Urban, Planning and Transport Research
An Open Access Journal

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rupt20

Digital twin applications in urban logistics: an overview

Abdo Abouelrous, Laurens Bliek & Yingqian Zhang

To cite this article: Abdo Abouelrous, Laurens Bliek & Yingqian Zhang (2023) Digital twin applications in urban logistics: an overview, Urban, Planning and Transport Research, 11:1, 2216768, DOI: 10.1080/21650020.2023.2216768

To link to this article: https://doi.org/10.1080/21650020.2023.2216768

Published online: 01 Jun 2023.

URBAN, PLANNING AND TRANSPORT RESEARCH
2023, VOL. 11, NO. 1, 2216768
https://doi.org/10.1080/21650020.2023.2216768

Digital twin applications in urban logistics: an overview

Abdo Abouelrous, Laurens Bliek and Yingqian Zhang

Department of Information Systems, Faculty of Industrial Engineering and Innovation Sciences, Technical University Eindhoven, Eindhoven, The Netherlands

ABSTRACT

Urban traffic attributed to commercial and industrial transportation is observed to largely affect living standards in cities due to external factors like pollution and congestion. To counter this, smart cities deploy technologies such as digital twins (DT)s to achieve sustainability. Research suggests that DTs can be beneficial in optimizing the physical systems they are linked with. The concept has been extensively studied in many technology-driven industries like manufacturing. However, little work has been done with regards to their application in urban logistics. In this paper, we seek to provide a framework by which DTs could be easily adapted to urban logistics applications. To do this, we survey previous research on DT applications in urban logistics as we found that a holistic overview is lacking. Using this knowledge in combination with the identification of key factors in urban logistics, we produce a conceptual model for the general design of an urban logistics DT through a knowledge graph. We provide an illustration on how the conceptual model can be used in solving a relevant problem and showcase the integration of relevant DDO methods. We finish off with a discussion on research opportunities and challenges based on previous research and our practical experience.

ARTICLE HISTORY
Received 23 March 2023
Accepted 17 May 2023

KEYWORDS
Digital Twins; Artificial Intelligence; Machine Learning; Urban Logistics; Smart Cities; Optimization

1. Introduction

Urban logisticshas been growing rapidly in recent years due to rising consumer demand and online shopping, among other trends relating to population growth and urbanization (Savelsbergh & Van Woensel, 2016). As a result, operational planning and policy-making in urban logistics has become increasingly complex. The associated challenges require smart cities to develop technologies that can assist with solving problems in urban logistics Büyüközkan and Ilcak (2021)).

Such technologies include Artificial Intelligence (AI), which has managed to acquire significant interest with its promising capabilities. Specifically, AI has witnessed many industrial applications in urban logistics to deal with real-life planning challenges as discussed in Jucha (2021), Sonneberg et al. (2019) and Shi et al. (2019).

CONTACT Abdo Abouelrous a.g.m.abouelrous@tue.nl Department of Information Systems, Faculty of Industrial Engineering and Innovation Sciences, Technical University Eindhoven, Eindhoven 5612 AZ, The Netherlands

Among the various AI-driven technologies presented to tackle urban logistics problems, we are particularly interested in one because of its holistic approach in combining knowledge from different quantitative fields such as machine learning and mathematical optimization to model and optimize the operational environment through continuous data exchange with it. We refer to this as the Digital Twin (DT).

Despite the DT term dating back almost two decades, it still lacks a common definition across different industries (Marcucci et al., 2020). In particular, the definition of a DT is often determined by the application context (Semeraro et al., 2021). However, we believe that having a common cross-industry definition is crucial to launch any research initiative on DTs in a new field such as urban logistics to help specify its functionalities and technical requirements.

For the large part, DT applications have largely been manufacturing-based as in Rosen et al. (2015) and Tao et al. (2019). There has been very limited focus on the area of logistics as Haße et al. (2019) mentions, despite its importance and emphasis on how it could benefit from Big Data analytics (Pan et al., 2021). This benefit only grows with time as cities are becoming increasingly smarter and collect data from a multitude of sources (White et al., 2021). By using this data, DTs could be used to improve the quality of life, mobility and services of the inhabitants of a city (Botn-Sanabria et al., 2022)).

To emphasize the difference in setting up an urban logistics DT compared to a 'factory-floor' one, we consider the associated design and deployment phases. For instance, a manufacturing DT may be subjected to semi-physical simulations as part of a validation process in the system design phase (Leng, Wang, et al., 2021)), (Leng, Zhou, et al., 2021). This is not possible in the urban setting where semi-physical tests come at a great cost and risk, and therefore, model validation and training have to occur 'offline'.

In order to define a framework for building urban logistics DTs, we first have to identify the most relevant aspects in urban logistics to DTs. The human aspect plays an important role in the urban environment as determined by the stakeholders and their interactions (Lagorio et al., 2017). This aspect is less significant in other domains such as manufacturing where robotic equipment operating in an exclusive environment guarantee some consistency in implementation and decision-making. Urban environments, on the other hand, are seen to be more complex (Rydin et al., 2012).

Our objective is to provide a characterization of urban logistics DT by providing definition, technical anatomy, functionalities and set-up methodology. To the best of our knowledge, there is no existing research that contains a holistic overview of all four topics.

Additionally, the integration of Data-Driven Optimization (DDO) methods has rendered an obstacle in the development of DTs. DDO methods have been extensively developed and can leverage the computational power of DTs to significantly improve decision-making. For urban logistics, this has been manifested in numerous use cases like Gutierrez-Franco et al. (2021), Zdolsek Draksler et al. (2023), Miao and Lan (2021) and Shen et al. (2022). For the large part, the focus has been on software integration. The absence of clear guidelines on DDO integration limits the margin by which we can benefit from DTs (Teng et al., 2021).

In response to the aforementioned problems, we strive to deliver the following contributions through this study: [noitemsep]

(1) Identify the most relevant factors in urban logistics operations for DT development.

(2) Summarize previous findings from literature on DTs in urban logistics in terms of definition, technical anatomy, functionalities and set-up methodology.
(3) Provide a conceptual model of urban logistics DTs in terms of a knowledge graph.
(4) Provide a technical illustration on how our conceptual model could be leveraged to solve a common urban logistics problem and the integration of DDO methods.
(5) Specify potential opportunities and challenges in future research.

That said, the rest of this article is organized as follows. Section 2 describes our search procedure in academic literature. Section 3 provides the dynamic characterization of urban logistics (Contribution 1) in 3.1 and the detailed survey of DT applications in urban logistics in 3.2 (Contribution 2). Section 4 proposes the conceptual framework (Contribution 3). Section 5 offers the technical illustration (Contribution 4). Section 6 discusses the results of this study along with research opportunities and challenges. (Contribution 5). Section 7 summarizes the conclusions of this study.

2. Literature review

A systematic and thorough research for literature was conducted. Before we proceed with describing it, we had to specify a definite research direction by which we are able to formulate research queries. Specifically, we opted to look for Digital Twin applications that are exclusive to city logistics and its sub categories like last-mile deliveries. We ignored applications from other fields such as manufacturing or other transportation and/or logistics areas such as cross-border transportation or warehousing where the environments characterizing the DT are significantly different from those in cities, and as such have little theoretical insight to offer.

The major challenge that we encountered is the limited availability of literature. To that end, we had to employ additional measures to cultivate more literature that, although not exclusive to urban logistics, contains elements that relate sufficiently to the topic. In spite of the limited availability, the literature we found embodies a great deal of information as each paper discusses a somewhat distinct aspect of urban logistics DTs in a great level of detail, allowing us to construct a rather informative overview.

Our search procedure largely resembles that of Pan et al. (2021). We define four search criteria:

- (C1) Time period: The time-frame was rather unrestricted in our search. We are aware that this is a relatively new topic where most work has been done in recent years, as will be shown below. Furthermore, we avoided any restrictions on the search due to the limited availability of literature on our topic.
- (C2) Sources: We were open to all available academic sources. We disregarded working papers. Articles published in non-academic venues were also discarded.
- (C3) Language: only papers written in English are considered.
- (C4) Key words: Search queries were coupled with the term “Digital Twin”. We used synonyms of urban logistics such as city logistics and last-mile deliveries. We also made use of the term supply chain as an alternative to logistics. We avoided queries with the term logistics and/or supply chain alone as this produces ample amount of literature that does not directly deal with the our definition of urban logistics (see Section 3.1).

We used the Scopus search engine with criteria (C1)-(C4) and ran the following query: ***"TITLE-ABS-KEY (digital AND twin AND (((city OR urban) AND logistics) OR ((last-mile AND delivery AND supply AND chain) OR last-mile AND delivery))) "***. We obtained a total of 35 results.

Thereafter, we proceed to a selection stage where we navigated the content of the 35 papers and only discovered 13 to be sufficiently related to the topic of digital twin applications in urban logistics. We were also able to identify two more papers through cross-referencing, giving a total of 15 papers. Our contribution is, however, not restricted to summarizing previous findings. We also propose and analyze a conceptual model with the support of other literature that is not part of the survey itself.

The histogram in Figure 1 depicts the research trend for the papers. Since it is a new topic, we see that all publications are from 2020 up to May 2023 (The time during which this article was being completed), peaking at 2021, and declining afterwards possibly due to unresolved challenges identified in previous literature. In this paper, we hope to identify as many of these challenges and associated solutions as possible to lay the fundamentals for future progress in the field.

3. Urban logistics digital twin

We first provide a brief characterization of Urban Logistics in Section 3.1. Thereafter, we analyze DT applications in urban logistics from the literature for the factors mentioned in our second contribution in Section 3.2.

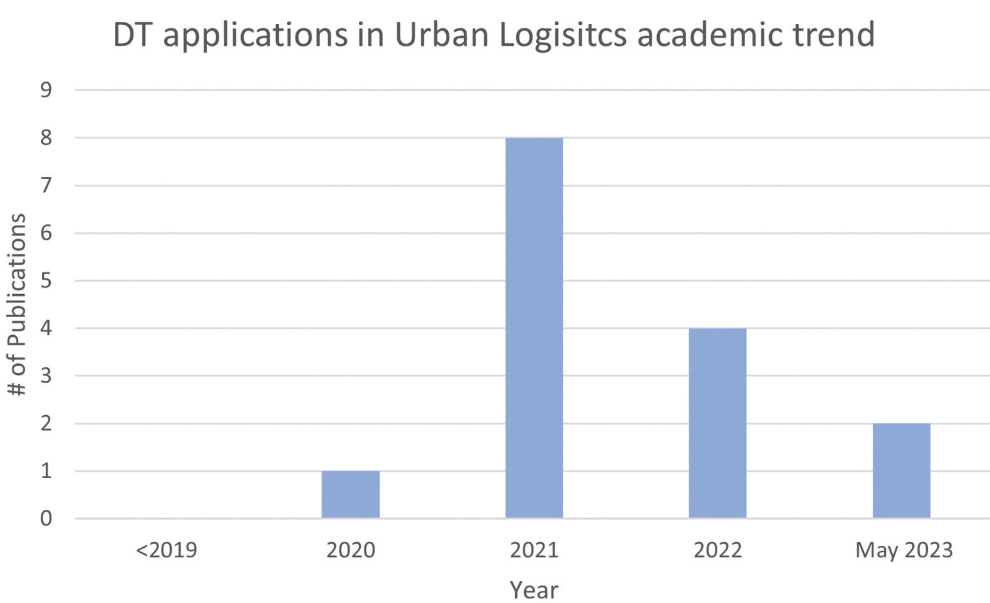

Figure 1. Trend of research of DT applications in Urban Logistics up to May 2023.

3.1. Urban logistics

We first need to establish the important aspects of an urban logistics environment that a DT ought to operate in. Savelsbergh and Van Woensel (2016) define urban logistics as the efficient and effective transportation of goods in urban regions. The scope of our research thus reduces to transportation problems only in contrast to other logistical problems that deal with warehousing, staffing etc.

Anand et al. (2012) provide an ontology for urban logistics whereby important factors are identified. We only consider a subset of them that we find relevant for dynamic decision-making. These are stakeholders, Key Performance Indicators (KPI)s, resources and measures and decisions. We elaborate on them below.

3.1.1. Stakeholders

The government, businesses and citizens in the urban logistics supply chain are referred to as stakeholders. For a detailed survey on the roles of stakeholders in urban logistics, we refer to Lagorio et al. (2016). The authors of Lagorio et al. (2017) explain how stakeholders have an integral function in defining the ecosystem of urban logistics network through their interests, interactions and decisions.

3.1.2. KPIs

As explained above, stakeholders have interests. These interests translate to objectives which are measured using KPIs as stated in Morana et al. (2015). KPIs could be used to guide optimization procedures for logistical operations as they can be used to represent objective functions. An example can be found in van Heeswijk et al. (2020) who use an agent-based simulation to verify routing schemes. The schemes are assessed by predetermined KPIs representing the objective functions. For an exhaustive list of some of the most popular KPIs for urban logistics, we refer to Griffis et al. (2007) and Gunasekaran and Kobu (2007).

3.1.3. Resources

Resources refer to all the available resources possessed by all stakeholders in the urban logistics network. Szmelter-Jarosz et al. (2020) explains how urban logistics resources fall into four categories, namely material, human, capital and information. Material resources include machines like trucks, IT platforms etc. Human resources refer to all the laborers involved in executing decisions in the urban logistics supply chain and the decision-makers themselves. Capital refers to the financial resources. Information refers to the intellectual resources such as knowledge and experience.

3.1.4. Measures

Measures represent the rules under which the resources of the digital twins operate like regulations imposed by policy-makers such as in Russo and Comi (2010) and Muñuzuri et al. (2005). Examples include restricting goods vehicle access to roads in heavily congested residential areas. Note that these rules are not embedded in the resources themselves, unlike the maximum capacity of a vehicle for example, but are rather circumstantial. Being practical constraints, the measures could be used to configure modelling constraints when setting up mathematical optimization models for urban operations, so that the corresponding real-life decisions remain feasible.

3.1.5. Decisions

Activities refer to the actions made by the agents in the urban logistics supply chain who are also stakeholders. Specifically, the engage in activities using their resources to maximize their KPIs while taking into account the measures of the urban environment. The decision factor is the most important entity in the classification as it defines how we interact with the environment to create positive outcomes. A common challenge with decision-making is realizing and enforcing important decisions when no stakeholder has enough power to do so (Lagorio et al., 2016). Therefore, innovative methods may be needed with a holistic overview to accommodate stakeholders as much as possible. The DT seems like a suitable candidate to achieve that.

3.2. Digital twins

In this section, we use the papers resulting from our search queries to answer questions on the definition, technical anatomy, functionality and set-up of urban logistics DTs.

3.2.1. Definition

Defining a DT may differ from one application to another, making it difficult to find a cross-industry definition. For instance, Semeraro et al. (2021) provide a definition that is largely inclusive of a DT's distinctive features, emphasizing the bidirectional control between the virtual model (the DT) and the physical model, and how the DT emulates the physical system, rather than just simulate it. Their definition however is resultant to surveying many applications, mainly in manufacturing, and mentions a product life cycle, which is an unfamiliar term in the context of urban logistics. Therefore, we can not use it.

Alternative definitions have been presented by papers dealing directly with urban logistics applications. Jeong et al. (2022) defines a DT as 'an intelligent technology platform for synchronizing physical objects and digital objects imitating them in (quasi) real-time, analyzing situations according to various purposes, and optimizing physical objects by predicting them based on analyzed results'.

Schislyaeva and Kovalenko (2021) list numerous definitions which imply that it is a virtual model of a real object that simulates the physical state and the behavior of the object, updating itself in response to changes in the operational environment. They emphasize its uniqueness to one object, while noting that it can exist before its physical counterpart. Likewise, Marcucci et al. (2020) offer a plethora of definitions such as 'a digital informational construct where a physical system is represented as a separate digital entity but linked to the physical system in question'.

Botn-Sanabria et al. (2022) use 'a virtual representation of a physical object or process capable of collecting information from the real environment to represent, validate and simulate the physical twin's present and future behavior' while Moshood et al. (2021) proposes 'a form of cyber-physical device that uses numerous IoT sensors and produces a high-fidelity visual image of a physical asset'.

In Section 6, we will introduce a general definition of our own in the hopes of standardizing it in urban logistics applications, taking into account the aforementioned propositions.

3.2.2. Technical anatomy

From a software perspective, there are many components in a DT. Examples include components such as Internet of Things (IOT), cloud-computing and Application

Programming Interfaces (APIs) asMoshood et al. (2021) mentions when referring to linking to Google Maps. The software engineering aspect, however, is of minor interest to us. Instead, we focus on the technical abstract design. For a detailed discussion on how software is integrated into the DT framework, we refer to Botn-Sanabria et al. (2022).

Belfadel et al. (2021) propose a framework into the technical anatomy of twins. We present an illustration based on their anatomy in Figure 2. The red arrows depict the data flow between hierarchies of the DT system. They explain that a typical DT model is composed of the following hierarchies: the top-level hierarchy which is known as the Physical World, the intermediate level known as the Data and Model Management System and the bottom level known as the Storage System.

The Physical World represents the external physical entities and sensors such as city operational data, IoT entities and sensors, and APIs.

This secondary level is the Data and Model Management System that is composed of two main systems: Data Ingestion System (DIS) and Model Management System (MMS). The DIS aims to integrate contextual data entities to the system and keep the DT updated about the status of the physical system. The MMS manages the models library which is a set of software applications that provide analytic tools. Most importantly, the MMS contains the Model Library Manager (MLM) which holds an overview of all available

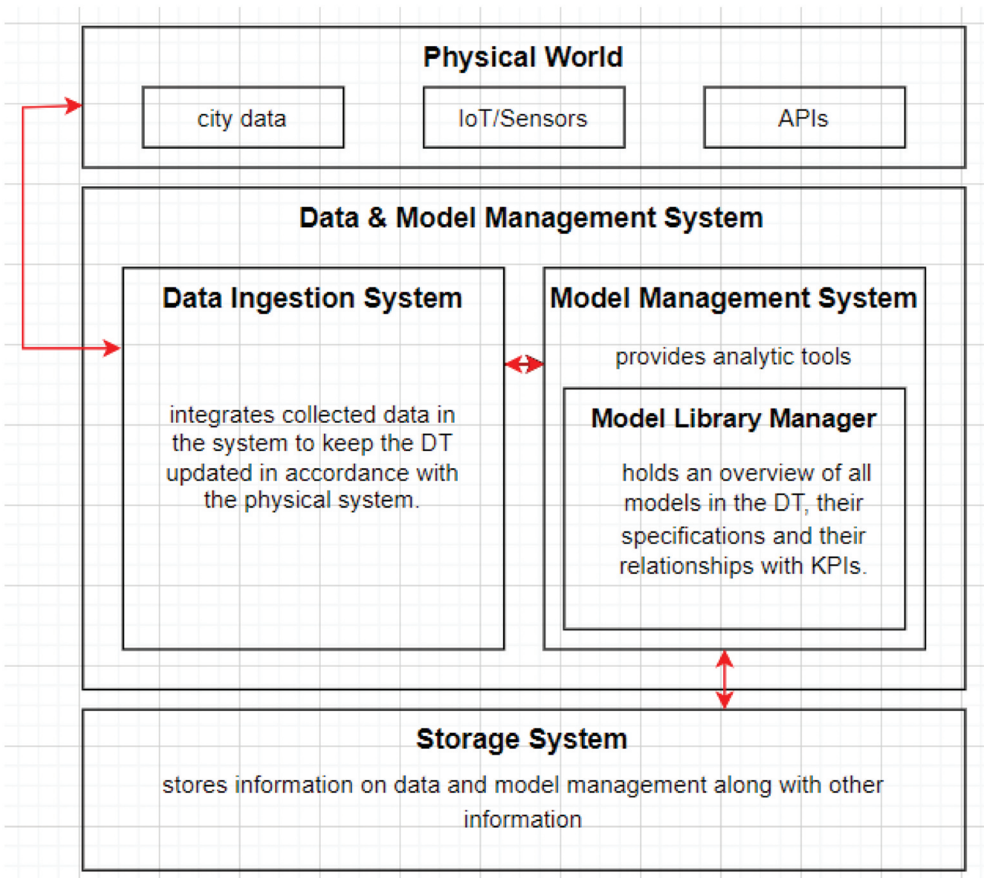

Figure 2. General technical anatomy of an urban logistics DT based on Belfadel et al. (2021).

models in the DT, their specifications and their relationships with KPIs. The Decision System in the MMS is the decision-making engine of the DT. It is responsible for assessing scenarios in terms of how likely they may occur, examines the KPIs of the selected scenario and recommends the necessary interventions in the physical world through the DIS to achieve the predicted outcome.

The Storage System stores information on the management of model libraries and data along with other general storage as simulation scenarios, their configuration and related models etc.

In the context of Jeong et al. (2022), the digital twin is a collection of smaller digital twins that are synchronized together to jointly optimize the overall complex real-life system, such as a city, that they are twinning. The authors refer to this as DT Federation.

3.2.3. Functionalities

In Jeong et al. (2022), the DT is described not as a technology but as a shared platform that synchronizes several technologies. Its technologies can be mainly categorized into

- Visualization and operation technology
- Analysis technology
- Multi-dimensional modeling and simulation technology
- Connection technology
- Data and security technology
- Synchronization technology

From a computational perspective, Marcucci et al. (2020) mention that DTs in smart cities can describe, capture and simulate policy implications of decisions to optimize them with respect to a given set of objectives. Schislyaeva and Kovalenko (2021) survey functionalities of DTs of logistic networks on the higher-level, emphasizing how they can dynamically prescribe and optimize the urban physical system. They also discuss how DT simulation models could be used for stress tests while their predictive analytics tools can predict how their physical counterpart evolves. Gutierrez-Franco et al. (2021) state that DTs can predict possible future scenarios and evaluate so that vehicle dispatchers can find appropriate responses for the most likely ones.

Gutierrez-Franco et al. (2021) mention that DTs can raise alerts when exceptional situations are detected so that controllers can intervene. Anomaly detection could be pressing in some situations such as hazardous ones. For instance, traffic accidents are a common theme in the urban environments. Moshood et al. (2021) also emphasize on the importance of exception handling when physical assets exist in unsafe environments to improve safety protocols. Jeong et al. (2022) mention how DTs can help analyze the cause of situations due to the DT being able to replicate past scenarios from collected data.

DTs could also efficiently manage disruptions where the difficulty of real-time re-planning is better addressed by real-time data connectivity and great computational power, improving the responsiveness of a Logistics Service Provider (LSP) (Moshood et al., 2021). Parking operations as well could be carried out more efficiently through real-time information on available parking spaces, thereby reducing time spent on searching for parking, and the resulting fuel consumption and GHG emissions (Golinska Dawson & Sethanan, 2023). This latter case is analyzed in greater detail in Liu et al. (2021). This real-time connectivity can be used to position vehicles and analyze delivery status through sensor technology and GPS tools (Gutierrez-Franco et al., 2021).

DTs also encompass large sets of KPIs that are generated from its diagnostics. Gutierrez-Franco et al. (2021) mentions that DTs can support accurate calculation of performance indicators of logistics operations through their scenario prediction and assessment mechanisms. Moshood et al. (2021) also mentions how DT sensors could be used to generate new data types on the supply chain flows, which as Gutierrez-Franco et al. (2021) suggests could create even new relevant KPIs. Schislyaeva and Kovalenko (2021) confirm this by saying that DTs retain data that can not be (easily) obtained from the physical model. Examples of such data types included vehicle interiors and working diagnostics. As Belfadel et al. (2021) explains",The decisive factor is how this data is processed further in order to offer real added value". where the added value is created with the help of dedicated KPIs.

DTs can also bestow an urban logistics supply chain with visibility using its augmented reality features. Moshood et al. (2021) explain that visibility depends on an organization's ability to be transparent and clear about its internal and external processes of its supply chain. Visibility is not only important because of the enhanced interpretability it allows by visually depicting operations, but it also plays a collaborative part due to the involvement of multiple stakeholders who can be easily informed in a standardized manner of expected outcomes. Marcucci et al. (2020) also stresses the importance of DTs in translating complex ideas into more intuitive ones through visualization. Golinska Dawson and Sethanan (2023) state that urban visualization can be attributed to the DT's ability to map networks.

To that end, stakeholders have to be able to exchange data with ease which a DT can catalyze with its data-integration infrastructure. Moshood et al. (2021) confirm the importance of this by stating that it is essential to provide as much information as possible at the higher-degrees of strategic decision-making. This is relevant when predicting demand for goods which can guide decisions regarding budgeting. Moshood et al. (2021) also highlight the importance of data-exchange among stakeholders to achieve visibility. The data-integration of DTs with the city, in turn, can encourage multi-disciplinary decision-making as different actors involved in the DT model or agents in the city environment can exchange data through the common platform (Jeong et al., 2022). This may in turn lead to more coordination and collaboration among stakeholders.

DTs can also automate monotonous tasks that could be subject to human error (Moshood et al., 2021). The advantages of automated processes are countless and can be explored in manifold applications. Furthermore, Schislyaeva and Kovalenko (2021) mention that it can troubleshoot remote equipment and perform remote maintenance as an extension of its automation capabilities.

The concept of DTs is normally coined with a self-learning feature where the virtual system consistently tries to improve its modelling of the physical system through the data it retrieves from it. Gutierrez-Franco et al. (2021) mention 'a learning process based on the KPIs', where the modelling parameters of the DT can be calibrated by comparing the actual outcome of the operations with results from the simulation and optimization models. DTs can, thus, learn from daily operations using machine learning models that facilitate the acquisition and accumulation of knowledge from the urban environment. In turn, this knowledge can be used to predict the outcomes of future operations when data about these operations is not available. Belfadel et al. (2021) give examples of this like in route recommendations.

3.2.4. Set up & illustration

In principle, setting up a DT is a complex process. Moshood et al. (2021) state that this is a relatively new area of research and that its precise implementations are scarce. This goes in synergy with the findings of Belfadel et al. (2021), implying 'that existing architectures are too generic for usage in logistics'. For smart cities, there have been several partial implementations such as Lyon (Belfadel et al., 2021) and cities in the Netherlands (LCB, 2022). Botn-Sanabria et al. (2022) also survey studies of implemented smart city DTs in Asia and Europe, of which some address urban logistics.

Some research initiatives such as Ivanov et al. (2020) propose the concept of a DT of a city from a governance perspective, with limited focus on urban logistics. Other initiatives like Guo and Lv (2022), although discussing urban transportation briefly, focus more on listing the contemporary software packages and technologies that could be used to implement the virtual model as opposed to the functional steps.

In line with the preceding remarks, Jeong et al. (2022) mention that a DT is a complicated technology where a step-by-step implementation is necessary as opposed to conceptual and abstract guidelines. Jeong et al. (2022) list five evolution stages for a DT. They are Mirroring (duplicating a physical object into a digital twin), Monitoring (monitoring and controlling the physical object based on the analysis of the DT), Modeling and Simulation (Optimizing the physical object through the simulation results of the digital twin), Federation (configuring federated DTs, optimizing complex physical objects, and inter-operating federated digital twins and complex physical objects) and Autonomous (autonomously recognizing and solving problems in federated digital twins and optimizing physical objects according to the federated digital twin solution).

Each of these stages has its own considerations. For instance, the second stage makes extensive use of synchronization engines to manage various sensors to ensure consistency with the real world. Furthermore, the processes of the second and fourth stages should not be automated to prevent drastic malfunctions in the physical system making manual intervention necessary. The fifth stage can also only be achieved after the model is deemed 'stable, reliable, and dependable for automatic action to the real world'. At that point, it largely resembles an ecosystem.

Jeong et al. (2022) address each of the five stages through five specific implementation layers or steps. These are [noitemsep]

- Layer 1 Digital virtualization: digital representation of components making up the real world, such as people, things, and spaces.
- Layer 2 Digital twin synchronization: real-time mutual synchronization between real-world and virtual-world.
- Layer 3 Modeling and simulation: analyzing and predicting the real world by simulating conditional changes.
- Layer 4 Federated digital twin: inter-working for collaboration between DTs. •
- Layer 5 Intelligent digital twin services: Managing DT's life-cycle based on intelligent and autonomous technologies.

During all implementation layers, data must be continuously validated and failures must be detected and managed by observing DT operation and ensuring that thresholds are not crossed. Jeong et al. (2022) also offer a detailed classification of the technology elements needed for each implementation layer so that any initiative to build a DT is acquainted with the hardware and software needed.

As an emphasis on the challenge associated with building DTs, Moshood et al. (2021) stress that 'a completely integrated Digital Twins is a long-term approach that does not happen immediately' insisting that it will be long before it can be used by industry. Much of the difficulty is attributed to the dense technological requirements such as Internet of Things Sensors, Cloud computing etc. Consequently, Moshood et al. (2021) proposes to start simple and focus on maintaining data accuracy while incrementally reducing the chance of human error.

Marcucci et al. (2020) provides an example of a collaborative initiative between policy-makers through Living-Labs. They suggest that Living-Labs are the most up-to-date data-driven methodology to tackle the management of urban logistics. The major idea is to involve all potential stakeholders in the urban logistics network in the design of the DT to agree on common objectives and functionalities. The concept is being tested in cities like Gothenburg, London and Rome (Marcucci et al., 2020). There, Living Labs are developed to create efficient and shared solutions among stakeholders. Moshood et al. (2021 also state that knowledge ought to be exchanged among the multiple stakeholders, a factor catalyzed by visibility. Jeong et al. (2022) support knowledge exchange by encouraging the usage of existing twin systems and associated knowledge to avoid 'reinventing the wheel'.

Another important aspect regarding the design of a DT is the modeling one. Jeong et al. (2022) state that the replicated elements should be selected to make the virtual replication easier. They mention traffic volumes and road-maps as examples of what could be replicated in the urban environment. Marcucci et al. (2020) also explain how DTs should strive to provide a simplified version of the physical model as they should never replicate the physical system in every detail, since that would not make them models anymore that we could use to efficiently study urban environments. DT's purpose as a model is to abstract the complex environment of a city in a limited number of variables. This compels us to be selective in what factors to include in the model. More variables could be included in the future as the requirements of its user base expand.

Several use cases have been identified from the literature. We mention them in Table 1. we found Gutierrez-Franco et al. (2021) to be the most comprehensive of them, listing practical steps of deploying a DT and representing its decision-making pipeline through a series of quantitative (AI) models. They consider an LSP conducting routing operations for urban distribution in a mega-city.

Their 6-step procedure starts with data collection, which is largely dictated by the availability of data and interests of LSP using the DT. In Step 2, data has to be suitably processed for a particular purpose such as devising diagnostic statistics that prescribe the operational situation and can then be fed to a mathematical model. For the latter purpose in Step 3, a mathematical optimization model could be set up by which decisions are recommended. The recommended planning then has to be verified by means of a simulation in Step 4 in a setting that is more representative of the urban environment. Once the solution has been verified, it is set to be implemented in Step 5, with KPIs on its actual performance in the city being generated and monitored in real-time. The realized KPIs from Step 5 are compared with the estimated ones in Step 4. Major deviations are corrected for in Step 6 through configured learning processes such as reinforcement learning in order to ensure more accurate modelling and better decision-making in the future.

Table 1. Use cases of Urban Logistics DT in literature.

Paper	Application
Gutierrez-Franco et al. (2021)	Urban distribution by a retailer in a developing mega-city
Zdolsek Draksler et al. (2023)	cross-border postal-logistics
Shen et al. (2022)	Tobacco Supply Chain
Vallejo et al. (2021)	Urban food supply chain for carbon food-print reduction
Miao and Lan (2021)	Image processing for intelligent logistics distribution management
Liu et al. (2021)	Freight Parking Management
Ghandar et al. (2021)	Urban agriculture and distribution.

The design proposed in Gutierrez-Franco et al. (2021) is specific to an LSP. An urban logistics DT in general could be utilized by different stakeholders such as policy-makers in different cities. This poses new implications on the design of the urban logistics DT. For instance, different data types could be collected in Step 1 depending on the requirements of the stakeholder(s). Additionally, LSPs may deal with different problems for which they have different approaches that deviate from the sequential procedure in Gutierrez-Franco et al. (2021). To that end, different stakeholders may require different 'versions' of the DT. This is adhered in Schislyaeva and Kovalenko (2021) which states that 'One object can have more than one twin, with different models created for different users and use cases'. Therefore, it is necessary to come up with a general conceptual model upon which the general design of an urban logistics DT could be established to accommodate all these needs.

Furthermore, the different use cases in Table 1 make use of different optimization methods that heavily determine the design of the DT. It is not clear how the design might change with an alternative optimization method. Therefore, our conceptual model in Section 4 addresses the general integration of AI methods.

4. Conceptual model

In this section, we present our own conceptual model of the urban logistics DT in the form of a knowledge graph and explain how different AI models, namely machine learning and optimization, can be integrated in it.

4.1. Knowledge base

Using the characterization in Section 3.1 and an overview of mathematical models that are generally embedded in DTs – such as in Gutierrez-Franco et al. (2021) - we are able to devise an ontology of an urban logistics DT. This ontology is similar to the one used in Anand et al. (2012). To specify the high-level entities, we use a mix of the five key factors in Section 3.1 and define several others based on literature. Specifically, we have the following entities: stakeholders, resources, KPIs, measures, decisions, data, statistical analysis tools, mathematical optimization, simulation and machine learning.

We deem the Data entity to be self-explanatory as it represents any data collected by the DT through sensors for example, so we do not expand it further here. Specifically, the latter four entities which represent mathematical models that could be categorized as AI tools have often been used to solve urban logistics problems. Statistical analysis of data has been used in many urban logistics studies such as Zou et al. (2020) and Alho and E Silva (2015), mathematical optimization in Montoya et al. (2017) and Dabia et al. (2017), simulation modelling in Jlassi et al. (2018) and Karakikes et al. (2018) and machine learning in El Ouadi et al. (2020) and Giuffrida et al. (2022), to give some examples.

Referring to the technical architecture in Section 3.2.2, the four AI entities would be embedded in the MLM. The MLM is an integral component of DTs as it contains its analytic tools. In turn, human controllers should consistently strive to improve the embedded models so as to equip the DT sufficiently to analyze very complex processes and add value through optimization. In order to arrive at a compact design of the ontology, we merge these four into a single high-level entity which we refer to as the AI component. This is because their relationships with other entities in the ontology and among each other are identical.

At the high-level, our ontology is given in Figure 3. The feedback-loop constituted by the bidirectional data exchange between the DT and the physical environment is given by the red arrows. In particular, data is collected from resources and used as input to the AI component. The AI component processes the data to support decision-making through optimization. Once decisions have been implemented, KPIs are generated which are collected again as data to evaluate the decisions and learn from them.

At a secondary level, the ontology of the AI component itself is given in Figure 4. The four components interact regularly with each other to support their functionalities. The output of one component can be used as the input to another. Figure 4 can also be viewed as an arbitrary pipeline of mathematical models.

The ontology prescribed in Figure 4 provides a fundamental design for pipelines using the AI component. Since all relations among all entities in Figure 4 are bidirectional, any possible ordering of the entities in a pipeline is allowed. Other pipelines may omit some of the entities if they do not use them.In the following section, we provide a model specification of DTs which we will use in Section 5 when showcasing the integration of DDO models.

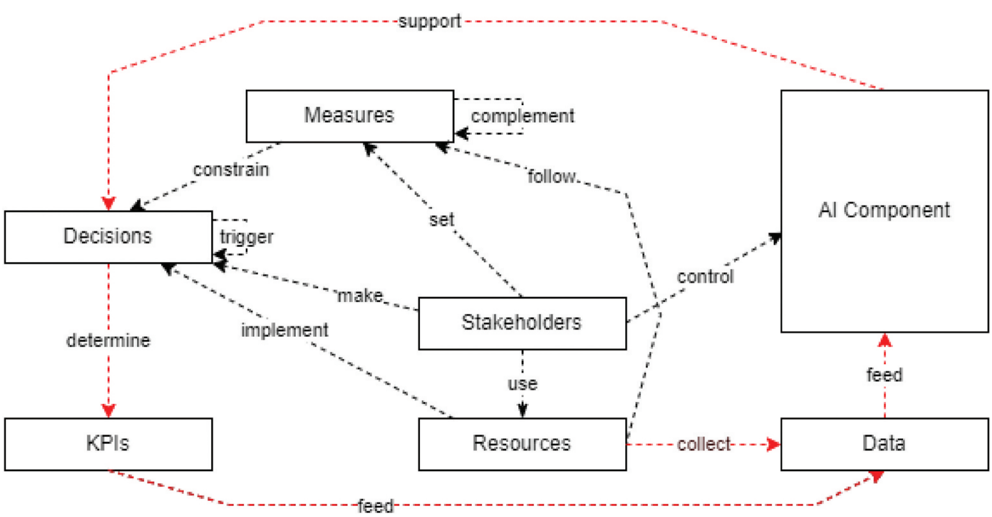

Figure 3. Our proposed high-level urban logistics DT ontology.

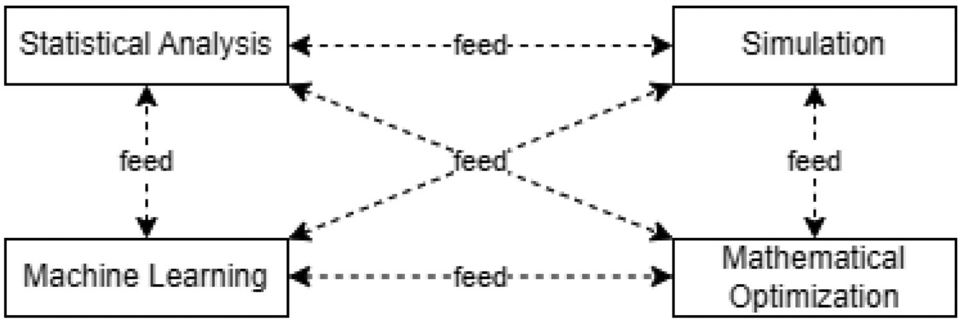

Figure 4. Our proposed ontology for the AI component in Figure 3.

4.2. DT model specification

Let $P(t)$ be a high-dimensional vector representing the parameters of the underlying quantitative models of the DT at continuous time t. In that case, the model can be completely prescribed by $\{P(t), t > 0\}$ at any arbitrary time t. Furthermore, let Δ be some time interval after t so that $\mathcal{D}(\Delta)$ represents the data collected from the physical system in that interval. The virtual model can be defined as follows:

$$P(t + \Delta) = f(\mathcal{D}(\Delta), P(t)) \tag{1}$$

where $f(.)$ is a concatenation of vectors of functions responsible for updating the virtual model's parameters given some data intake and previous parameter estimates. That is to say that the current status of a DT depends on the previous status and recently collected data through its learning algorithms. The frequency by which data updates the virtual model is determined by the human controllers. It is crucial to have a high data-updating frequency while taking latency into account (Marcucci et al., 2020).

We now provide a brief overview of previous research on how tools in the AI component complement each other in decision-making with a focus on Vehicle Routing Problem (VRP). Our focus on VRP stems from the academic and industrial interest surrounding it. Thereafter, we provide an illustration for solving a VRP variant. We explain how a pipeline could be constructed from an algorithmic set-up, how it integrates into the framework of the DT and how the DT uses its capabilities to solve the problem.

5. Technical illustration

5.1. Data-driven optimization in VRP

Among the AI components, we focus mostly on Machine Learning and Mathematical Optimization. They jointly comprise the concepts of DDO which we regard as the primary computing asset of DTs. DDO refers to optimization procedures that apply learning algorithms to data to improve results. This could be data on parameters of the problem such as travel times in cities or solution data such as routing decisions. For simulation, there is already ample literature on its integration in the DT framework (Boschert & Rosen, 2016) and methods employed in VRP (Amaran et al., 2016).

Papers like Lombardi and Milano (2018) and Bengio et al. (2021) survey the general integration of machine learning into combinatorial optimization for different learning mechanisms. Mazyavkina et al. (2021) survey a more detailed application of reinforcement learning to combinatorial optimization. Khalil et al. (2017) extend on this by providing applications in graph related problems and along with a framework from learning common heuristics for these problem.

Historically, the application of machine-learning to optimize VRP has been rewarding. Bai et al. (2021) provide a comprehensive survey of machine learning applications in solving VRPs including stochastic variants. They consider the usage of machine learning as both, a modelling tool and an optimization one. More specifically, Niu et al. (2021) and Niu et al. (2022) use hypothesis generation to learn a genetic algorithm to solve a multi-objective VRP with uncertain demand. For the case with stochastic customers, Joe and Lau (2020) apply reinforcement learning to approximate the value-function of actions from a genetic algorithm.

Other applications of machine learning in solving deterministic VRP can be found in Morabit et al. (2021) who use supervised learning for column generation to solve a VRP with time windows. Furian et al. (2021) combine supervised learning with branch-and-price to predict the value of binary decision variables in the optimal solution, and the branching scores of fractional variables for capacitated VRP. Cooray and Rupasinghe (2017) consider a different heuristic-based approach where unsupervised learning is used to tune the parameters of a genetic algorithm for energy minimizing VRP.

Reinforcement learning, as a method, has been popular in the literature as well. da Costa et al. (2021) provide a general methodology for reinforcement learning of a meta-heuristic for standard VRP with actor-critic networks. Nazari et al. (2018) employ reinforcement learning to devise a parameterized stochastic policy with an actor-critic network for optimizing capacitated VRP. They also explain that their approach could be extended to other variants. Similarly, Hottung and Tierney (2019) learn a stochastic policy by reinforcement learning for capacitated VRP and split delivery VRP through an actor-critic model. However, they employ a novel concept where the training targets are defined by the objective of an infeasible solution so as to bridge the gap with the (best) feasible solution. J. Zhao et al. (2020) also use reinforcement learning with an actor-critic network to devise a stochastic policy whose output can be combined with a local search procedure to optimize standard VRP (with time windows).

The aforementioned papers compose a small sample of the numerous literature on applying machine learning to solve VRP. Surely enough, there are many other publications that address DDO in VRP that would be of great use to a DT. A summary of the papers cited above is given in Table 2.

5.2. Example application

Given the approaches prescribed above, we can use the knowledge graph to construct a design for an urban logistics DT to be deployed by an LSP in planning their daily operations. For a start, we need to define the entities. This is done in Table 3.

The next part is to define the AI component. We can easily construct a pipeline to solve a VRP variant. We consider a standard VRP with capacity constraints and time-windows similar to the one solved by many retailers in industry for planning routing operations. We refer to this problem as *CVRPTW1*. It is characterized by N customer

Table 2. Sample of the DDO applications in VRP from literature. We also mention the VRP variants they deals with and the associated learning and optimization techniques.

Paper	Problem	Methods
James et al. (2019)	green logistic system online routing	reinforcement learning, combinatorial optimization
Niu et al. (2021)	multi-objective stochastic VRP	hypothesis generation, genetic algorithm
Niu et al. (2022)	multi-objective stochastic VRP	hypothesis generation, genetic algorithm
Joe and Lau (2020)	stochastic VRP	reinforcement learning, genetic algorithm
Morabit et al. (2021)	VRP with time windows	supervised learning, branch-and-price
Furian et al. (2021)	capacitated VRP	supervised learning, branch-and-price
Cooray and Rupasinghe (2017)	energy minimizing VRP	unsupervised learning, genetic algorithm
da Costa et al. (2021)	standard VRP	reinforcement learning, local search
Nazari et al. (2018)	capacitated VRP	reinforcement learning, combinatorial optimization
Hottung and Tierney (2019)	split-delivery/capacitated VRP	reinforcement learning, local search
J. Zhao et al. (2020)	standard VRP/with time windows	reinforcement learning, local search

locations with properties such as time windows and demands $\mathcal{C}^N$. Furthermore, let $\mathcal{T}$ represent the travel time data repository of the DT where each observation t_{ij} corresponds to a travel time between locations i and j. The optimization problem could be simply prescribed by:

$$\{min_{\mu \in \mathcal{M}} \Omega(\mu)\} \tag{2}$$

where

$$\Omega(\mu) = \{\min c(x) | A(x) \leq b, x \in \mathcal{S}(\mu)\} \tag{3}$$

with μ being a vector of parameters of local search heuristic – such as k-exchange moves – in subspace $\mathcal{M}$ and $\mathcal{S}(\mu)$ being the search space created by calibrating the heuristic with parameters μ. $c(x)$ is an objective function expressed by $\mathcal{T}$ and routing decisions x and $A(x)$ being the constraint matrix on routing decisions x defined by $\mathcal{C}^N$.

Observe that $(\mathcal{T}, \mathcal{C}^N) \in \mathcal{D}(\Delta)$ represent city operational data that updates the DT on the current status of the customers and transit within the city. The technical process by which the data is absorbed by the DT can be explored in papers like Xu et al. (2022), Jeong et al. (2022) and Z. Zhao et al. (2022). Analogously, $\mu \in P(t)$ since it is among the set of parameters used by the DT model. This presents a rather important feature of optimization models embedded in DTs in the sense that the parameters defining their search procedure are updated according to collected data and are not static in nature. We explain how this is done in the following section.

Table 3. Entity specification for an urban logistics DT for an LSP carrying out urban distribution. The AI component is explained below.

Entity	Instances
Stakeholders	LSPs, customers, truck operators
Resources	Trucks
Measures	driving times, time windows
KPIs	total driving time, number of vehicles used, average number of stops per vehicle
Decisions	Routing order among customers; order cancellation
Data	customer locations, customer demands, traffic data etc.

Let the pseudo-code for solving *CRVPTW1* be given by Algorithm 4. It is worth mentioning that Algorithm 1 and the associated pipeline are high-level examples whose purpose is simply illustrative. Algorithm 1 takes $\mathcal{T}$ and $\mathcal{C}^N$ as input and outputs a set of routes R^* representing a feasible planning. It makes use of a heuristic where a reinforcement learning (RL) agent constantly interacts with a local search procedure such as in da Costa et al. (2021). Such a heuristic is an instance of a DDO method. The purpose of the RL agent is to approximate the value-function of actions and assign higher probabilities to more rewarding actions. The actions concern perturbations to the solution defined by the local search procedure such as k-exchange moves.

With algorithm 1, the pipeline in Figure 5 can be constructed. The pipeline illustrates the order in which entities from the AI component in Figure 4 interact with one another to output a solution $x = R^*$.

5.3. DDO integration in DTs

As mentioned, the major challenge entails integrating the complex optimization models developed in the literature into existing architectures. Unfortunately, the architectures provided in the use cases above do not extend naturally to other applications due to the complex structure of DTs and the novel optimization models in concern like the approach above based on da Costa et al. (2021).

Before we proceed, we propose an important distinction in DDO. We refer to DDO applications where the collected data concerns the environment of the problem such as learning model parameters as **environment-based**. On the other hand, applications where the data concerns solutions data such as learning solution patterns are called **solution-based**.

environment-based applications are generally simpler as they often make use of

Algorithm 1 Pseudo-code to solve *CVRPTW1*.

```
Input: 𝒩, 𝒞^𝒩, 𝒯.
Let R̄ = ∅.
Construct initial solution for CVRPTW1.
while termination criterion for optimization is not met do
    Use reinforcement learning agent to evaluate actions.
    Use actions to search for candidate solutions locally
    Generate candidate solutions R and add them to R̄.
end while
for solution R in R̄ do
    verify R using simulation
    if simulation objective of R is better than R* then
        R* = R.
    end if
end for
return R*
```

empirical data and static learning mechanisms like supervised learning applied. They are guided by some ground truth which represents the actual realized observations from the physical system. In the context of *CVRPTW1*, having accurate estimates of the travel times when planning occurs is an example.

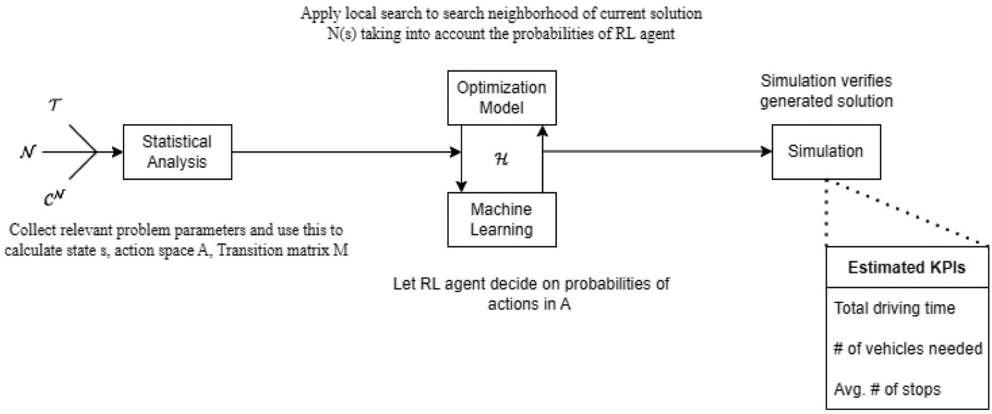

Figure 5. Example pipeline for solving CVRPTW1.

Works like Wang et al. (2020) deal specifically with environment-based applications in the DT framework. They make use of surrogate models to model the complex physics behind air-conditioning in a data center. Although their application is quite different from urban logistics, their methods can work quite well for other applications given the consistency in the input-to-output approaches of supervised learning. The methodology is also quiet suitable for DTs given their reliance on surrogate models (Bárkányi et al., 2021) and storage capacity (Belfadel et al., 2021).

The situation with solution-based applications is a little more complex. Returning to our pipeline in Figure 5, we see that a reinforcement-learning agent needs to interact with the optimization environment to learn favorable routing decisions based on previous solutions. Interaction with the physical urban environment is not possible. To counter this issue, Xu et al. (2022) propose a method where the agent interacts with the problem environment offline in a simulator without disturbing the physical system. Their method for crane deployment can work in any application provided that the DT is capable of simulating the problem with sufficient accuracy.

However, in the absence of live interaction with the environment, the rewards (KPIs) could significantly deviate from the ones used in the simulation. In such a case, KPI data can be collected after the operations have been implemented and fed back into the reinforcement learning agent for re-training. Figure 6 visually depicts the data flow in such a procedure. The estimated rewards $\hat{R}$ can be used when defining the transition tuples in the initial phase of training before the actual rewards R are collected after the decisions have been implemented for retraining. We understand that changing the rewards associated with the same actions and states might result in complications in training. Lu et al. (2018) investigate methods dedicated to learning under structural changes in relationships among variables which can be of profound advantage in this case.

This reinforcement-learning framework presented above is not to be mistaken with offline learning concepts introduced in works like Levine et al. (2020) and Agarwal et al. (2020) where transition data is generated from external sources and

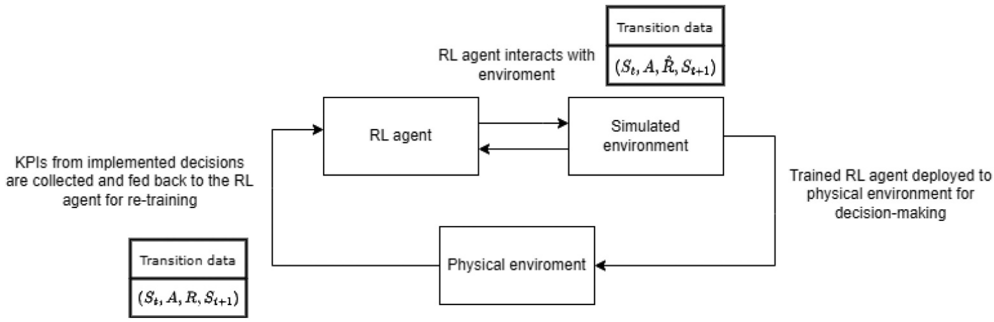

Figure 6. Data flow in reinforcement learning in a DT. Transition data contains current and succeeding states S_t and S_{t+1}, actions A, estimated and actual rewards $\hat{R}$ and R.

not through the agent's interaction with the environment. Such methods can be of interest if we decide to make use of expert's past decisions in training the reinforcement learning agent.

6. Results and discussion

6.1. Main findings

The impact of our findings are useful in many ways. For the DT, we have enough sources to formulate a precise definition for urban logistics:

An intelligent technology platform where a high-fidelity virtual replica of a physical system is emulated and updated in real-time in response to changes in the physical system it is synchronized with. The virtual model collects data from the physical one and analyzes it to prescribe interference mechanisms in the physical system for optimization purposes.

We believe that this definition is sufficiently inclusive of all the aspects from the definitions surveyed above. We identified a clear technical anatomy from Belfadel et al. (2021) and an implementation procedure from Jeong et al. (2022), along with a long listing of its potential numerous functionalities that could vary from one user to another. We also provided clear use cases to showcase practical implementations through works like Gutierrez-Franco et al. (2021). The use cases, however, do not justify the major design steps in a tractable order, and their integration of quantitative methods is rather case-specific. This makes it challenging to replicate the DT in another application or even with just another quantitative method like DDO.

Our conceptual model, on the other hand, forms the design framework for an urban logistics DT. Furthermore, we explained how DDO methods can be integrated in the DT through a reference to an approach and its learning component, something a lot of the literature neglects. We feel that the major problem with most literature is the assumption that expert knowledge on DTs is so prevalent to the point where design justifications are unnecessary. This is not true given how new the field is and how few the actual implementations are (if any).

To the best of our knowledge, there is no single work that covers all these aspects. We have attached a rather large overview of sources that deal with the integral topics in the subject area, even for topics that we do not discuss extensively such as the software engineering aspect. Moreover, we considered sources from different applications whose methodologies could be of great benefit for urban logistics applications, combining knowledge from multiple fields. We are convinced that our guidelines are enough for any entity with reasonable availability of resources to start building and deploying their own DT in urban logistics.

Despite all these findings, we can safely conclude their assertiveness only by conducting more detailed (numerical) experiments where they are properly verified. We currently lack the data and infrastructure to do that, not to mention that such a validation process, probably requires the set-up of a full use case, which is a much more detailed and demanding topic whose scope differs from our research questions.

6.2. Research opportunities and challenges

In analogy with the points discussed above, there are many possible benefits and challenges related to DTs. The most obvious benefit is its provision of a methodology to optimize the logistic network in a city. This would be reflected in reduced pollution and congestion volumes, more efficient logistics operations and increased consumer satisfaction through higher service levels. However, there are many costs that ought to be borne beforehand.

For a start, Botn-Sanabria et al. (2022) cite data security concerns and communication network-related obstacles. Additionally, the set-up costs of the technology-intensive DT are not negligible. Schislyaeva and Kovalenko (2021) also explain that the cost-sensitivity of logistic operations may explain the reluctance of some companies to invest in testing DTs. Many LSPs may be unwilling to enable the DT to control their resources due to cost and safety concerns. The absence of a link by which the virtual model can control the physical model for testing purposes poses a serious challenge to the credibility of current studies on DTs.

To counter this, some platforms already provide basic implementations based on expert knowledge and collaboration with industry. The Atlas Leefbare Stad DT by Logistics Community Brabant LCB (2022), which is a virtual replica of cities in the Netherlands, is one such example. It models relevant variables as dictated by the requirements of its user base of academic researchers and LSPs. In Atlas, however, the transfer of data is unidirectional – from the physical to the virtual system only, in contrast to definition from Section 3.2.1. Marcucci et al. (2020) refer to such a virtual model as a Digital Shadow (DS).

While a fully comprehensive study on DTs could not be met with a DS, a partial study is still feasible. Marcucci et al. (2020) mention that 'the primary function a DT addresses is descriptive in nature'. Examples of its descriptive functions include anomaly detection, warnings, predictive tasks and even recommending optimization-derived solutions without implementing them. By comparing its descriptive output with actual outcomes as interpreted by expert knowledge, experts can form opinions about the usefulness of the virtual model.

There are other challenges associated with building a DT. Marcucci et al. (2020) mentions 'that technological changes and strong attention towards global warming' may require more 'radical changes in technology and policy' than the incremental approach guiding the design and development of DTs. This places pressure on the benchmarks the DT is expected to meet as the gains of a fully functional DT may be too slow to realize in the short-term.

Furthermore, Marcucci et al. (2020) explain that relationships between variables is expected to change over the course of time due to external factors. The DT model, therefore, compels constant updates so that changes in relationships and knowledge are incorporated on time, otherwise its added value may be questionable.

The fruit of overcoming these challenges is a method by which strategic planning can be coordinated among different stakeholders. Botn-Sanabria et al. (2022) mention that shippers can plan more precisely in selecting the different modes of transportation at the different gateways connecting the supply chain. This collaboration among stakeholders by which inter-operable, low-cost, reliable and secure data exchange can implement the DT without requiring significant investments in IT infrastructure. In turn, Botn-Sanabria et al. (2022) stress the necessity of being able to respond to immediate and diverse circumstances and to cope with the demands of the modern e-commerce sector that requires increased fragmentation, complexity and integration level of DTs.

7. Conclusion

Returning to our contributions, we managed to define the DT model for urban logistics, anatomize it, list its functional requirements and present a technical implementation procedure. For the general design, we added a conceptual model based on the identification of imperative features for dynamic decision-making in urban logistics and relevant quantitative models for urban logistics problems. Through our model, one can take a step back to obtain a higher-level view on the design process whereby the implementation and operation are less challenging.

We illustrated the usage of our model in a case for solving VRP and explained how the associated DDO methods with different learning paradigms (supervised vs reinforcement) can be integrated in the DT. That is to lay the foundations for developers of DDO methods to integrate their knowledge in DTs which should help increase its added value.

We were not only concerned by the past and present status of the research fields, but also raised several issues that ought to be addressed by future research if DTs are expected to be a commonly trusted decision-support tool. This comes with opportunities that future research could also fulfill to bring about the added value of DTs.

That said, we aspire that future research expands on the knowledge we provided here, and specifically for future use cases to make use of our conceptual model. We urge researchers to make their knowledge more accessible to catalyze growth in the field.

Acknowledgments

Abdo Abouelrous is supported by the AI Planner of the Future programme, which is supported by the European Supply Chain Forum (ESCF), The Eindhoven Artificial Intelligence Systems Institute (EAISI), the Logistics Community Brabant (LCB) and the Department of Industrial Engineering and Innovation Sciences (IE&IS).

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The work was supported by the European Supply Chain Forum.

References

Agarwal, R., Schuurmans, D., & Norouzi, M. (2020). An optimistic perspective on offline reinforcement learning. In *International Conference on Machine Learning*, Vienna, Austria, (pp. 104–114). PMLR.

Alho, A. R., & E Silva, J. D. A. (2015). Utilizing urban form characteristics in urban logistics analysis: A case study in Lisbon, portugal. *Journal of Transport Geography*, *42*, 57–71. https://doi.org/10.1016/j.jtrangeo.2014.11.002

Amaran, S., Sahinidis, N. V., Sharda, B., & Bury, S. J. (2016). Simulation optimization: A review of algorithms and applications. *Annals of Operations Research*, *240*(1), 351–380. https://doi.org/10.1007/s10479-015-2019-x

Anand, N., Yang, M., van Duin, J. R., & Tavasszy, L. (2012). Genclon: An ontology for city logistics. *Expert Systems with Applications*, *39*(15), 11944–11960. https://doi.org/10.1016/j.eswa.2012.03.068

Bai, R., Chen, X., Chen, Z. -L., Cui, T., Gong, S., He, W., Jiang, X., Jin, H., Jin, J., Kendall, G., Li, J., Lu, Z., Ren, J., Weng, P., Xue, N., & Zhang, H. (2021). Analytics and machine learning in vehicle routing research. *International Journal of Production Research*, *61*(1), 1–27. https://doi.org/10.1080/00207543.2021.2013566

Bárkányi, Á., Chován, T., Németh, S., & Abonyi, J. (2021). Modelling for digital twins—potential role of surrogate models. *Processes*, *9*(3), 476. https://doi.org/10.3390/pr9030476

Belfadel, A., Hörl, S., Tapia, R. J., & Puchinger, J. (2021). Towards a digital twin framework for adaptive last mile city logistics. *In 2021 6th International Conference on Smart and Sustainable Technologies (SpliTech)*, Split, Croatia, (pp. 1–6). IEEE.

Bengio, Y., Lodi, A., & Prouvost, A. (2021). Machine learning for combinatorial optimization: A methodological tour d'horizon. *European Journal of Operational Research*, *290*(2), 405–421. https://doi.org/10.1016/j.ejor.2020.07.063

Boschert, S., & Rosen, R. (2016). Digital twin—the simulation aspect. *Mechatronic Futures: Challenges and Solutions for Mechatronic Systems and Their Designers*, 59–74.

Botn-Sanabria, D. M., Mihaita, A. -S., Peimbert-Garca, R. E., Ramrez-Moreno, M. A., Ramrez-Mendoza, R. A., & Lozoya-Santos, J. D. J. (2022). Digital twin technology challenges and applications: A comprehensive review. *Remote Sensing*, *14*(6), 1335. https://doi.org/10.3390/rs14061335

Büyüközkan, G., & Ilcak, Ö. (2021). Smart urban logistics: Literature review and future directions. *Socio-Economic Planning Sciences*, *81*, 101197. https://doi.org/10.1016/j.seps.2021.101197

Cooray, P., & Rupasinghe, T. D. (2017). Machine learning-based parameter tuned genetic algorithm for energy minimizing vehicle routing problem. *Journal of Industrial Engineering*, *2017*, 2017. https://doi.org/10.1155/2017/3019523

Dabia, S., Demir, E., & Woensel, T. V. (2017). An exact approach for a variant of the pollution-routing problem. *TransporReinforcement learning, as a methodtation Science*, *51*(2), 607–628. https://doi.org/10.1287/trsc.2015.0651

Da Costa, P., Rhuggenaath, J., Zhang, Y., Akcay, U., & Alp Anwd Kaymak. (2021). Learning 2-opt heuristics for routing problems via deep reinforcement learning. *SN Computer Science*, *2*(5), 388. https://doi.org/10.1007/s42979-021-00779-2

El Ouadi, J., Errousso, H., Benhadou, S., Medromi, H., & Malhene, N. (2020). A machine-learning based approach for zoning urban area in consolidation schemes context. *In 2020 IEEE 13th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA)*, Fez, Morocco, (pp. 1–7). IEEE.

Furian, N., O'Sullivan, M., Walker, C., & Çela, E. (2021). A machine learning-based branch and price algorithm for a sampled vehicle routing problem. *OR Spectrum*, *43*(3), 693–732. https://doi.org/10.1007/s00291-020-00615-8

Ghandar, A., Ahmed, A., Zulfiqar, S., Hua, Z., Hanai, M., & Theodoropoulos, G. (2021). A decision support system for urban agriculture using digital twin: A case study with aquaponics. *IEEE Access*, *9*, 35691–35708. https://doi.org/10.1109/ACCESS.2021.3061722

Giuffrida, N., Fajardo-Calderin, J., Masegosa, A. D., Werner, F., Steudter, M., & Pilla, F. (2022). Optimization and machine learning applied to last-mile logistics: A review. *Sustainability*, *14*(9), 5329. https://doi.org/10.3390/su14095329

Golinska Dawson, P., & Sethanan, K. (2023). Sustainable urban freight for energy-efficient smart cities—systematic literature review. *Energies*, *16*(6), 2617. https://doi.org/10.3390/en16062617

Griffis, S. E., Goldsby, T. J., Cooper, M., & Closs, D. J. (2007). Aligning logistics performance measures to the information needs of the firm. *Journal of Business Logistics*, *28*(2), 35–56. https://doi.org/10.1002/j.2158-1592.2007.tb00057.x

Gunasekaran, A., & Kobu, B. (2007). Performance measures and metrics in logistics and supply chain management: A review of recent literature (1995–2004) for research and applications. *International Journal of Production Research*, *45*(12), 2819–2840. https://doi.org/10.1080/00207540600806513

Guo, J., & Lv, Z. (2022). Application of digital twins in multiple fields. *Multimedia Tools & Applications*, *81*(19), 26941–26967. https://doi.org/10.1007/s11042-022-12536-5

Gutierrez-Franco, E., Mejia-Argueta, C., & Rabelo, L. (2021). Data-driven methodology to support long-lasting logistics and decision making for urban last-mile operations. *Sustainability*, *13*(11), 6230. https://doi.org/10.3390/su13116230

Haße, H., Li, B., Weißenberg, N., Cirullies, J., & Otto, B. (2019). Digital twin for real-time data processing in logistics. *In Artificial Intelligence and Digital Transformation in Supply Chain Management: Innovative Approaches for Supply Chains. Proceedings of the Hamburg International Conference of Logistics (HICL)*, Vol. *27* (pp. 4–28). Berlin: epubli GmbH.

Hottung, A., & Tierney, K. (2019). Neural large neighborhood search for the capacitated vehicle routing problem. *arXiv preprint arXiv:1911.09539*.

Ivanov, S., Nikolskaya, K., Radchenko, G., Sokolinsky, L., & Zymbler, M. (2020). Digital twin of city: Concept overview. *In 2020 Global Smart Industry Conference (GloSIC)*, Chelyabinsk, Russia, (pp. 178–186). IEEE.

James, J., Yu, W., & Gu, J. (2019). Online vehicle routing with neural combinatorial optimization and deep reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems*, *20* (10), 3806–3817. https://doi.org/10.1109/TITS.2019.2909109

Jeong, D. -Y., Baek, M. -S., Lim, T. -B., Kim, Y. -W., Kim, S. -H., Lee, Y. -T., Jung, W. -S., & Lee, I. -B. (2022). Digital twin: Technology evolution stages and implementation layers with technology elements. *IEEE Access*, *10*, 52609–52620. https://doi.org/10.1109/ACCESS.2022.3174220

Jlassi, S., Tamayo, S., & Gaudron, A. (2018). Simulation applied to urban logistics: A state of the art. *City LogisticsTowards Sustainable and Liveable Cities*, *3*(1), 65–87.

Joe, W., & Lau, H. C. (2020). Deep reinforcement learning approach to solve dynamic vehicle routing problem with stochastic customers. *In Proceedings of the international Conference on Automated Planning and Scheduling*, Nancy, France, *30*, (pp. 394–402).

Jucha, P. (2021). Use of artificial intelligence in last mile delivery. *In SHS Web of Conferences*, Zilina, Slovakia, (pp. 04011). EDP Sciences volume 92.

Karakikes, I., Nathanail, E., & Savrasovs, M. (2018). Techniques for smart urban logistics solutions' simulation: A systematic review. *In International conference on Reliability and Statistics in transportation and communication*, Riga, Latvia, *18*, (pp. 551–561). Springer.

Khalil, E., Dai, H., Zhang, Y., Dilkina, B., & Song, L. (2017). Learning combinatorial optimization algorithms over graphs. *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing*, Long Beach, CA, USA, *30*, 6351–6361.

Lagorio, A., Pinto, R., & Golini, R. (2016). Research in urban logistics: A systematic literature review. *International Journal of Physical Distribution & Logistics Management*, *46*(10), 908–931. https://doi.org/10.1108/IJPDLM-01-2016-0008

Lagorio, A., Pinto, R., & Golini, R. (2017). Urban logistics ecosystem: A system of system framework for stakeholders in urban freight transport projects. *IFAC-Papersonline*, *50*(1), 7284–7289. https://doi.org/10.1016/j.ifacol.2017.08.1402

LCB. (2022). Leefbare stad. Retrived July 27, 2022, from URL: https://www.lcb.nu/themas/details/?id=2722a341-a017-eb11-a813-000d3abaccb2.

Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in industry 4.0: A review. *Journal of Manufacturing Systems*, *60*, 119–137. https://doi.org/10.1016/j.jmsy.2021.05.011

Leng, J., Zhou, M., Xiao, Y., Zhang, H., Liu, Q., Shen, W., Su, Q., & Li, L. (2021). Digital twins-based remote semi-physical commissioning of flow-type smart manufacturing systems. *Journal of Cleaner Production*, *306*, 127278. https://doi.org/10.1016/j.jclepro.2021.127278

Levine, S., Kumar, A., Tucker, G., & Fu, J. (2020). Offline reinforcement learning: Tutorial, review, and perspectives on open problems. *arXiv preprint arXiv:2005.01643*.

Liu, Y., Folz, P., Pan, S., Ramparany, F., Bolle, S., Ballot, E., & Coupaye, T. (2021). Digital twin-driven approach for smart city logistics: The case of freight parking management. *In Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems: IFIP WG 5.7 International Conference, APMS 2021*, *Nantes, France*, September 5–9, 2021, *Proceedings, Part IV* (pp. 237–246). Springer.

Lombardi, M., & Milano, M. (2018). Boosting combinatorial problem modeling with machine learning. *arXiv preprint arXiv:1807.05517*.

Lu, J., Liu, A., Dong, F., Gu, F., Gama, J., & Zhang, G. (2018). Learning under concept drift: A review. *IEEE Transactions on Knowledge and Data Engineering*, *31*, 2346–2363. https://doi.org/10.1109/TKDE.2018.2876857

Marcucci, E., Gatta, V., Le Pira, M., Hansson, L., & Bråthen, S. (2020). Digital twins: A critical discussion on their potential for supporting policy-making and planning in urban logistics. *Sustainability*, *12*(24), 10623. https://doi.org/10.3390/su122410623

Mazyavkina, N., Sviridov, S., Ivanov, S., & Burnaev, E. (2021). Reinforcement learning for combinatorial optimization: A survey. *Computers & Operations Research*, *134*, 105400. https://doi.org/10.1016/j.cor.2021.105400

Miao, J., & Lan, S. (2021). Application of visual sensing image processing technology under digital twins to the intelligent logistics system. *Advances in Civil Engineering*, *2021*, 1–13. https://doi.org/10.1155/2021/5743387

Montoya, A., Guéret, C., Mendoza, J. E., & Villegas, J. G. (2017). The electric vehicle routing problem with nonlinear charging function. *Transportation Research Part B: Methodological*, *103*, 87–110. https://doi.org/10.1016/j.trb.2017.02.004

Morabit, M., Desaulniers, G., & Lodi, A. (2021). Machine-learning–based column selection for column generation. *Transportation Science*, *55*(4), 815–831. https://doi.org/10.1287/trsc.2021.1045

Morana, J., Gonzalez-Feliu, J., Allaoui, H., & Alok Choudhary, P. (2015). A sustainable urban logistics dashboard from the perspective of a group of operational managers. *Management Research Review*, *38*(10), 1068–1085. https://doi.org/10.1108/MRR-11-2014-0260

Moshood, T. D., Nawanir, G., Sorooshian, S., & Okfalisa, O. (2021). Digital twins driven supply chain visibility within logistics: A new paradigm for future logistics. *Applied System Innovation*, *4*(2), 29. https://doi.org/10.3390/asi4020029

Muñuzuri, J., Larrañeta, J., Onieva, L., & Cortés, P. (2005). Solutions applicable by local administrations for urban logistics improvement. *Cities*, *22*(1), 15–28. https://doi.org/10.1016/j.cities.2004.10.003

Nazari, M., Oroojlooy, A., Snyder, L., & Takác, M. (2018). Reinforcement learning for solving the vehicle routing problem. *Advances in Neural Information Processing Systems 31*.

Niu, Y., Kong, D., Wen, R., Cao, Z., & Xiao, J. (2021). An improved learnable evolution model for solving multi-objective vehicle routing problem with stochastic demand. *Knowledge-Based Systems*, *230*, 107378. https://doi.org/10.1016/j.knosys.2021.107378

Niu, Y., Shao, J., Xiao, J., Song, W., & Cao, Z. (2022). Multi-objective evolutionary algorithm based on rbf network for solving the stochastic vehicle routing problem. *Information Sciences*, *609*, 387–410. https://doi.org/10.1016/j.ins.2022.07.087

Pan, S., Zhou, W., Piramuthu, S., Giannikas, V., & Chen, C. (2021). Smart city for sustainable urban freight logistics. *International Journal of Production Research*, *59*(7), 2079–2089. https://doi.org/10.1080/00207543.2021.1893970

Rosen, R., Von Wichert, G., Lo, G., & Bettenhausen, K. D. (2015). About the importance of autonomy and digital twins for the future of manufacturing. *IFAC-Papersonline*, *48*(3), 567–572. https://doi.org/10.1016/j.ifacol.2015.06.141

Russo, F., & Comi, A. (2010). A classification of city logistics measures and connected impacts. *Procedia-Social & Behavioral Sciences*, *2*(3), 6355–6365. https://doi.org/10.1016/j.sbspro.2010.04.044

Rydin, Y., Bleahu, A., Davies, M., Dávila, J. D., Friel, S., De Grandis, G., Groce, N., Hallal, P. C., Hamilton, I., Howden Chapman, P., Lai, K. -M., Lim, C. J., Martins, J., Osrin, D., Ridley, I., Scott, I., Taylor, M., Wilkinson, P., & Wilson, J. (2012). Shaping cities for health: Complexity and the planning of urban environments in the 21st century. *The Lancet*, *379*(9831), 2079–2108. https://doi.org/10.1016/S0140-6736(12)60435-8

Savelsbergh, M., & Van Woensel, T. (2016). 50th anniversary invited article—city logistics: Challenges and opportunities. *Transportation Science*, *50*(2), 579–590. https://doi.org/10.1287/trsc.2016.0675

Schislyaeva, E. R., & Kovalenko, E. A. (2021). Innovations in logistics networks on the basis of the digital twin. *Academy of Strategic Management Journal*, *20*(Special Issue 2), 1–17.

Semeraro, C., Lezoche, M., Panetto, H., & Dassisti, M. (2021). Digital twin paradigm: A systematic literature review. *Computers in Industry*, *130*, 103469. https://doi.org/10.1016/j.compind.2021.103469

Shen, X., Zhang, Y., Tang, Y., Qin, Y., Liu, N., & Yi, Z. (2022). A study on the impact of digital tobacco logistics on tobacco supply chain performance: Taking the tobacco industry in Guangxi as an example. *Industrial Management & Data Systems*, *122*(6), 1416–1452. https://doi.org/10.1108/IMDS-05-2021-0270

Shi, H., Sun, L., Teng, Y., & Hu, X. (2019). An online intelligent vehicle routing and scheduling approach for b2c e-commerce urban logistics distribution. *Procedia computer science*, *159*, 2533–2542. https://doi.org/10.1016/j.procs.2019.09.428

Sonneberg, M. -O., Leyerer, M., Kleinschmidt, A., Knigge, F., & Breitner, M. H. (2019). Autonomous unmanned ground vehicles for urban logistics: Optimization of last mile delivery operations. *In Proceedings of the 52nd hawaii international conference on system sciences*, Maui, Hawaii, USA.

Szmelter-Jarosz, A., Rześny-Cieplińska, J., & Jezierski, A. (2020). Assessing resources management for sharing economy in urban logistics. *Resources*, *9*(9), 113. https://doi.org/10.3390/resources9090113

Tao, F., Qi, Q., Wang, L., & Nee, A. (2019). Digital twins and cyber–physical systems toward smart manufacturing and industry 4.0: Correlation and comparison. *Engineering*, *5*(4), 653–661. https://doi.org/10.1016/j.eng.2019.01.014

Teng, S. Y., Touš, M., Leong, W. D., How, B. S., Lam, H. L., & Máša, V. (2021). Recent advances on industrial data-driven energy savings: Digital twins and infrastructures. *Renewable & Sustainable Energy Reviews*, *135*, 110208. https://doi.org/10.1016/j.rser.2020.110208

Vallejo, M. E., Larios, V. M., Magallanes, V. G., Cobián, C., Castañeda, M. D. L. L. G., & Téllez, G. B. (2021). Creating resilience for climate change in smart cities based on the local food supply chain. *In 2021 IEEE International Smart Cities Conference (ISC2)* (pp. 1–7). IEEE.

van Heeswijk, W. J., Mes, M. R., Schutten, J., & Zijm, W. (2020). Evaluating urban logistics schemes using agent-based simulation. *Transportation Science*, *54*(3), 651–675. https://doi.org/10.1287/trsc.2019.0971

Wang, R., Zhou, X., Dong, L., Wen, Y., Tan, R., Chen, L., Wang, G., & Zeng, F. (2020). Kalibre: Knowledge-based neuralLearning 2-opt heuristics for routing problems via deep reinforcement learning surrogate model calibration for data center digital twins. *In Proceedings of the 7th ACM*

International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (pp. 200–209).

White, G., Zink, A., Codecá, L., & Clarke, S. (2021). A digital twin smart city for citizen feedback. *Cities*, *110*, 103064. https://doi.org/10.1016/j.cities.2020.103064

Xu, Z., Chang, D., Sun, M., & Luo, T. (2022). Dynamic scheduling of crane by embedding deep reinforcement learning into a digital twin framework. *Information*, *13*(6), 286. https://doi.org/10.3390/info13060286

Zdolsek Draksler, T., Cimperman, M., & Obrecht, M. (2023). Data-driven supply chain operations —the pilot case of postal logistics and the cross-border optimization potential. *Sensors*, *23*(3), 1624. https://doi.org/10.3390/s23031624

Zhao, J., Mao, M., Zhao, X., & Zou, J. (2020). A hybrid of deep reinforcement learning and local search for the vehicle routing problems. *IEEE Transactions on Intelligent Transportation Systems*, *22*(11), 7208–7218. https://doi.org/10.1109/TITS.2020.3003163

Zhao, Z., Zhang, M., Chen, J., Qu, T., & Huang, G. Q. (2022). Digital twin-enabled dynamic spatial-temporal knowledge graph for production logistics resource allocation. *Computers & Industrial Engineering*, *171*, 108454. https://doi.org/10.1016/j.cie.2022.108454

Zou, X., Somenahalli, S., & Scrafton, D. (2020). Evaluation and analysis of urban logistics competitiveness and spatial evolution. *International Journal of Logistics: Research & Applications*, *23*(5), 493–507. https://doi.org/10.1080/13675567.2019.1703916