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Cognitive digital twins for freight parking management in last mile delivery under smart cities paradigm

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ABSTRACT

This paper examines the Freight Parking Management Problem (FPMP) of last-mile delivery within the context of Smart Cities where objects are managed by Digital Twins. Specifically, we investigate how Cognitive Digital Twins - Digital Twins with augmented semantic capabilities - can enhance instantly updated knowledge of parking connectivity to optimize logistics operations planning and urban resource allocation. We present a four-layer architectural framework to integrate individual logistics objects and systems into Smart Cities at a semantic level, with underlying enabling technologies and standards including Property Graph, Web Ontology Language (OWL), and Web of Things. Next, we conduct a case study of parcel delivery in Paris using a real-life Digital Twins platform called Thing in the future (*Thing'in*) by Orange France, coupled with an agent-based simulation model on *AnyLogic*, to demonstrate a real-world application of our approach. The results suggest that semantics-enabled Digital Twins connectivity can increase the comprehensive understanding of the delivery environment and enhance cooperation between heterogeneous systems, ultimately resulting in improved logistics efficiency, reduced negative externalities, and better utilization of resources. Furthermore, this work showcases potential new business services for logistics service providers and provides managerial insights for city planners and municipal policymakers. An actual mobile application prototype is presented to showcase the applicability of the work.

1. Introduction

Last Mile Delivery (LMD), also known as city logistics or urban freight transport, addresses the challenge of efficiently and effectively transporting goods in urban areas, from distribution centers or warehouses to their final destinations to meet consumer demands (Savelsbergh and Van Woensel, 2016). Its importance to cities is twofold. First, it serves as an essential building block for the economic and social development of cities. Second, it generates freight traffic and logistics activities that are sources of multiple externalities in urban areas, such as congestion, accidents, noise, air pollution, and gas emissions.

Freight Parking Management Problem (FPMP) is one of the key issues of LMD, which aims to optimize the use of existing parking infrastructure to improve LMD efficiency. Freight parking is critical for both business-to-business and business-to-consumer deliveries, for example, with curbside parking accounting for 95% of all freight parking in London (IET, 2019). However, the current approach to freight parking is fraught with inefficiencies and sustainability issues, particularly in megacities like London, Paris, and New York City (Dablanc 2015; Schmid et al., 2018; Cruz-Daraviña and Bocarejo Suescún, 2021). One noticeable problem is illegal parking. In Paris, for example, a survey published in 2015 reported that over 50% of vehicle deliveries in the city were made by double-parked vehicles, and more than 60% of freight parking operations were illegal, often using sidewalk, bus, or bicycle lanes (Dablanc 2015). Similar observations were made in New York City in 2018, where nearly 60% of vehicle deliveries were performed by double-parking, and 80% of delivery vehicles were parked illegally (Schmid et al., 2018). This problem is often exacerbated by the need for vehicles to cruise around in search of parking spaces, which not only contributes to illegal parking but also results in unnecessary vehicle-km and traffic congestion. A study conducted in Seattle's downtown area in 2020 found that 85% of delivery vehicles engaged in parking cruising behavior, which accounted for 28% of the trip time and added up to more than an hour per tour (Dalla Chiara and Goodchild, 2020). The

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social and environmental concerns raised by the FPMP have come to the city manager's and logistics service providers' (LSPs) attention.

The FPMP has garnered significant research attention, particularly from the fields of urban design and parking management. For instance, to tackle illegal parking in New York City, Schmid et al. (2018) recommended providing four to eight times the currently available parking spaces. However, cities have limited capacity and space to accommodate the ever-increasing dedicated space for logistics use, and mobilizing the existing but underused infrastructures for logistics operations is a key for urban sustainability, as stressed in Schachenhofer et al. (2023). Hence, increasing freight parking spaces may not fundamentally solve the imbalance problem of spatial-temporal supply and demand but could even aggravate the underused resources problem. Knowing that the demand in the off-hour period can only be accounted for one-third of the peak hour and the duration of parking can vary according to the on-site operations (Jaller et al., 2013). From an operations management perspective, researchers have drawn attention to the effective and efficient use of the existing parking resources. Parking information, especially instantly updated availability, and accessibility, is critical to this end. Dalla Chiara et al. (2022) found that the availability of information could reduce cruising parking time by 27.9% and distance by 12.4%.

The fast-advancing IoT/ICT technologies offer new opportunities and solutions for effective freight parking management. Recently, some researchers have identified Smart Cities as a game-changing paradigm that will reshape the research landscape of city logistics. Broadly speaking, Smart Cities are cities, where objects are connected via IoT devices, and data generated, are collected and consolidated on clouds via ICT technologies (such as 5 G, Bluetooth, and Wi-Fi) for data analytics, decision-making, and planning (Harrison et al., 2010; Neirotti et al., 2014; Zanella et al., 2014). While parking management for private cars is a promising application of this paradigm studied in the literature, freight parking is vastly different from car parking and has received less attention. Little attention has been paid to investigating how logistics systems can interact with Smart Cities to improve the efficiency of freight parking and LMD.

This paper aims to make significant contributions to the research on the FPMP in the context of Smart Cities by exploring the practical applications of semantic technologies and Digital Twins (DTs) to manage LMD and parking operations. We consider Smart Cities as a holistic semantic system to explore how the semantic interactions between individual digital logistics systems (or objects) and the delivery environment can provide solutions to the FPMP and improve logistics efficiency and urban sustainability. The research questions are designed to address the gaps in the current literature on this topic.

RQ1: How to model the DTs of individual physical objects and systems related to last mile delivery, while considering the requirements of Smart Cities? We propose that the complexity of city logistics operations requires a comprehensive Property Graph-based DT model, which includes the properties and inner relationships of the objects.

RQ2: How to seamlessly integrate the modelled DTs into Smart Cities for semantic interactions, and enhance the context-awareness of the DTs regarding the dynamic operational environment? This work follows the concept of Cognitive Digital Twins (CDTs) discussed by Zheng et al. (2021), which refers to DTs with augmented semantic capabilities. A four-layer architectural framework is developed based on semantic technology standards and in the context of the Web of Things (WoT). The latter provides standard web protocols to overcome the segmentation of IoT devices and systems (Lu and Asghar, 2020; Guinard and Trifa, 2016).

RQ3: How integrated logistics CDTs in a semantic delivery environment can benefit stakeholders and serve as a solution at the operational level to the FPMP by optimizing resource allocation and assisting in LMD operations management? Valuable information queried from the states of CDTs is used in simulations to test various scenarios, which can provide useful guidance to multiple stakeholders and enable them to gain maximum benefit from a holistic and systematic view.

To demonstrate the effectiveness of our proposed framework and its practical application, a real-life case study was conducted in Paris. The study resulted in the development of a mobile application prototype that provides new business services to LSPs for freight parking in LMD operations. A demo of this prototype was presented at the EUCNC & 6 G Summit 2022, which focuses on the experimentation and application of future communication systems and networks.

The next section will provide a brief review of related concepts and prior research. Then, Section 3 will give an overview of the proposed architectural framework for modeling and implementation procedures. The use case and simulation results will be presented in Section 4, providing managerial insights and guidance for multiple stakeholders. Section 5 will conclude this work.

2. Related works

2.1. Digitalization of freight parking management

The ongoing digitalization of logistics has spurred research interest in optimizing freight parking management, also known as loading or delivery bays, using historical or instantly updated data for dynamic planning. One approach suggested by Letnik et al. (2018) involves clustering receiver addresses using fuzzy k-means algorithm and selecting the best loading bays (for example the least crowded ones according to historical data) to determine the best route for each cluster. A simulation was conducted to evaluate the operational performance in terms of walking distance and truck waiting time. Some other studies have proposed dynamic freight parking locations to cope with spatial and temporal demand variation, see Wilson et al. (2022) for example. With the same insight, Roca-Riu et al. (2017) et al. have proposed dynamically locating freight parking to reduce traffic disruption.

Pre-booking of delivery bays is another important research topic in the field. This is especially investigated from a practical perspective, see some experimental projects like *Smart Loading Zone* in Hamburg or *Parkunload* in Barcelona among many others. From an academic perspective, Mor et al. (2020) proposed a booking system to reduce double parking by having municipalities centrally assign and control the utilization of freight parking. LSPs are required to pre-book loading bays by providing a fixed or partially flexible start time. In their research, all requests have been treated equitably, it is fair but not always the perfect solution. There are mainly two reasons, one is part of the loading bays will inevitably become competitive during the peak hour or in the delivery-dense areas, then the assignment of these parking needs to be further considered. Another reason is that the resource wastes because the reserved time is much longer than the actual use time. Hence, Yang et al. (2019) were motivated to study the auction-based booking system by taking both time preference and parking duration into account, their pricing rules aim at allocating resources efficiently to maximize the system performance. Accordingly, some research attention has been paid to the conflict between reservation and utilization which is crucial to booking systems in general. McLeod and Cherrett (2011) performed a proof-of-concept of a loading bay booking and control system and found that the actual using of the reserved time slots is highly dependent on the vehicle arrival time, which is decided by live traffic drivers are facing. To deal with the issue, Comi et al. (2017) emphasized the importance of telematics applications to enable last-minute booking, i.e., reserving parking only when a vehicle is approaching the loading bay.

The related literature has shown an interest in digitalizing freight parking management via IoT technologies and data techniques. But so far, few studies have considered building semantic connections between logistics services providers' systems/objects and the Smart Cities environment for dynamic operations planning. This study aims to fill this gap and investigate how to establish the semantic connection and interaction of digital twins (logistics assets, city infrastructures, etc.), and how to perform dynamic planning on this basis.

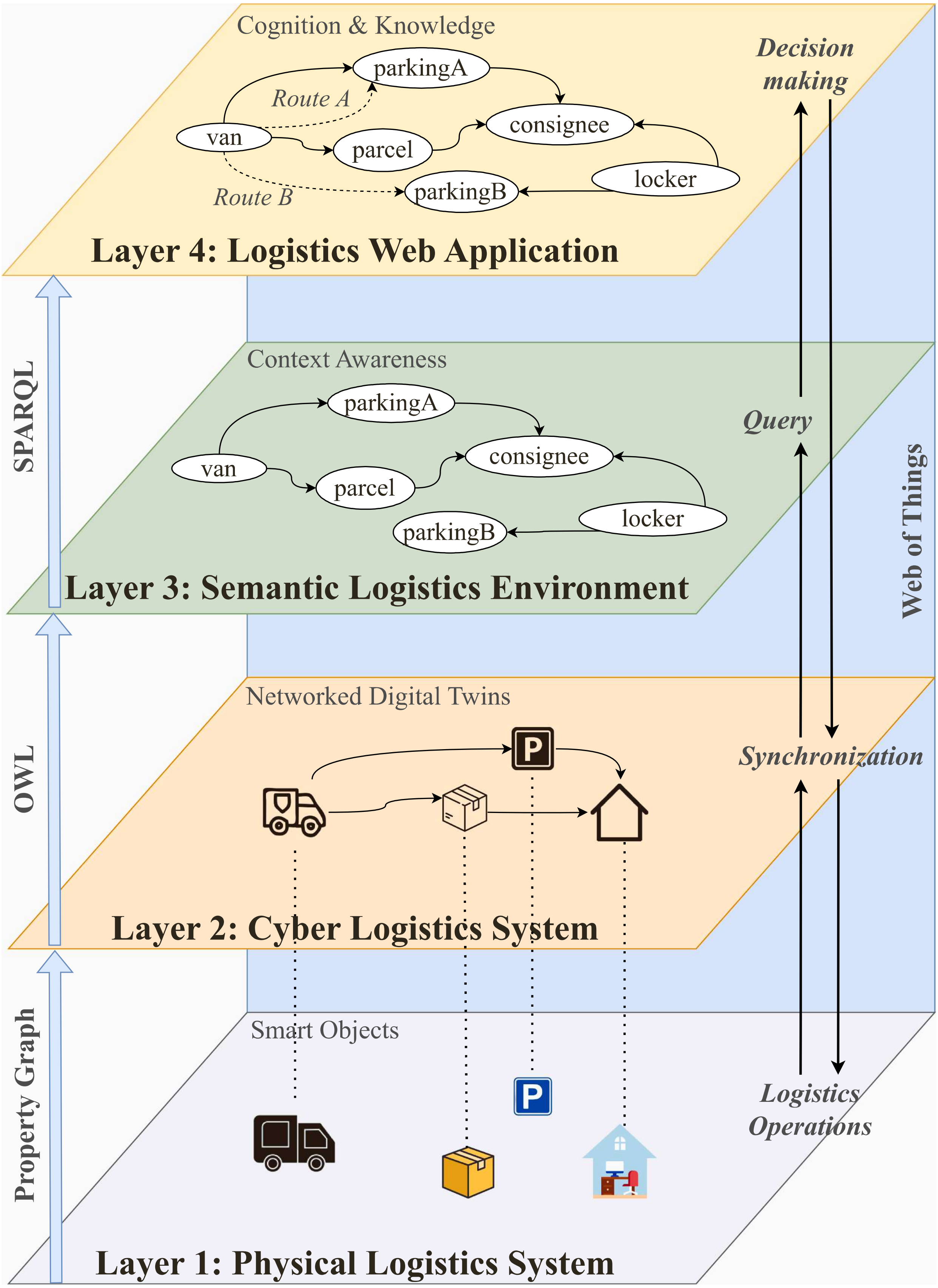


Fig. 1. The architectural framework for implementing dynamic freight parking management.

2.2. Semantic and cognitive digital twins in logistics

Cognitive Digital Twins (CDTs) have emerged as a prominent concept originating from Industry 4.0 and Smart Cities, which are defined as DTs with augmented cognitive capabilities and support to execute autonomous activities (Zheng et al., 2021; Rožanec et al., 2022). There is a substantial body of literature that delves into the definition and applications of DTs within various industries. Most define DTs as a digital counterpart that faithfully replicates a physical system (encompassing objects, components, processes) through seamless interactions and data exchange between the digital and physical realms, with the aim of improving the physical system's performance. On this basis, recent works argued that semantic technologies, such as ontology and Knowledge Graph (KG), can interlink DTs in virtual space by eliminating ambiguity across heterogeneous systems to enhance digital interoperability enabling cooperative decision-making and acting (Pan et al., 2021a). As defined by Guarino et al. (2009), ontology provides a set of formal and explicit vocabularies with shareability and reusability, to describe the knowledge in a specific domain, including the attributes of the things and their relationships. Early research mostly focused on the use of ontology for data modeling and sharing (Pan et al., 2021a). However, recent studies focusing on the next generation of DTs argue that the integration of semantics and DTs technologies will further move forward their capability and interoperability of autonomous and cooperative decision-making, namely CDTs (Rožanec et al., 2022). Since that, KG has gained increasing attention in supporting the development and management of CDTs, owing to its potential to illustrate the relationship between real-world entities or to link data (Zheng et al., 2021). For example, some recent works have explored the potential of KG and DT for managing assets and tasks in smart manufacturing systems (Zheng et al., 2023), or for inspecting underwater ships (Waszak et al., 2022). Some research focuses more on the methodologies to take the advantage of KG to create semantic data models for shaping DTs (Steinmetz et al., 2022).

Nevertheless, the application of the CDT concept and related technologies in the field of city logistics has yet to be extensively studied, despite their immense potential for achieving logistics sustainability. To fill the gap, this work investigates the potential of these concepts and technologies in freight parking management within the framework of Smart Cities. The latter can be viewed as a complex operating system that comprises multiple stakeholders, each with its own systems and objects (such as LSPs, city managers, shippers, and their assets), thereby emphasizing the criticality of digital interoperability (Pan et al., 2021a). More specifically, our work follows the previous research suggesting WoT standards to manage the objects and their DT for the applications in Smart Cities (Privat et al., 2019). Our research also aligns with the emerging paradigms of Smart Logistics, which represent novel approaches to digitalization in logistics and provide new opportunities for interdisciplinary research and application, encompassing computer and data science and operations management (Song et al., 2020).

3. Architectural framework of Smart City Logistics paradigm

In the first step, an architectural framework based on the WoT standards was devised to guide the research and application (see Fig. 1). Our architecture draws inspiration from the extensive body of literature on multi-layered smart system architectures, especially those IoT or DT architectures that are centering on data collecting and processing from objects/systems for decision-makings or (close-loop) system control. Differently, our architecture is devised with a specific emphasis on Smart City Logistics paradigm (Pan et al., 2021b), a domain characterized by the dynamic interplay of open and closed-loop systems. Within this distinctive context, semantic connections and cognitive capabilities of systems will become necessary to manage the systems and objects for applications and service innovation, as argued in some recent works (Zheng et al., 2021; Rožanec et al., 2022). Motivated by such a difference, our architecture places a central focus on the semantic and cognitive capabilities of logistics system, to establish robust interoperability and interconnectivity among these systems, harmonizing them with the broader context of Smart Cities.

The layered framework adopts a *bottom-up modeling approach*, whereby physical logistics systems are first modeled as DTs with their properties and relationships. Then, semantic technologies are employed to establish interoperability among DTs for cooperative decision-making processes. The details of each layer are presented as follows.

Layer 1 Physical Logistics System aims at delineating the physical system(s) of interest and the related smart objects. Fig. 1 illustrates a simplified example of freight parking, involving the objects of vehicle, parcel, destination, and parking nearby. It is assumed that the objects are equipped with IoT devices to collect local data for DTs modelling. Moving up to *Layer 2 Cyber Logistics System*, objects and their connections and properties are modeled with Property Graph (PG), which is considered a versatile and expressive existing approach to describe and store DT-related data in IoT/WoT environment, as suggested in Privat et al. (2019). It is for two reasons that at this step we adopt PG rather than other standard graph data models directly (like RDF-Resource Description Framework). First, most graph databases of enterprises use PG for their data model. Second, the nodes in PG only represent physical entities, which is beneficial to identify the complex relationship between the objects and clearly capture the structure of a physical system (Privat et al., 2019). Through the PG modelling, the instantly updated states and inner relationships of physical objects can be comprehensively and precisely mapped into the cyber layer, represented by system-wide interlinked DTs. Furthermore, the relevant data generated from IoT (or open data sources) should be injected into the system to synchronize instantly updated states of DTs for monitoring or decision-making. Accordingly, the closed-loop Cyber-Physical Logistics Systems (*Layer 1&2*) are constructed for each system owned by heterogeneous stakeholders, which will be the building blocks of the complex and collaborative smart city logistics system.

Layer 3 focuses on the development of CDTs by augmenting the semantic capacities of the modelled DTs. Note that in Layer 2, PG approach is applied to model DTs by providing an effective framework to describe the properties and relationships of DTs. Moving to Layer 3, ontology technology is employed to augment the semantic capabilities of DTs established in Layer 2, with the aim to render DT-related data more unambiguous, understandable, and interoperable. This step is crucial to enable seamless interactions between DTs and support decision-making in logistics operations. Subsequently, *Layer 4 of decision-making and applications* will rely on the dynamic status of DTs updated from their physical counterparts (*Layers 1&2*) and semantic interactions (queries) results between CDTs in the semantic environment (*Layer 3*). This comprehensive information and knowledge about the objects and the entire system context form the basis for making informed decisions. Then, the decisions made in Layer 4 will be communicated to the corresponding DTs in *Layer 2* for reaction in Layer 1. We should clarify that this work is not yet based on assumptions of fully autonomous objects (like autonomous vehicles or robots), which means self-acting is not considered. We assume that the behaviors of objects will be determined by the decisions made in *Layer 4*.

The development of the architectural framework is based on dynamic closed-loop logic, allowing instantly updated information from the physical world to update and synchronize with the digital world. By enabling this synchronization, the cyber world can better respond to changes in the physical world, leading to improved simulation models. Subsequently, physical objects' states will change and perform the reactions in the physical world.

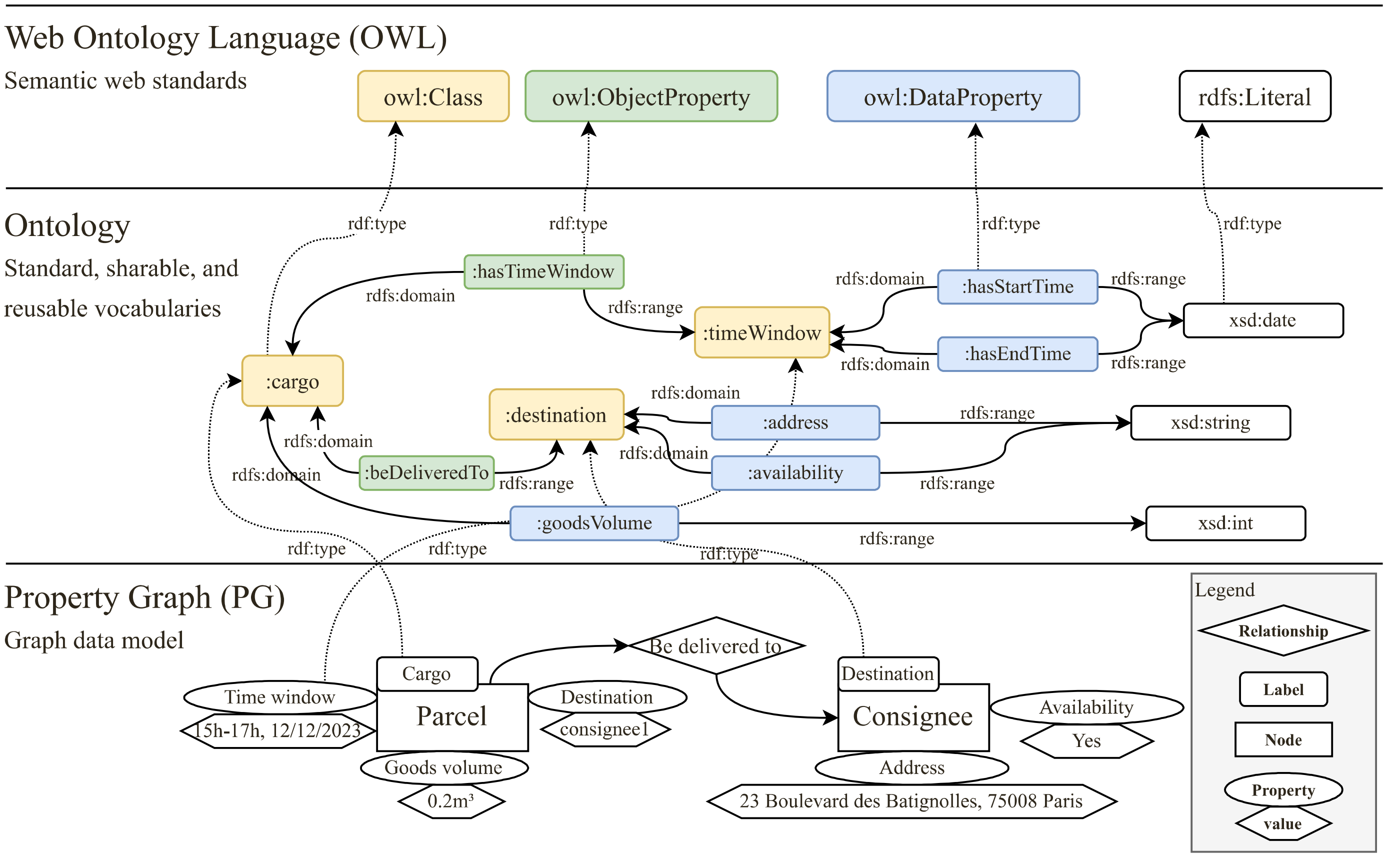


Fig. 2. An example of PG-stored DT-related data abstracted into ontology with OWL.

4. Application case and modeling

4.1. Case presentation

To assess the applicability and performance of the proposed approaches and framework, a real-life use case considering freight parking spaces, a.k.a. delivery spaces, for parcel delivery in Paris is conducted. The case is designed from LSPs' point of view, with data from industry and the city to assess economic, environmental, and social impacts.

In detail, a driver (also called a deliveryman as he/she could also handle the final delivery) will deliver parcels from a depot as the departure point to multiple final destinations. The journey is composed of two legs, from depot to delivery spaces (called the to-parking leg) and from delivery spaces to consignees' addresses (called the to-door leg). The objective is to provide the driver with the locations of optimal parking and routes to deliver the parcels within the city. The case is daily and involves the delivery of 145 parcels to 54 different destinations situated in the 17th district of Paris. According to Paris Open Data[1], there are 658 freight vehicle parking spaces in the district (due to regulatory constraints, only freight parking spaces are considered in this work, generally called parking hereinafter). From a practical point of view, parking located in the surrounding districts and outer boundary cities is also considered, such as the 8th, 16th, and 18th districts in Paris, Levallois-Perret, etc. In total, 3253 parking spaces are considered as input data of parking candidates (see Fig. 5).

[1] https://opendata.paris.fr/explore/dataset/stationnement-voie-publique-emplacements/information/?disjunctive.regpri&disjunctive.regpar&disjunctive.typsta&disjunctive.arrond&disjunctive.zoneres&disjunctive.locsta&disjunctive.parite&disjunctive.signhor&disju.

4.2. Bottom-up modeling

The architectural framework and the related technologies presented in Fig. 1 is applied here to model the case. *The first step* of modeling follows *Layers 1&2* of the architectural framework to construct the closed-loop Cyber-Physical Logistics Systems and the DTs of the objects involved. DT-related data collected from two different sources, e.g., LSPs for logistics assets and city planners for infrastructures, are modeled via Property Graph (PG). Objects' properties and relationships are modelled via four components of PG, namely nodes (physical entities), their properties expressed with key-value pairs (parameters, states, etc.), links (relationships), and labels (classes). More details of the PG modeling can be found in our former research (Liu et al., 2021).

The second step focuses on Layer 3, which involves enhancing the semantic capacity of the cyber models in Layer 2 to establish semantic connections. This step is essential to develop and empower DTs with the semantic capability toward CDTs (Zheng et al., 2021). This capability is crucial to integrate multiple heterogeneous components into the operating context as a unified whole. To this end, the DTs data stored via PG in Layer 2 need to be modeled with an ontologies catalog to address the diverse and heterogeneous meanings associated with the integrated DTs data from various stakeholders. *Web Ontology Language (OWL)* -a semantic web standard language proposed by W3C for things' knowledge descriptions- is adopted in this step. With the transformation illustrated in Fig. 2, the knowledge contained in the DTs (in the form of PG) can be unambiguously described and then share between heterogeneous stakeholders. Further, query language such as *SPARQL* (Xiao and Corman, 2021) is used to query the ontologies in Layer 3, which will provide actual information for operations management in Layer 4. *Protégé* -an open-source OWL-based ontology editor (Musen, 2015)- was exploited to develop the ontologies of the case. The ontology prefixes are shown in Fig. 3.

Ontology prefixes:

Prefix	Value
dbp-owl	https://dbpedia.org/ontology/
fun	http://w3id.org/sparql-generate/fn/
geosparql	http://www.opengis.net/ont/geosparql#
gml	http://www.opengis.net/gml/
imt	http://www.minesparistech.logistics#
iter	http://w3id.org/sparql-generate/iter/
mobivoc	http://schema.mobivoc.org/#
ns1	https://uri.etsi.org/ngsi-ld/
org-iot	http://orange-labs.fr/fog/ont/iot.owl#
owl	http://www.w3.org/2002/07/owl#
rdf	http://www.w3.org/1999/02/22-rdf-syntax-ns#
rdfs	http://www.w3.org/2000/01/rdf-schema#
schema	http://schema.org/
uc1	http://www.thingin.com/pelican/v2/
xml	http://www.w3.org/XML/1998/namespace
xsd	http://www.w3.org/2001/XMLSchema#

Fig. 3. Ontology prefixes in Protégé used in the case.

Fig. 4. Connected objects (nodes: destinations, parcels, parking) with relationships (links) and properties (on the top).

4.3. Thing'in: a federative online digital twin platform

To demonstrate the applicability of the research, the built ontology model is injected into a federative online DT platform, named *Thing in the future,* or simply *Thing'in*, which is a graph-based platform used to manage the structure and semantic connections of the living IoT objects in the physical world (Orange, 2018). Via the platform, the DTs' dynamic state can be managed and synchronized to support operations planning, as shown in Fig. 4. More importantly, data from objects can be shared between heterogeneous stakeholders based on semantic interoperability. To respect data privacy, *Thing'in* also provides the data (object) owners with the possibility to adjust the data visibility level, as can be seen at the top of Fig. 4. The platform has already experimented in different use cases and projects, like Digital Building Twin in Construction (BIM2TWIN.eu) and Smart City Logistics (smarturbanlogistics.eu).

Fig. 5 displays the DTs injected into *Thing'in*, located on a map of the area. Blue nodes represent destinations (aggregated), and orange is for parking spaces. The connections between destinations, parcels, and destinations are shown in Fig. 4. SPARQL is used for querying information from the platform. For example, for each destination, it is possible to query the number (and location) of the parking surrounded within a certain radius, as shown in Table 1 in Section 4.1. This information can help the driver to find the closest available parking.

The last step concerns decision-making based on instantly updated information including operations (vehicle location for example) and environment information (parking occupancy for example), which can be queried from the Layer 3 model. *AnyLogic* is adopted here as a decision-making tool to simulate the decision-making processes and the performance. It should be specified that the optimization models and algorithms (Section 3.4) are also coded in *AnyLogic* to build an integrated decision-making tool. This is only for demonstration (see Section 4.5 for an example of practical application). The sequence diagram in Fig. 6 shows the interaction between LSP (referred to as deliveryman), *Thing'in*, and *AnyLogic*.

4.4. Optimization models

Two decisions should be made by the deliveryman based on actual information: parking selection (like assignment problem) and route planning (like VRP-Vehicle Routing Problem). A straightforward strategy *parking-first-route-second* is applied here. Since the related optimization problems are well-studied in the literature and are not the focus of this work, we adopted well-known modeling approaches and algorithms to solve the problems without making further contributions to them.

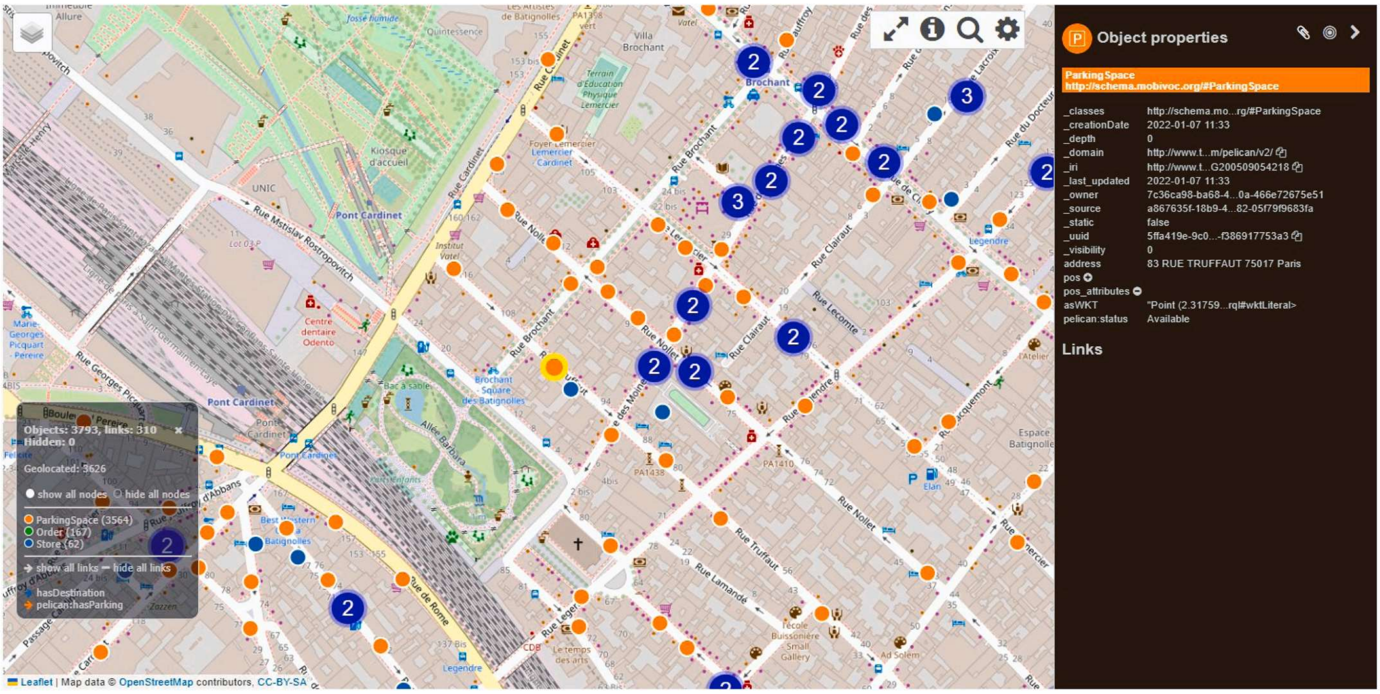


Fig. 5. Demonstration and visualization of DTs in Thing'in.

Table 1
Queried results in the semantic layer as the input for the application layer (a link represents the relationship between objects).

Catchment radius (m)	Parking pool	Parking-destination links	Parking-parcel links
100	182	264	665
150	320	588	1498
200	466	1037	2660
250	566	1562	4042
300	647	2267	5966

4.4.1. Parking selection

Choose the best parking places for each parcel from the list of available parking. We adopt the following assumptions regarding the operational environment: (1) An order (a destination address) has only one parcel and it can be assigned to only one parking place (but it could have more than one candidate parking). (2) All orders must be delivered. (3) Some operational constraints are not considered, such as parking capacity or temporal availability (due to the lack of data), and vehicle or deliveryman capacity (since the total number of parcels in the case is reasonable for one vehicle).

The objective of parking selection is to minimize the total number of parking visited (Eq. 1), where p_i is the decision variable of the problem,

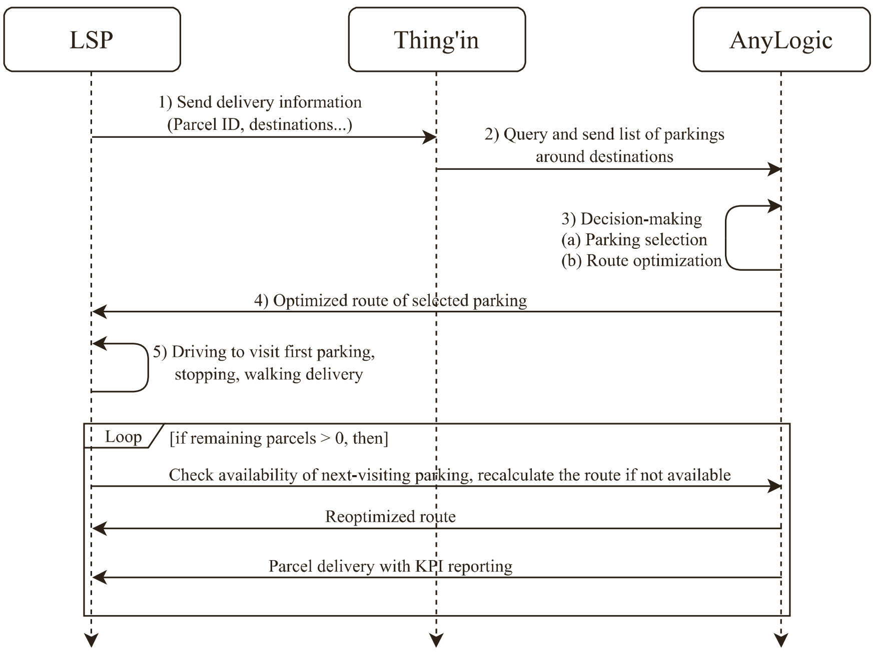


Fig. 6. Sequence diagram between operators, DT platform, and decision-making tools.

and $p_i = 1$ if parking i is visited; 0 otherwise (Eq. 4). It is expected that such an objective will have three major outcomes, firstly maximize parcel consolidation per parking to improve last leg efficiency, secondly reduce freight parking land in the city, and thirdly reduce the inefficient cruising time by parking fewer times. Other notations are present as follows: J is the set of orders, each order $j \in J$, and $j = \{1\ldots n\}$; I is the set of parking spaces, each parking $i \in I$, and $i = \{1\ldots k\}$. o_i^j is a binary matrix given by *Thing'in*, i.e., $o_i^j = 1$ means order j can be delivered from parking i; otherwise, 0 (Eq. 5). The key constraints considered are: i) all orders must be assigned to parking for fulfillment (Eq. 2); ii) only one parking can be chosen for each order to avoid repeated fulfillment (Eq. 3).

$$\min \sum_{i=1}^{k} p_i \tag{1}$$

s.t.

$$\sum_{i=1}^{k}\sum_{j=1}^{n} p_i o_i^j = |J| \tag{2}$$

$$\sum_{i=1}^{k} p_i o_i^j = 1, \forall j \in J \tag{3}$$

$$p_i = \{0, 1\} \tag{4}$$

$$o_i^j = \{0, 1\} \tag{5}$$

The problem is formulated as a combinatorial optimization problem that can be efficiently solved by Greedy Algorithm since it has a clear submodular structure and the optimized sub-problem can lead to global optimization (Cormen et al., 2022). In our tailed Greedy Algorithm, the parking that can deliver the most orders will be regarded as the most important and be selected first. The rest of the parking will be chosen following the same rule until all the orders have been assigned. The pseudo-code is presented below.

Algorithm 1. Greedy Algorithm for parking selection optimization.

Input: I: a set of parking spaces; J: a set of orders; K: a set of destinations;
L_j^i: a set of orders covered by parking i; L_k^i: a set of destinations covered by parking;
o_j^i: order j can be delivered via parking i
Output: the selected parking set P

1: *Assigned order set* $D = \emptyset$
2: *Selected parking set* $P = \emptyset$
3: **while** *order set* $D < J$ **do**
4:   **for** *all parking* $i \in I$ **do**
5:     *delivery capability* c_i of $i \leftarrow$ count_order (o_j^i) in L_j^i
6:     **COMPUTE** *maximum* c_m to find parking m that can deliver most orders
7:     *remove the furthest destinations in* L_m^k *gradually until to-door time* $\leq$ *30min*
8:     $o_j^m \leftarrow 1, D \leftarrow o_j^m$
9:     **for** *all parking* $i \in I, i \neq m$ **do**
10:       $o_j^i \leftarrow 0$
11:     **end for**
12:     *parking selection set* $P \leftarrow$ *parking* m
13:   **end for**
14: **end while**

4.5. Routing

Upon the list of parking selected, the visiting sequence needs to be decided. The problem can be formulated by VRP models. Since the capacity constraint of the vehicle (or deliveryman) is not considered at this stage, the problem is equivalent to Travelling Salesman Problem (TSP) which is modeled as follows. A set of selected parking are represented by $V = \{1, 2, \ldots, n-1\}$, plus $\{0\}$ signifying the departure point, so that $V^+ = V \cup \{0\}$, of which the set size is n. All nodes and arcs can be noted in a directed graph $G = (V^+, A)$. Each arc $(i,j) \in A$ is associated with travel distance $d_{ij} > 0$. x_{ij} equals 1 if arc (i,j) is included in any route, otherwise, equals 0. Accordingly, the TSP problem can be formulated by the following integer linear programming model from Miller et al. (1960).

$$\min \quad \sum_{i \in V^+} \sum_{j \in V^+} d_{ij} x_{ij} \tag{6}$$

s.t.

$$\sum j \in \mathrm{V} + x_{ij} = 1, \quad i \in V \tag{7}$$

$$\sum_{i \in V^+} x_{ij} = 1, \quad j \in V \tag{8}$$

$$u_i + 1 \leq n(1 - x_{ij}) + u_j, 0 \leq u_i, 0 \leq i \neq j \leq n \tag{9}$$

In light of practical applications on large-scale cases, Genetic Algorithm is adopted to solve the VRP problem in this work, as suggested by Tasan and Gen (2012). The initial population is set to 50 feasible routes, with different sequences of chromosomes being the various visiting sequences of the selected parking. Fitness is the driving distance accumulated by visiting the parking in sequence. The crossover probability is set to 0.8 and the mutation probability to 0.2, which are determined after several experimentations. The crossover operator is the Alternating Edges Crossover (AEC). The mutation operators are swap mutation, scramble mutation, and inversion mutation. Iteration will stop when the population evolves to 500 generations, which shows a good trade-off between computing time and acceptable optimal results.

Algorithm 2. Genetic Algorithm for Routing Optimization.

Input: R: population of routes; Pb_c: crossover probability;
Pb_m: mutation probability; G: number of generations;
Output: r in R with the shortest delivery distance

GenerationCount = 0;
while *GenerationCount* $< G$ **do**
  $i = 0$;
  if $i < Pb_c * |R|$
    offspring = crossover of (r_i, r_j), $r_i, r_j \in R, j \neq i$;
    insert *offspring* into R, $i++$;
  end if
  $GenerationCount \mathrel{+}= 1$;
  $Rnd = [0, 1]$;
if $Rnd < Pb_m$
    r_x mutated into r_x', $r_x \in R$ *and not the best performed in* R;
  replace r_x with r_x' in R;
  $GenerationCount \mathrel{+}= 1$;
end if
descend and reduce the extended population to $|R|$
select r in R with the shortest driving distance
end while

5. Simulation and industrial application

5.1. Scenarios description

Three scenarios were simulated, as illustrated in Fig. 7. In all scenarios, parking information, e.g., the closest candidate parking or those within a radius of each destination, are queried from the *Thing'in* platform, as shown in Table 1. Links here represent the relationships between objects, e.g., a parking-destination link meaning that the destination can be accessed via the surrounding parking of the link, or a parking-parcel link meaning that a parcel can be delivered from a parking.

S1 of Status-quo scenario simulating the current practices: It is designed that the deliveryman drives from the depot and stops at the closest parking of each parcel's destination address, then walks to the consignees and walks back to the parking for heading to the next stop. Consequently, parcels are not consolidated in this scenario (we recall the assumption that each destination receives only one parcel).

S2 of parcel consolidation: The deliveryman may deliver a bundle of parcels to different destinations from one parking through on-foot routing. We aim to investigate the impact of parking selection on parcel consolidation, that is, the potential to deliver a higher number of parcels during each parking stop within the designated catchment area of the parking facility. Five catchment radius settings have been studied: 100, 150, 200, 250, and 300 m. 100 m is calculated upon the dataset,

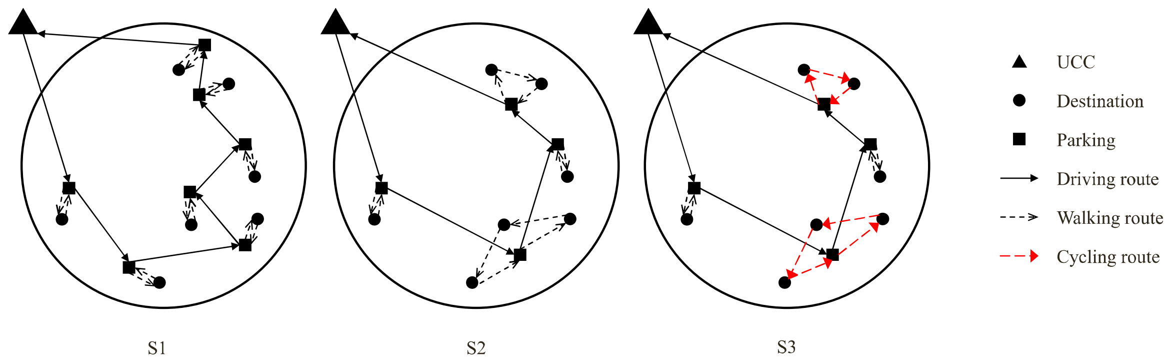


Fig. 7. Schematic view of current operations (S1) and two tested scenarios (S2, S3).

which is the distance to find at least one parking for each destination, whilst 250 m was suggested by Letnik et al. (2018) as the acceptable walking distance regarding the walking willingness of the deliveryman. However, the experimental results showed that 300 m is an interesting turning point in the case study to show the effect of consolidation (see Section 4.2). This is of particular interest for investigating a freight-related regulation in Paris, which is the use of freight parking spaces is free but limited to 30 min (Dablanc 2015). Regulatory and environmental insights are expected from a study of the impact of such a regulation on delivery consolidation, parking occupation time, and land use.

S3 of eco-friendly modality: It is to investigate how our approach can help facilitate a modal shift from vehicle to E-cargo bike at selected parking serving as transit points. This initiative stems from the belief that the increasing volume of consolidated parcels necessitates environmentally friendly solutions for the last meters. It is designed to enable the deliveryman (in a vehicle) to transfer parcels to an E-cargo bike rider at selected parking so that the parcels can be delivered to the door via bike routing. Unlike S1 and S2, S3 involves separate operators for the to-parking leg and the to-door leg. This setup aims to minimize both vehicle waiting time and parking occupation time.

Table 2
Parameters used in the simulation.

Parameter	Notions	Value	Unit
Vehicle rental cost	C_v	13	€/h
Labor cost	C_l	30	€/h
E-cargo bike cost	C_{EC}	11	€/h
Diesel price	P_{fl}	1.83	€/L
Emissions factor	e_{CO_2}	158	g/km
Fuel consumption rate	C_{fl}	0.13	L/km
Picking time per parcel	t_{ser}	0.5	min
Operating time per stop	t_{op}	1	min
Transshipment time	t_{tsp}	3	min
Vehicle speed	S_v	20	km/h
E-cargo bike speed	S_{EC}	10	km/h
Walking speed	S_w	4	km/h

5.2. KPIs and parameter setting

The three scenarios are simulated on *AnyLogic*, by real-time simulation models with actual data, e.g., roads, average speed in the city, parcel delivery information, and parking location (recall that live traffic information is not considered in this step). A set of KPIs (Key Performance Indicators) is established from economic, environmental, and social perspectives, which are defined as follows (related parameters are listed in Table 2).

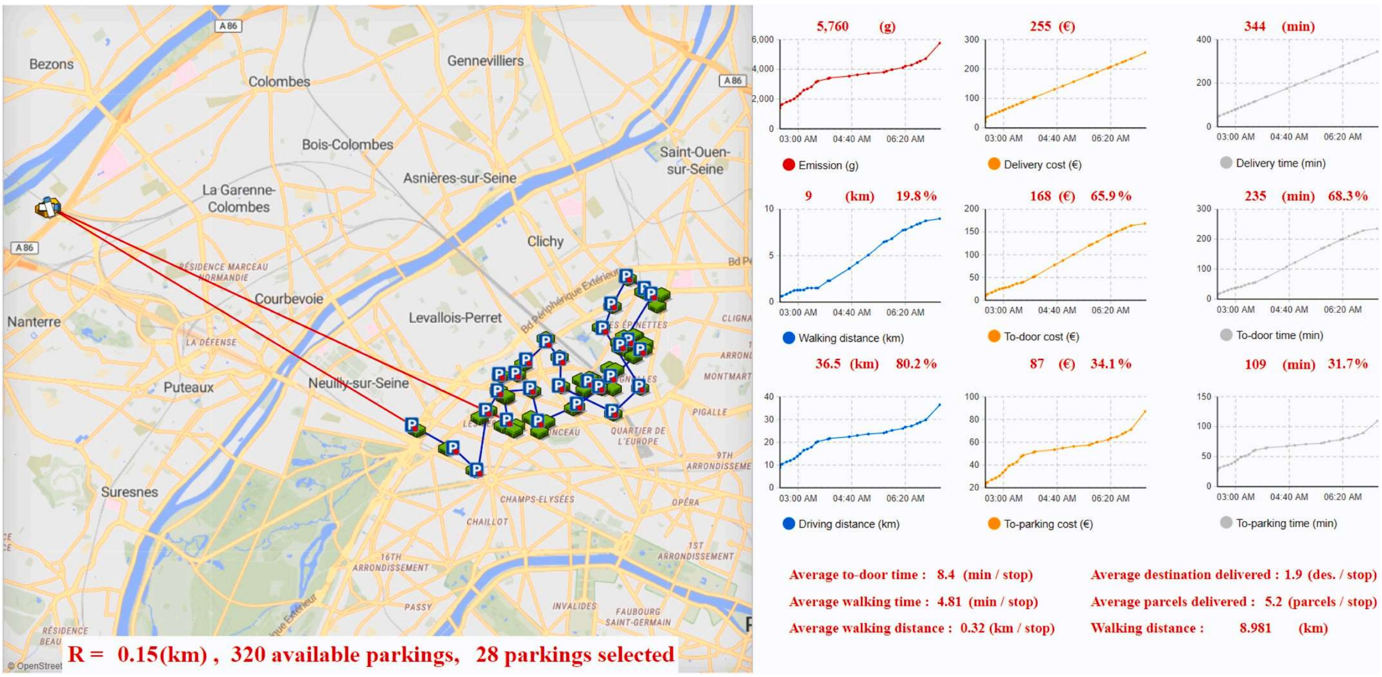
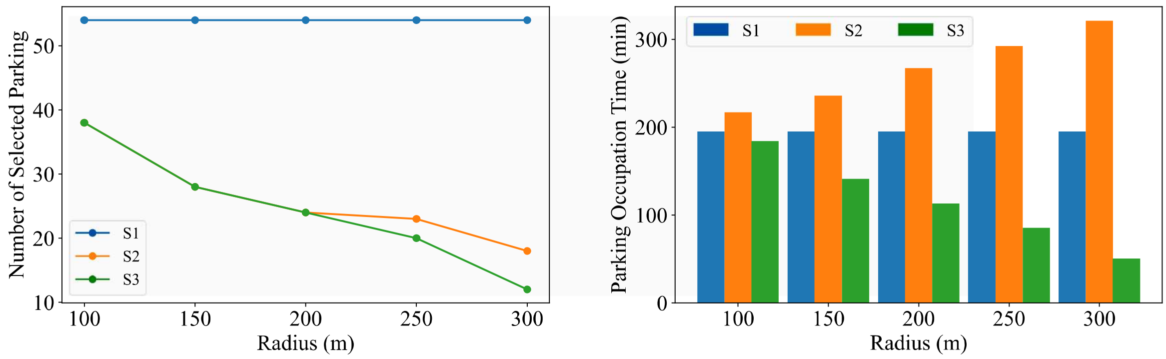


Fig. 8. An illustrative example of route planning and performance reporting in AnyLogic.



(a) The number of parking selected (b) Parking occupation time

Fig. 9. Parking demand and the use time (the constant value of S1 is for illustrative and benchmarking purposes and has no correlation with the catchment radii).

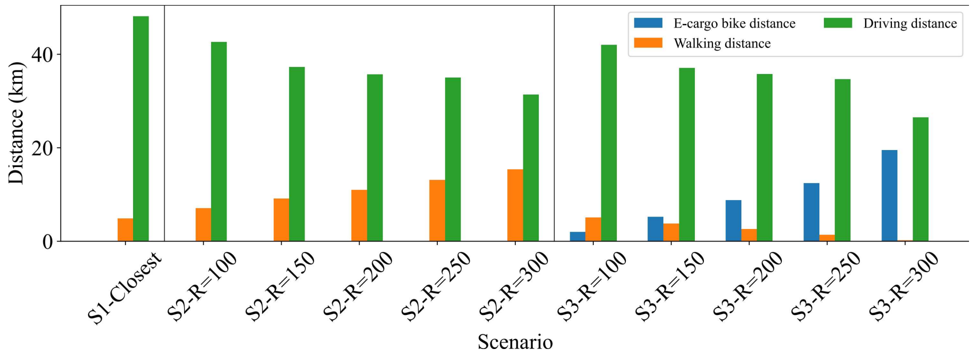
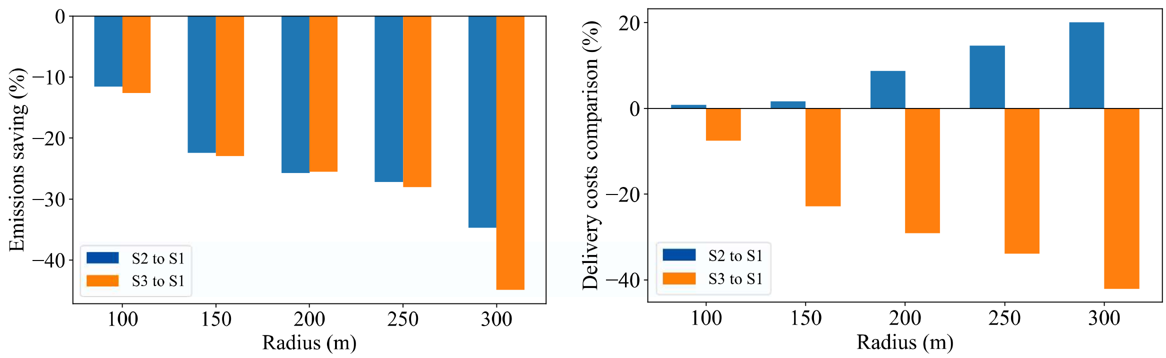


Fig. 10. To-parking distance (driving) and To-door distance (on foot or by E-cargo bike).



(a) CO2 emissions saving (b) Delivery costs comparison

Fig. 11. Emission saving and delivery cost comparison in different catchment radii.

$$E_{CO_2} = \sum d_{to-p} * e_{CO_2} \tag{10}$$

$$D_d = \sum d_{to-p} + \sum d_{to-d} \tag{11}$$

$$C_d = \sum C_{to-p} + \sum C_{to-d} \tag{12}$$

$$C_{to-p} = (C_v + C_l) * t_{to-p} + d_{to-p} * C_{fl} * P_{fl}, \text{for each parking visited} \tag{13}$$

$$C_{to-d} = (C_v + C_l) * \left(t_w + t_{op} + t_{ser} * n_p^i\right), \text{for each parking visited in S1\& S2} \tag{14}$$

$$(C_{EC} + C_l) * (\frac{d_{to-d}}{S_{EC}} + t_{op} + t_{ser} * n_p^i) + t_{tsp} * (C_{EC} + 2 * C_l + C_v)\langle(14) \tag{15}$$

The CO_2 emissions from vehicles are considered as environmental KPI, which equals the multiplication of the total vehicle driving distances (km) from depot to parking d_{to-p} and the unit emission per km e_{CO_2} (Eq. 10). Eq. 11 calculates the total delivery distance D_d which is the sum of the total vehicle driving distance d_{to-p} and to-door distance d_{to-d} (by foot in S1 & S2, or by E-cargo bike in S3). Distance between points is calculated based on OpenStreetMap provided in *AnyLogic*, and the gap compared to Google Maps is within 2%. The total delivery costs C_d is the sum of the total to-parking cost C_{to-p} and to-door cost C_{to-d} (Eq. 12). For each parking visited, to-parking costs are composed of vehicle usage, labor, and fuel consumption, as shown in Eq.13 in which C_v is hourly van

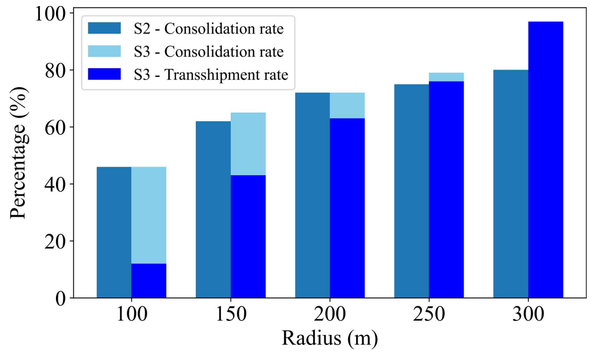


Fig. 12. The percentage of consolidated or transshipped parcels.

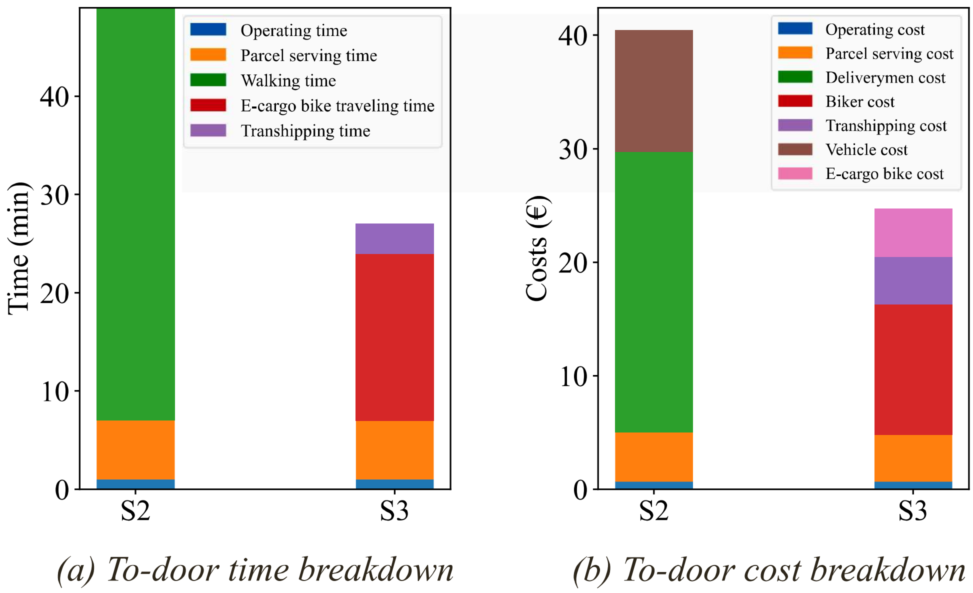


Fig. 13. Example of To-door time and costs in a stop having 12 parcels to 5 destinations.

rental cost[2], C_l hourly labor cost, C_{fl} van's fuel consumption rate[3] , and P_{fl} diesel price. The parameters are used for calculating the costs in function of driving time and distance. Differently, in S1 and S2, to-door costs (Eq. 14) are time-based only, including vehicle costs (waiting time at parking) and labor costs due to on-foot delivery time t_w, parking operations time t_{op}, and the parcels picking time (search, scan, unload) computed by time per parcel t_{ser} and the total number of parcels n_p^i at the stop. Especially in S3, it is assumed that transshipment to the E-cargo bike should happen only if it financially outperforms the scheme with driver on-foot routing, which is verified by Eq.15. Here the transshipment time t_{tsp} is set to 3 min, including the hand-over and checking time between the driver and E-cargo cycler, as well as the loading time to the cargo bike. The speed settings have taken the issues of congestion and safety into account.

5.3. Simulation results and key findings

Fig. 8 illustrates an example of a simulation scenario (view in *AnyLogic*) of the case with a catchment radius of 150 m. The vehicle leaves the depot (on the left-hand side of the map) to visit the selected parking spaces (marked out with red dots) and back to the depot. The blue lines represent only the visiting sequence, as OpenStreetMap in *AnyLogic* is used for calculating the actual distance. On the right-hand side, the dashboard displays the instantly updated performance of the delivery operations.

The simulation results reveal key insights from various aspects of urban delivery schemes. The first is relating to sustainability, considering the influence of freight policies and resource utilization performance. The second is an in-depth operation performance analysis to help LSPs identify key activities to implement these delivery schemes effectively. The third is to dive deeper into the modal shifting, gaining the critical factors to support the adoption of the multi-modal scheme. Quantitative results are detailed in Appendix.

5.3.1. Resource utilization

Finding 1.1: Parking demand is significantly reduced because of parcel consolidation, but the reduction is limited by regulations on freight parking utilization.

Compared to S1 with one parking per destination, expanding parking's catchment area in S2 and S3 allows for delivering to multiple destinations from single parking, leading to parking demand reduction. As a result, the number of selected parking shows a compelling contrast, decreasing at least two-thirds in S2 and S3 (Fig. 9(a)). The benefits are in various aspects. From the LSPs perspectives, fewer parking searches equate to reduced inefficient cruising time and costs. Additionally, this advancement yields broader societal benefits such as improved road

[2] IEA Tracking Fuel Consumption of Cars and Vans 2020: https://www.iea.org/reports/tracking-fuel-consumption-of-cars-and-vans-2020-2.
[3] Example from IKEA Services of Van Hire: https://www.ikea.com/gb/en/customer-service/services/van-rental-pubfae74391.

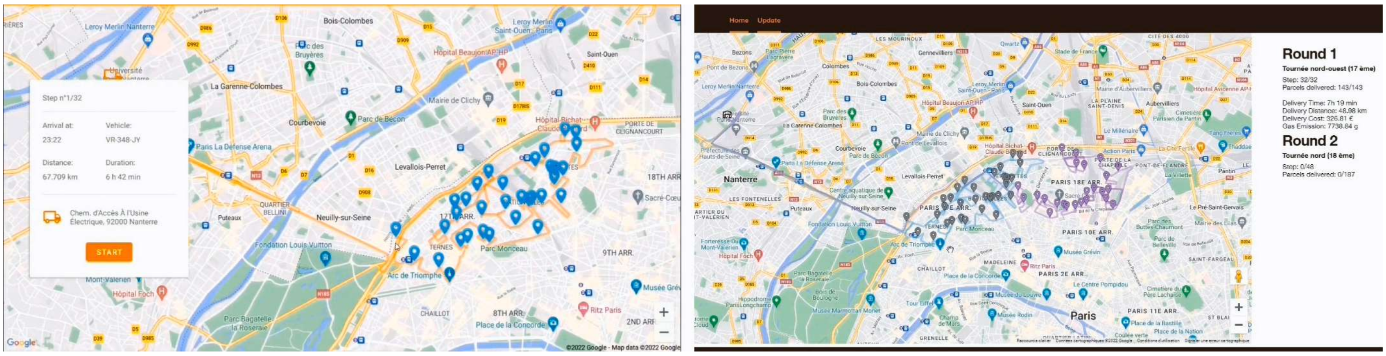
utilization and reduction of negative externalities, e.g., congestion, pollutions, emissions.

However, S2 also shows the impacts of the freight parking-related regulation in Paris on the consolidation of parcels in single stop, i.e., freight parking duration limited to 30 min. Because the number of parcels per stop can easily be constrained by this regulation. Compared to S2, modal shift to cargo-bike in S3 may effectively respect the use time constraint, while resulting in a greater decrease in parking demand, which increases with the increase of radius as shown in Fig. 9(a): three and six less parking are needed at the radii of 250 m and 300 m respectively. The impacts of model shift can be observed apparently on driving distance (Fig. 10), emission reduction (Fig. 11(a)), and consolidation rate (Fig. 12).

Finding 1.2: Noticeable parking occupation time savings via *modal shifting.*

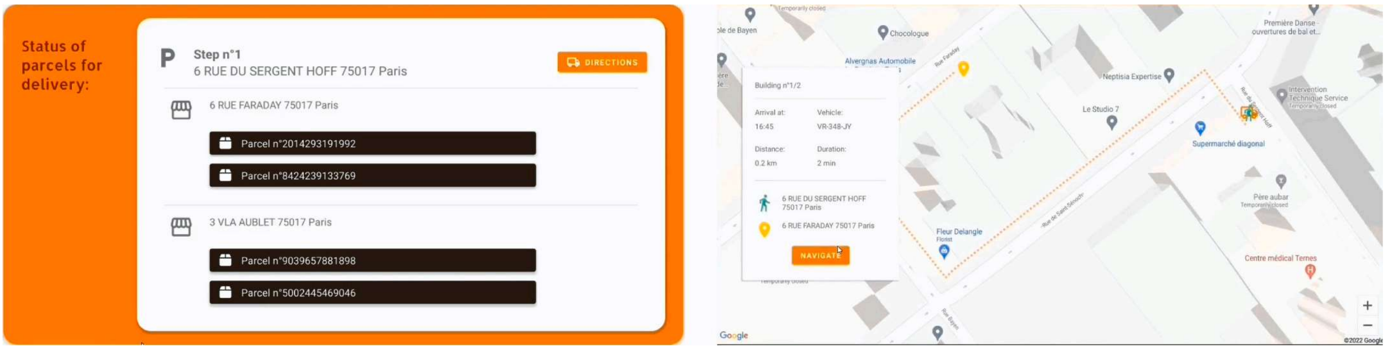
This work considers parking occupation time by freight vehicle as an KPI of resource utilization. Although much less parking is needed in S2, the occupation time increases significantly, as shown in Fig. 9(b). This results from the extended to-door distances and, therefore, time by walking, which can be intuitively observed in Fig. 10. Transitioning to S3, the adoption of E-cargo bikes becomes more time-efficient in parking usage, where parking is used shortly for transshipping. At a radius of 300 m, this shift results in nearly 80% parking occupation time-saving, showing a substantial improvement over S1 and S2.

These findings carry profound implications for urban planning and management. Parking demand can be substantially reduced by



(a) Overview of the delivery round (b) Reporting the status of the delivery rounds

Fig. 14. Delivery rounds overview and performance reporting.



(a) List of steps to guide walking delivery (b) Walking delivery navigation

Fig. 15. The delivery sequence in stop and walking routes in the neighborhood.

(a) Status synchronizing with DTs (b) Selected parking unavailability alerts

Fig. 16. The status of parcels and parking synchronizing with their DTs.

integrating multi-modality in last-mile delivery and orchestrally operating with time-changing urban resource states. This would contribute significantly to improving urban logistics efficiency, potentially alleviating issues related to parking shortages and parking cruising behaviors.

5.3.2. Costs and emissions

Finding 2.1: Less visited parking results in decreased driving distance and emissions.

Fig. 10 illustrates the distance travelled by different means: vehicle driving distance, on-foot porter walking distance, and e-cargo biking distance (only in S3). Comparing these three scenarios, it is observed that in a wider catchment area, the driving distance diminishes gradually, saving over 40% distance at most. Emissions shown in Fig. 11(a) only consider the part directly generated from vehicles (Scope 1 only), which means E-cargo bike generates no emissions. In S2, when the catchment area becomes larger, emissions decrease by 12–35%. Incorporating E-cargo bikes minimizes parking demand, achieving a notable emission reduction of 45% at a 300 m radius.

Finding 2.2: As the catchment area enlarges, walking distance stably increases in S2, while it rapidly decreases and replaced by E-cargo bikes in S3.

In S2, larger catchment area leads to stable and obvious growth in walking distance, where drivers perform the to-door delivery on foot. In S3, walking delivery dominates when in a small catchment area since the condition of transshipment has not been satisfied (Eq. 15). As the catchment radius increases, modal shifting becomes more prominent. This trend continues until the radius of 300 m, at which point E-cargo bikes take over all the to-door deliveries that need to be handled by leg-work (see Fig. 10 and Fig. 12).

Finding 2.3: Delivery cost increases in S2 but remarkably decreases in S3 via *modal shifting.*

Comparing S2 to S1, delivery costs show generally increase as the catchment area enlarges, as shown in Fig. 11(b). This rise is due to a longer to-door time, which can be interpreted as increased walking time (labor cost) and vehicle waiting time (vehicle cost). More specifically, the cost changes at radii of 100 m and 150 m are not significant, which is less than 5%. It is because to-door cost increases and to-parking cost savings are almost offset. However, at a radius of 300 m, the to-door cost increase becomes quite pronounced, resulting in a total delivery cost increase of 20%. The result suggests that parcel consolidation via driver delivery can cause a non-linear cost increase, depending on the parcel distribution and the size of the catchment area, so the setting of the catchment radius need to be well considered when adopting this scheme.

When comparing S3 to S1, significant cost savings are apparent, ranging from around 10% to over 40% (see orange bar in Fig. 11(b)). Although E-cargo bikes still need to be used as a replacement of vehicle, due to shorter to-door time (results from higher E-cargo bikes' speed), the savings are obvious. In addition, instead of waiting and occupying the parking, vehicles will go towards the next stop after a short transshipment, which is a cost- and time-effective solution regarding operations and resource utilization.

5.3.3. Opportunities for modal shift

Finding 3.1: Consolidation rate rises in S2 and S3 while the role of transshipment is increasingly significant in S3.

More parcels are delivered via consolidation at parking as the catchment area becomes larger. At a radius of 300 m, the consolidation rate (the number of consolidated parcels to the totality) is only 80% in S2 compared to nearly 100% in S3, which shows the advantages of modal shifting in a large catchment area with respect to use time limit. In S3, as the to-door catchment expands and more parcels are consolidated, modal shifts are adopted more frequently, until take over all consolidated parcels at a radius of 300 m.

Finding 3.2: High to-door cost in S2 and noticeable transshipment costs in S3.

Fig. 13 shows a detailed breakdown of the to-door time and costs in a selected parking, aimed at providing a clear understanding of the factors contributing to these differences. Two significant insights emerge from this breakdown. First, in S2, it can be observed that more than 80% of the to-door time has been spent on walking, which is nearly double that of cycling in S3 (Fig. 13(a)). This is also aligning with the costs shown in Fig. 13(b), the cost associated with vehicle use is substantially higher than E-cargo bike costs, more than double. This reflects the low efficiency of walking delivery in such a large catchment area. Second, although the transshipment time (in purple) is not particularly lengthy compared to other operation times, it incurs substantial costs due to the involvement of two vehicles and two delivery personnel during the transshipment. Hence, the way to organize the transiting operations will impact the cost heavily. The dynamic information about the infrastructure and related personnel are key, as emphasized and involved in this work.

In summary, the breakdown indicates that parking acting as a transshipping point can yield considerable savings, both in terms of parking occupation time and delivery cost, exceeding 40% in both cases. Therefore, S3 exhibits superior performance in terms of both time and cost efficiency, proving to be a promising strategy for last-mile delivery.

5.4. Application prototype

An application prototype, demonstrating the approach in a real-case scenario, has been developed using the same dataset as the simulation. In the future, this application could be applied in real world. Serving as another option for *Layer 4* implementation (Fig. 1), this mobile application gives delivery personnel an overview of the round (Fig. 14 (a)). Blue markers on the map represent parking for parcel bundle delivery, grouped by properties such as destinations. It also provides an estimate of the total distance, delivery duration, and Estimated Time of Arrival (ETA) for the next stop. Upon completion of the round, delivery performance is measured via KPIs, which are accessible for LSP managers through a web portal. Grey markers on the map indicate parking locations already visited by the delivery personnel (Fig. 14 (b)).

When the deliverymen start the round, a list of steps is displayed in their mobile application, see Fig. 15 (a). Each step stands for parking and the related destination of a parcel bundle. Once the deliverymen arrive at the parking space, the application provides a walking route to navigate them to the destinations and displays the parcels to be delivered, as shown in Fig. 15 (b).

Once the deliverymen arrive at a destination, the parcels will be scanned before handing the parcel to the receiver, the status of parcels will be synchronized with its Digital Twin, which will change from "in delivery" to "delivered", see Fig. 16 (a). When deliverymen deliver all parcels on foot and back to the parking, the system will double-check if the next parking space is still available before he heads to the next parking, with the hypothesis that all parking is equipped with sensors and their availability information is synchronized with the DT of the parking. When the planned parking is no longer available, a pop-up dialog box will alert the deliveryman on the application, and the new parking will be selected while the route will be recalculated, as shown in Fig. 16 (b).

6. Conclusion

This research addresses the Freight Parking Management Problem (FPMP) in last-mile delivery, specifically focusing on the efficient utilization of urban infrastructure and resources to support urban freight transport, involving multiple stakeholders. We deploy Digital Twin (DT) technology and semantic technologies. DT acts as virtual representations of physical objects for asset management from individual stakeholder perspectives, while semantic technologies offer standardized vocabularies for DT description and sharing, the so-called Cognitive Digital Twins. This enables distributed DTs integration in Smart Cities to represent the urban delivery environment and facilitates