareggio with a transshipment in Lucca.

The total capacity of each node is allocated: (i) in sorting the items, when the node acts as a depot, and (ii) in routing the received items from the other nodes, when the node acts as a customer of the first level. These constraints have been introduced due to the machine installed in the node that cannot perform the two kinds of operations at the same time.

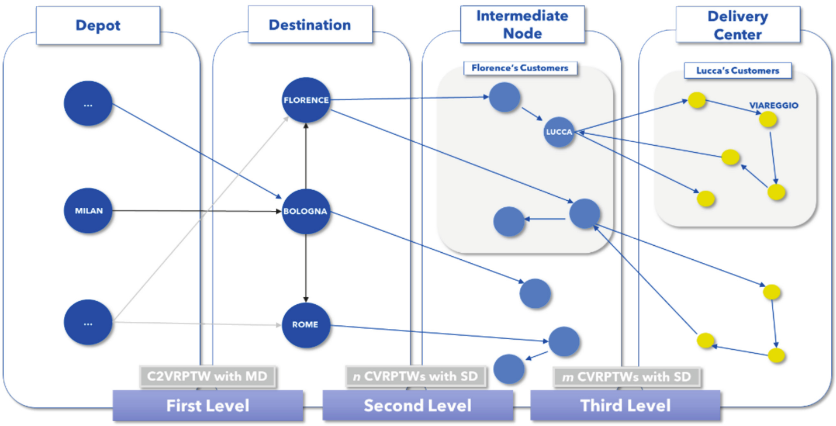

Fig. 2. Mapping of the three-layer architecture with three instances of VRPs.

The second level oversees connection of sorting center, acting as a depot, to the intermediate nodes which are customers without the processing or sorting needs. For this reason, we use for this level a simplified CVRPTW with SD solved by an exact algorithm for the limited number of nodes involved. The last level considers the intermediate nodes as depot and the delivery centers as customers to be served.

The delivery centers have their own time windows, without routing needs and so for this level we can use a CVRPTW with SD. It is a single node because we consider for each intermediate nodes a set of customers to be served with their own vehicle (small tracks or vans). Therefore, the third level is solved by m problems where m is the number of transshipment nodes. In other words, Fig. 2 summarizes the three layers with the adopted VRP formulation: (i) First Layer: long-distance routing between depots and destination hubs, i.e., transportation of goods from depot to key destination hubs, (ii) Second Layer: regional routing from hubs to intermediate nodes, (iii) Third Layer: goods are delivered from intermediate nodes to the end customers or smaller delivery centers (e.g., from Lucca to Viareggio). Each layer of the system ensures a smooth, optimized flow of goods through the hierarchical network, addressing specific constraints and objectives at each stage.

4.2 Simulation Engine for Arrival Time Estimation

We propose a tool for simulating routes and delivery times at varying the network configuration for logistics and delivery route optimization. The system is described in Fig. 3 which outlines the process of retrieving the delivery time per destination and the number of vehicles, routes, and stops. As input the tool requires the number of nodes in the network, a matrix of distances to solve, volumes of collected goods to be delivered in accordance with a fixed service level agreement (e.g., within 2 days), and delivery time windows that is the working time per node.

The Simulator Engine elaborates the results by implementing the following steps: (i) the problem is decomposed by means of the proposed three-layer architecture, (ii) the system starts solving Capacity Vehicle Routing Problem with MD for the first mile and evaluate the arrival time at first level node at destination, (iii) considering the active first level nodes, the system assigns all the second level nodes to a single first level node, (iv) the system solves the resulting Capacity Vehicle Routing Problems with SD and evaluate the arrival time at second level node at destination, (v) considering the active second level nodes, the system assigns all the third level nodes to a single second level node, and (vi) the system solve the resulting VRPs with SD.

4.3 Fitness Function

In order to compare quantitatively the results arising by the different simulation, we propose a fitness function able to look for a trade-off among different criteria as node saturation, estimated arrival time and network cost, providing a score to the logistic experts to compare solutions and extract the optimal one. The fitness is a weighted average of three components: (i) saturation, (ii) delivery time, and (iii) network costs. In the simulations, the best scenario for saturation is to have centers engaged in processing between 60% and 80% (considering 100% as the maximum value, equivalent to 19 working hours). With the aim of minimizing the fitness function, we have conceived a saturation function with: (i) a minimum value if the center operates between 11 and

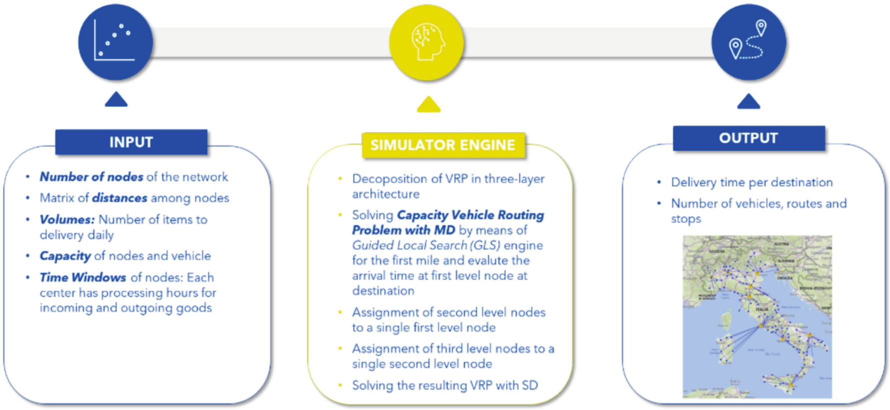

Fig. 3. Simulating routes and expected delivery times at destination

15 h per day (60–80% of its capacity); (ii) a maximum value if the center operates less than 30% of its capacity, e.g., 6 h (strongly undersaturated centers) or if the center is overloaded by working more than 19 h a day (saturated centers).

Figure 4 illustrates the fitness values (y-axis), ranging from 0 (optimal) to 1 (worst), as a function of the saturation level (x-axis). For the entire network assessment, we include in the fitness the average node saturation as the first component.

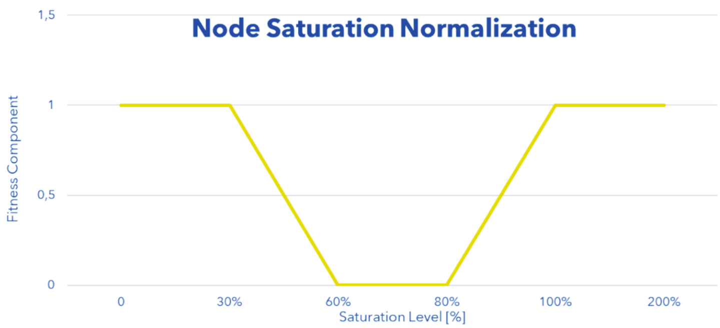

Fig. 4. Fitness Function: Node Saturation Component

The second fitness component keep into account the expected delivery time resulting by addressing the CVRPTW with a fixed number of vehicle and a specified number of active nodes. This addendum considers the average and the maximum elapsed time occurred between a depot and the delivery center closest to the addressee. Finally, the third component simulates the direct cost of the network which is directly proportional to the number of active nodes. Each component has been normalized for providing a value between 0 and 1. Therefore, the simulator provides a fitness value to quantitatively measure the adherence of the proposed solution to the optimal configuration at varying nodes and network parameters.

5 Experimental Results

5.1 Materials and Methods

For our experimentation we consider 3 layers made by 10 sorting centers, 149 intermediate nodes and 715 delivery centers. The sorting center have their own capacity expressed in parcels per hour in sorting activities that is the set of activities performed for routing the items toward other regions and process the item received from the network for the area served. The first layer of architecture is modelled by the proposed C2VRPTW with MD in order to collect in each node the demand and route it to the target nodes. The second layer of architecture is depicted in Fig. 5 where each sorting center is connected to the transshipment nodes. Finally, the last layer of the architecture is modelled by several VRPTWs with SD, one solution per transshipment node that serve a set of customers (i.e., the delivery centers of the logistic network).

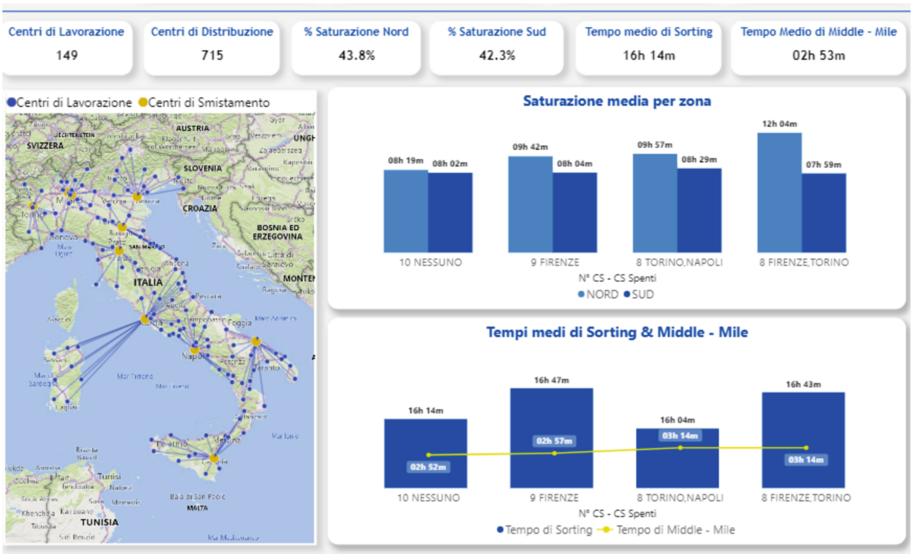

Fig. 5. Power BI Dashboard with sorting centers in yellow and the transshipment node in blue.

5.2 Software

The solution is implemented in Databricks using Python language, while the simulator is realized with Power BI. As computational cluster, we used 8 cores and active memory of 28 GB with Databricks Runtime Version 14.3 LTS that includes Apache Spark 3.5.0, Scala 2.12. Moreover, we integrate Python libraries for the evaluation of distances between nodes and for adapting the VRP solvers, respectively TomTom library and Google OR-Tools [15]. OR-Tools allows executing heuristics and meta-heuristics to solve the VRP and has been developed by Google. CVRPTW is solved by heuristics and meta-heuristics algorithms, respectively. Coordinates, demands (items to be delivered), distance matrix, number and capacities of vehicles, and the sorting centers are inputs of our model. The algorithm implements a solution strategy, i.e., local search option, in order to generate a valid solution. Christofides' algorithm [3] is selected as initial solution strategy and ensures the generation of a feasible solution. Then, Guided Local Search (GLS) option tries to improve initial solution generated by Christofides' algorithm. In our implementation the local search is limited by a fixed number of iteration (avoiding the time limit due to possible reproduction of this experiments in a compute node with different performances) that refers to the maximum number of attempts for algorithm can search for each node.

5.3 Experiment 1: Fixed Nodes and Varying Workload

In this section we focus on the results, the data used in C2VRPTW model and the related constraints. We collected the information related to: (i) the incoming volume i.e., the number of items picked up and delivered from each sorting center (items from origin to destination), (ii) the working time slot per node, (iii) the number and the types of machines installed in each sorting center in order to estimate the related capacity.

To address the real-world logistic capabilities of each center, we estimated the total time requested to process the incoming volume based on machines and human resources. The estimated total time is then directly proportional to the number of items to be delivered (or picked up), to the machine's type used to process them and the number of human resources in the specific sorting center as well.

Once we defined the distance matrix, we developed the first layer using the C2VRPTW model applied to 10 fully connected sorting center. Additionally, we assumed that post offices and local senders collect the items by the 5 pm daily and these items are processed by each sorting center from 6 pm daily. The solution provides the routes and the arrival time in the network for each depot.

To deal with logistic constraints related to the non-parallelization of processing activities within the sorting centers, mainly due to a limited number of machines handling sorting jobs and the available human resources, we did not allow processing job into sorting centers when they are engaged in processing items coming from sorting center within the network. In other words, the time slot allocated to collecting the items and send them to the entire networks differs from the working time allocated for processing the incoming volume.

The model also allows the monitoring of sorting centers' working time, aiming at identifying centers where a volume increase may lead to delivery time increases. For this purpose, we run the model in three different scenarios: (i) a standard load, (ii) volumes with 20% of increase per each segment, and (iii) volumes increased of 50% compared to the annual average daily load. If we consider that a sorting center can perform sorting operations maximum 19 h per day (leaving 5 h for maintenance or administrative tasks), Fig. 6 shows that if the volume increase by 50%, Padova is not able to process them in a single day, resulting in an increase of the delivery times.

Our experimentation is extended to the second and third level of the proposed architecture as described in Sect. 4. As example of application (see Fig. 7), we run the

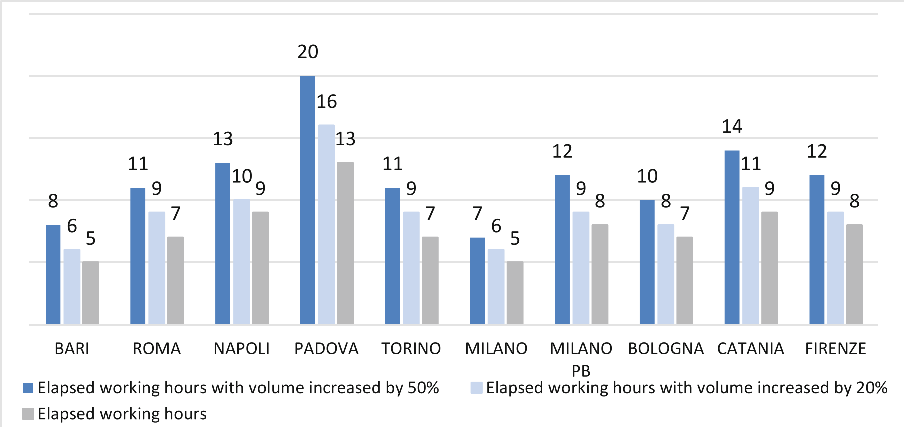

Fig. 6. Sorting centers' working time in three different scenarios

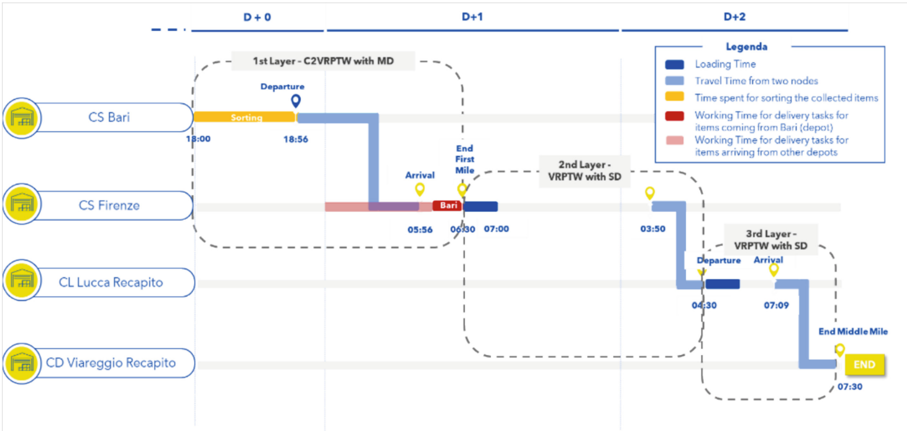

Fig. 7. Analysis of mail flow from Bari (depot) to Viareggio (end customer)

VRPTW instance with SD, because the set of customers is fixed per each sorting center at destination (e.g., Firenze) and each transshipment node (e.g., CL Lucca Recapito).

5.4 Experiment 2: Varying the Number of Sorting Nodes

The tool also provides a mean to compare the different performance when different nodes have been activated. From the one hand, the more the sorting centers are adopted the higher the network costs increase. On the other hand, a reduced network could not satisfy the time constraints and could not lead to a viable routing solution. For this reason, we compare the results obtained with 4 different scenarios by means of the defined fitness function which is described in Sect. 4.3. For the normalization of the fitness components, we consider the maximum allowed sorting and delivery time and we divided the resulting time in order to have a simulated value equals to 1 in this worst case scenario. Similarly for the nodes, we consider as the worst scenario 10 active nodes (maximum value) for cost implications and 8 active nodes as the ideal configuration (minimum value). The VRP does not produce a solution that does not satisfy the specified time constraints.

Table 2. Scenario 1: 10 Sorting Centers - Fitness components and overall value.

Fitness component	Normalized Value	Simulated Value
Average Saturation of Centers (Nord area)	0.38	8 h and 20 min
Average Saturation of Centers (South Area)	0.36	8 h
Number of nodes	1	10 nodes
Average Sorting Time	0.35	16 h and 30 min
Average Delivery Time in middle-mile endpoint	0.14	3 h
Total Fitness Value	**0.44**	

All the scenarios have a standard daily workload but differs for the network configuration: (i) Scenario 1 includes all the 10 sorting centers as depicted in Fig. 6, (ii) Scenario 2 foresees 9 sorting centers (i.e., Firenze is not considered in this daily simulation), (iii) Scenario 3 foresees 8 sorting centers (i.e., Firenze and Torino have not been activated in the daily activities), and (iv) Scenario 4 maintains 8 sorting centers, but deallocates Napoli and Torino, i.e., in the day of the simulation only 8 sorting centers process the national collected workload.

Table 3. Scenario 2: 9 Sorting Centers - Fitness components and overall value

Fitness component	Normalized Value	Simulated Value
Average Saturation of Centers (Nord area)	0.46	9 h and 40 min
Average Saturation of Centers (South Area)	0.36	8 h
Number of nodes	0.5	9 nodes
Average Sorting Time	0.39	17 h
Average Delivery Time in middle-mile endpoint	0.14	3 h
Total Fitness Value	**0.38**	

The results of the first two scenario are depicted in Table 2 and in Table 3 respectively where the benefits obtained by reducing the value of number is only partially mitigated by the increased sorting time for reaching Florence area and the increased saturation of nodes that are replacing the inactive one. The average time needed by sorting centers located in north of Italy increase of 80 min due to deallocation of Firenze in the Scenario 2. The last two scenarios investigate the configuration with 8 nodes at varying the active ones and prove the sustainable benefits of the reduced costs due to the reduction of 2 nodes (from 10 nodes of Scenario 1 to 8 nodes of Scenario 3 and 4). As depicted in Table 4 and in Table 5, the negative impacts are the increased saturation of remaining sorting centers, but the simulator prove the sustainable scenario in term of delivery time and the resulting fitness expresses an optimized solution decreasing from original 0.44 of Scenario 1 to 0.27 value reached in Scenario 4.

Table 4. Scenario 3: 8 Sorting Centers - Fitness components and overall value

Fitness component	Normalized Value	Simulated Value
Average Saturation of Centers (Nord area)	0.60	12 h
Average Saturation of Centers (South Area)	0.36	8 h
Number of nodes	0	8 nodes
Average Sorting Time	0.39	17 h
Average Delivery Time in middle-mile endpoint	0.15	3 h and 10 min
Total Fitness Value	**0.30**	

Table 5. Scenario 4: 8 Different Sorting Centers - Fitness components and overall value

Fitness component	Normalized Value	Simulated Value
Average Saturation of Centers (Nord area)	0.47	10 h
Average Saturation of Centers (South Area)	0.39	8 h and 30 min
Number of nodes	0	8 nodes
Average Sorting Time	0.33	16 h
Average Delivery Time in middle-mile endpoint	0.15	3 h and 10 min
Total Fitness Value	**0.27**	

6 Conclusions and Future Works

In the vehicle routing problem with capacity and time window (CVRPTW), the objective is to minimize the number of vehicles with a fixed capacity and then minimize the total time travelled. In this paper we considered time constraints and the limited capacity of logistic nodes for real-world application in logistic domain. We propose a tool that incorporating information about sorting nodes, delivery nodes, travel distances, and daily demand, allows the simulation of arrival times at each destination point. Computational experiments are presented to demonstrate the effectiveness of the proposed approach. Execution time of each simulation is strongly related to the compute instance of Databricks environment and the specified stopping criteria of Guided Local Search component (i.e., specified number of iterations). This formulation and the proposed solution allow logistic designers to evaluate the impact of volume and capacity changes on the final delivery times at the expected delivery points for the design of same-day delivery services. In our model the distance between nodes of the networks is expressed in time by means an asymmetrical matrix that consider the average travel time between two nodes. As future work, we plan to investigate how the solution varies across different days and times of day. This will be achieved by incorporating a time-of-day-dependent distance matrix to account for potential traffic jams and delays. Moreover, we will propose an optimization engine for the network design by means of Genetic Algorithm approach [14] which provide promising results in optimization problems and can suggest the optimal configuration of the problem parameters.

Disclosure of Interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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