Digital Twin Applications in Urban Logistics: An Overview

Abdo Abouelrous[1] [0000−0003−3670−5136], Yingqian Zhang[1] [0000−0002−5073−0787], and Laurens Bliek[1] [0000−0002−3853−4708]

[1] Eindhoven University of Technology, 5612 AZ Eindhoven, The Netherlands.
2

Abstract. Urban traffic attributed to commercial and industrial transportation is observed to largely affect living standards in cities due to external effects pertaining to pollution and congestion. In order to counter this, smart cities deploy technological tools to achieve sustainability. Such tools include Digital Twins (DT)s which are virtual replicas of real-life physical systems that control the systems. Research points that DTs can be very beneficial in how they control a physical system by constantly optimizing its performance. The concept has been extensively studied in other 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 networks. To do this, we provide a characterization of key factors in urban logistics for dynamic-decision making. We also 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 characterization, we produce a conceptual model that describes the ontology, learning capabilities and optimization prowess of an urban logistics digital twin through its quantitative models. We finish off with a discussion on potential research benefits and limitations based on previous research and our practical experience.

Keywords: Digital Twins· Artificial Intelligence· Machine Learning· Urban Logistics· Smart Cities· Sustainability· Optimization

1 Introduction

Urban Logistics has been growing rapidly in recent years due to rising consumer demand and online shopping, among other trends relating to population growth and urbanization [30]. As a result, operational planning and policy-making in urban logistics has become increasingly complex. The associated challenges require the development of 'smart' technologies that can assist with planning and resource allocation in urban logistics [6]. Such technologies are often attributed with smart cities that enjoy a fortified technological infrastructure by which city data can be collected and processed to improve decision-making by stakeholders within the city.

Smart technologies are normally derivatives of Artificial Intelligence (AI) which has managed to acquire significant interest from research and industry with its promising capabilities. Specifically, AI has witnessed manifold industrial applications in urban logistics to deal with real-life planning challenges as discussed in [14], [36] and [35]. Among the manifold AI-driven technologies presented to tackle urban logistics problems, there is one that we are particularly interested in, namely because of its holistic approach in combining knowledge from different computational models. More precisely, all the AI models that we have encountered in our studies could be categorized as sub-components of it. We refer to this as the Digital Twin (DT).

The DT term has been first proposed in 2003 at Michigan University by Professor Grieves to prescribe product life-cycle management as explained in [33]. Despite dating back almost two decades, there is still no standardized industrial or academic definition for what constitutes a DT. The term is generally used to refer to any virtual replica of a real-life model but provides no guidelines or technical requirements on the functionalities of this replica. This often leads to confusion among parties with regards to what a DT is and how it is distinct from many existing simulation/decision support systems. We believe that this confusion has presented an obstacle to the development of research in DTs.

In particular, the definition of what a DT is, its functional requirements and conceptual components was often determined by the application context as mentioned in [33]. For the large part, DT applications have largely been manufacturing-based as in [27] and [38]. On the other hand, there has been very limited focus on the area of logistics compared to manufacturing as [11] mentions, despite its importance and emphasis on how it could benefit from Big Data analytics associated with DTs [26]. This benefit only grows with time as cities are becoming increasingly smarter and collect data from a multitude of sources [40]. Specifically, and by using this data, DTs could be used to improve the quality of life, mobility and services of the inhabitants of a city [5].

In order to define a framework for building DTs, we first have to provide a characterization of urban logistics operations in terms of the key factors that govern it. The human aspect plays an important role in the urban environment as determined by the stakeholder's and their interactions [18]. This aspect is not significant in other domains such as manufacturing, and therefore requires a specific characterization upon which DTs could be built.

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

1. Characterize urban logistics operations in terms of defining factors for dynamic decison-making. We arrive at four major input components we take to be resources, stakeholders, KPIs and measures.
2. Summarize previous findings from literature on DTs in urban logistics in terms of 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 three topics as previous papers tend to focus on a subset of these topics.

3. Provide an framework on the conceptual anatomy of urban logistics DTs in terms of the AI methods employed. This refers to a framework incorporating a knowledge base, machine learning and optimization.
4. Specify potential opportunities and challenges in future research of urban logistics DTs based on previous literature and our practical experience.

That said, the rest of this article is organized as follows. Section 2 provides the characterization of urban logistics (Contribution 1). Section 3 discusses previous literature on DTs in urban logistics (Contribution 2). Section 4 proposes the conceptual framework (Contribution 3). Section 5 lists the potential benefits and limitations (Contribution 4).

2 Urban Logistics

We first start by providing a definition for DT in urban logistics. To arrive at a domain-specific definition - as conventional in the research of DTs - we first need to establish the important aspects of an urban logistics environment that a DT ought to cover. The author of [30] defines 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, shift-scheduling etc.

Urban logistics operations can be categorized into many subsets. For instance, B2B delivery that involves a business or a Logistics Service Provider (LSP) delivers goods to another business. B2C is another category that involves delivery from a business to consumers, also known as last-mile delivery. To construct a DT model for urban logistics, it is imperative to identify key factors that characterize this spectrum of operations. [2] provide an ontology for urban logistics whereby these factors are identified. We only consider a subset of the factors that we find relevant as input for dynamic decision-making in urban logistics. These are stakeholders, Key Performance Indicators (KPI)s, resources and measures. Note that decisions are also a key factor in this ontology. However, they are an output factor in response to the aforementioned input factors. We elaborate on the four input factors below.

Stakeholders. The government, businesses and citizens in the urban logistics supply chain are referred to as stakeholders, whereby the participation is defined by their interests. For a detailed survey on the roles of stakeholders in urban logistics, we refer to [17]. The authors of [18] explain how stakeholders have an integral function in defining the ecosystem of urban logistics network through their interests, interactions and decisions. Consequently, there is a need to employ a framework to build a conceptual model in which their interests are incorporated while the model is used to aid them with understanding and managing the complicated business environment of city logistics. Further studies on constructing such frameworks for sustainable urban logistics only support the development of a holistic model like the DT. In [32], the authors study a collaborative approach utilized for route-planning through a multi-criteria optimization procedure. Here, the different criteria represent the different stakeholders' perspectives. Approaches such as that of [32], could be easily included in the holistic framework of the DT. On the other hand, the presence of the human element induces other complications that would not be present in other industries like manufacturing with regards to the DT design. For instance, uncertain preferences and execution inaccuracies are among the major concerns that our proposed framework has to deal with.

KPIs. As explained above, stakeholders have interests. These interests translate to objectives which are measured using KPIs as stated in [22]. KPIs could be used to guide optimization procedures as they can be used to represent objective functions. An example can be found in [12] who use an agent-based simulation to verify routing schemes. The schemes are assessed by predetermined KPIs representing the objective functions. Sustainable urban logistics networks KPIs normally include - and are not restricted to - CO2 emissions, cost, lead time and delivery travel time as given in [29]. For an exhaustive list of some of the most popular KPIs for urban logistics, we refer to [8] and [9]. DTs, in turn, are very suitable for KPI-based optimizations as they can use data collected from all over the city through their sensor's to generate interesting KPIs, of which some could not be easily generated otherwise due to the absence of an appropriate linkage with relevant data sources.

Resources. Resources refer to all the available resources possessed by all stakeholders in the urban logistics network. [37] 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. The DT's holistic approach should manifest itself in coordinating all these resources to achieve the target KPIs specified by the stakeholder. It should pay special attention into how material and human resources are used to execute decisions generated from the information resources, not only of the human experts but also its own information resources. The capital resources are less relevant for dynamic-decision making, although they are quite important when setting up the DT, something we will discuss extensively below.

Measures. Lastly, the measures represent the rules and regulations under which the resources of the digital twins operate. Most often these measures include regulations imposed by policy-makers such as in [28] and [24] and include goods vehicle access to certain roads. Note that these rules correspond to constraints that are not embedded in the resources themselves, unlike the maximum capacity of a vehicle or the maximum shift length of an operator for example, but rather imposed by the rule of law. This means that although not following measures is technically feasible, the measures must always be followed.

Being practical constraints, the measures could be used to configure modelling constraints when setting up quantitative models such as mathematical optimization ones. Any resulting solutions to the models ought to respect the constraints, so that the corresponding real-life decisions remain feasible. Below we explain how (mathematical) optimization plays an important role in DTs, which should incorporate the measures for an accurate and representative model of reality. The DT itself could also be used to study the effect of measures through its quantitative models. The authors explain how quantitative approaches could be employed to study public measures, and help design suitable ones [7].

3 Digital Twins

We provide a general definition for DTs based on a survey of definitions from manifold applications from [33]. We then inspect literature that specifically discussed DT applications in urban logistics and use this to assemble information on the technical anatomy, functionalities and set-up of an urban logistics DT. Other literature with different application scopes is disregarded here.

3.1 Definition

The abundant definition as per previous research initiatives goes along the lines of DTs being digital reconstructions of real-life physical systems that mimic the behavior of the systems and their integral components through real-time linkage with the systems.

So far, the definition above resembles closely that of simulation in the sense that they are both virtual representations of physical entities. However, the part on real-time linkage bears huge importance in defining the distinction as explained in [33]. A DT is synched to the physical system - which is a city in our case - in the sense that the status of the twin always corresponds to the current real-life status, and is updated once the real-life status changes. The status of the twin should not depict anything that is not happening in real-time. For instance, traffic jams should not be depicted by the virtual model when traffic is not building up in reality, even when empirical traffic data implies otherwise. Nonetheless, the DT may visualize phenomena that are not currently happening in real-life through its simulation tools as will be explained below. The distinction between the simulated visualizations and the status of the virtual model, however, ought to remain clear.

In particular, [33] states that "The Digital Twin should evolve synchronously with the real system along its whole life cycle", thereby modifying its initial configuration to adapt to the current situation. That said, the DT does not only update its status but also the quantitative models it embeds. The autonomous procedure by which it does will be stressed below. The targeted outcome of this procedure is that the modelling accuracy of the DT steadily improves.

Returning to the distinction from simulation, the DT's dynamic replication of a physical system resembles emulation more closely as [33] explains. The DT ensures that the integral components of the system it models are accurately represented through the data it collects about them rather than simply model the general behavior of the system. The increased level of representation offered by emulation serves a considerable benefit as it provides a closer replication of reality in contrast to the more static concept of simulation.

DTs also control the physical system through data that they transfer to it. A unidirectional data flow - from the physical to the virtual model - is not sufficient for a virtual model to be labelled a DT. [33] state that the interaction with the physical system should be bidirectional as data collected from the physical space updates the virtual model, while the physical twin improves its operational performance by exploiting knowledge acquired from the virtual model's processing of the data. For instance, an analytic insight generated from the DT regarding traffic should be communicated to the logistic planners/traffic controllers to assist them with decision-making. This may not be the case with a simulation model, since it is not linked to the physical system and thus, the analysis it produces need not be relevant for the current situation.

To conclude their findings, [33] provide the following definition of a DT:

> "A set of adaptive models that emulate the behavior of a physical system in a virtual system getting real time data to update itself along its life cycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real-time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system".

The definition above is not specific to urban logistics indeed. Nonetheless, we feel that the literature is in pressing need for an established basis upon which other features of DTs could be built for different applications.

3.2 Technical Anatomy

From a software perspective, there are manifold components of a DT. Generally speaking, the literature refers to components such as Internet of Things (IOT), cloud-computing and Application Programming Interfaces (APIs) such as in [23]. The software aspect, however, is of minor interest to us. For a detailed discussion on how software is integrated into the DT framework, we refer to [5].

From a technical standpoint, [4] propose a framework into the anatomy of twins. An abstract visualization of this anatomy can be found in Figure 1. 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 level is linked to 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 physical system. The MMS manages the models library which is a set of software applications that provide analytic tools. The

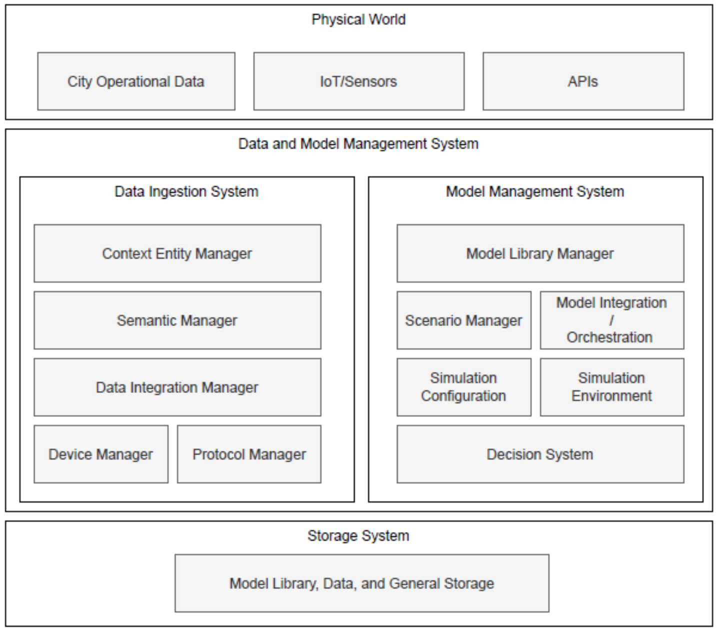

Fig. 1. Conceptual anatomy of a complete DT model according from [4].

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

Returning to the architecture described above, this is the task of the Decision System in the MMS which 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. In the following subsections, we provide a listing of the relevant quantitative models that compliment DTs along with a brief description.

3.3 Functionalities

The main application area of DTs that is relevant for our study is smart cities. The introduction of DTs is supposed to help overcome many issues that urban models generally suffer from. [25] provide examples of these issues such as a degree of simplification of urban processes, shortages in data requirements, complications involved in data collection and inadequately handling human behavior and its implications, among others.

From a computational perspective, [20] mention that DTs in smart cities "describe, capture and simulate policy (both real and potential) implications of alternative solutions for optimizing them with respect to a given objective or set of them". [31] survey functionalities pertaining to DTs of logistic networks on the higher-level, emphasizing on 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 be used to predict the state of their physical counterpart. [10] state that DTs can predict possible future scenarios and evaluate them to find appropriate responses for the most likely ones.

These functionalities are of utter relevance to urban logistics. For instance, big-data from traffic movements could be used to calculate travel times which can in turn be used to set-up optimization models for vehicle routing and configure simulation models to verify the proposed routing plans. Moreover, the analytics embedded in the twin can be used to predict possible vehicle failures judging by their working circumstances or other internal diagnostics that would otherwise be unobserved. [31] confirm this by saying that DTs retain data that can not be (easily) obtained from the physical model.

[10] 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 when a vehicle has been observed to remain stationary for a prolonged period of time. This could be the result of an accident in a distant location that would have otherwise remained undetected. Exception handling is especially relevant when physical assets exist in unsafe environments as [23] suggests, which improves the safety protocols. Not to mention the typical operational disruption consequent to accidents that could be efficiently managed by DTs where the difficulty of real-time re-planning is better addressed by real-time data connectivity and great computational power, improving the responsiveness of an LSP. This is because DTs can not only predict if a problem might happen, but also propose a solution.

DTs also encompass large sets of KPIs that are generated from its diagnostics. [10] mentions that DTs can support accurate calculation of performance indicators of logistics operations through their scenario prediction and assessment mechanisms. [23] also mentions how DT sensors could be used to generate new data types, which as [10] suggests could create even new relevant KPIs. As [4] explains,"The decisive factor is how this data is processed further in order to offer real added value. In this context, the added value is created with the help of KPIs tailored precisely to the targeted application". Additionally, KPIs play an even more important role in the learning process of a DT, something that will be extensively discussed below.

There is an additional benefit brought by the visual effects of a DT, and that is supply chain visibility. [23] explain that supply chain visibility depends an organization's ability to be transparent and clear about its internal and external processes of its supply chain. To that end, organizations have to determine the logistics operations that are most affected by lack of transparency and clarity, and devising techniques by which data could be easily exchanged between all participants. The visibility factor 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 along the supply chain who can be easily informed in a standardized manner of expected outcomes to any process. [23] 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 that can impact the supply chain as a whole.[20] also stresses the importance of DTs in translating complex ideas into more intuitive ones through visualization.

[23] reinforce the technological prowess of DTs by stressing how they could automate monotonous tasks that could be subject to human error, which is a benefit that could only come with its real-time connectivity. The advantages of automated processes are countless and can be explored in manifold applications. Furthermore, [31] 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. [10] mention "a learning process based on the KPIs" process, 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. Therefore, DTs can learn from daily operations using machine learning models hat facilitate the acquisition and accumulation of knowledge from the urban environment. In turn, accumulated knowledge can be used to make predictions about the outcomes of future operations when data about these operations is not available.

In continuation of this learning framework, [15] presents a study about how 'cognitive' DTs in agile supply chains increase their knowledge base as they learn more from data obtained from the physical model. They state that DTs should try to relate their predicted outcomes to the actual observed ones by learning how UP (desirable outcomes that were not predicted) and UU (undesirable outcomes that were not predicted) events affect the physical counterpart. By employing this framework, DTs can enhance their learning capabilities over time as it offers a guideline to train and improve DT models through knowledge gathered from past UP and UU events.

To sum up, and as [25] explains, the introduction of DTs compliments the 4th industrial revolution where "moving from a period of relative data scarcity to an era of 'digital abundance' may enable" the generation of more accurate models based on real-time Big Data of higher quality that can describe urban logistics processes in on a greater level of detail than before.

3.4 Set Up & Illustration

In principle, setting up a DT is a complex process. [23] states that is a relatively new area of research and that its precise implementations are scarce. This goes in synergy with the findings of [4], implying "that existing architectures are too generic for usage in logistics". For smart cities, there have been several partial implementations such as Cambridge [15], Lyon [4] and cities in the Netherlands as we will explain below. [5] also surveys other studies of smart city DTs in Asia and Europe, of which a subset is dedicated to urban logistics. Some research initiatives such as [13] propose the concept of a DT of a city from a governance perspective, with limited focus on urban logistics that involves other stakeholders such as LSPs.

From the design theory perspective, [23] stresses 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 intense technological requirements such as Internet of Things Sensors, Cloud computing etc. Consequently, [23] proposes to start simple and focus on maintaining the accuracy of data while incrementally reducing the chance of human error.

[20] provides an example of a collaborative initiative between policy-makers in the contest of so called Living-Labs. They suggest that Living-Labs are the most up-to-date data-driven methodology tackling the problem of managing 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. There, Living Labs are developed to create efficient and shared solutions among stakeholders.

[23] also states that knowledge ought to be exchanged among the multiple stakeholders, a factor catalyzed by visibility. An extensive analysis on sociotechnical interaction among government, industry and consumers is conducted in [25], who argue that there is a need to look beyond technological factors and incorporate a distinct societal aspect into the design and implementation of DTs if they were to make any resonating changes in the practical modelling of urban environments.

Another important aspect regarding the design of a DT is the modeling one. [20] also explains that DTs should strive to provide a simplified version of the physical model as they should never replicate the physical system in every detail, as that would not make them models anymore that we could use to efficiently study urban environments. The purpose of the DT as a model is to abstract the complex environment of a city in a limited number of variables. This sets many implications on what factors to include in the model. For instance, the Atlas DT carefully considers modelling relevant variables as dictated by the requirements of its user base of academic researchers and LSPs. More variables could be included in the future as the requirements of the user base expand.

For the learning part, [15] say that it is necessary to create a data set for which observed behaviors of the virtual model can be categorized among the four classifications (PD, PU, UP, UU). This process, however, involves considerable data-manipulation and cleaning. For instance, they mention how "removing unpredicted and undesirable behaviors" is necessary when configuring a DT model to ensure that the training data is undisturbed. This is subsequent to experimenting with different scenarios and concluding on a particular desired behavioral model, so that only behaviors of interest are included in the design.

There are other less technical factors that should also be carefully contemplated when designing a DT. These could include legal issues regarding data-sharing. Since the DT is a broad model that encompasses multiple stakeholders, some with conflicting objectives, it is important to govern how data is shared and used such that each and every party knows exactly what it needs to know. This is discussed in detail in [15]. Working in environments with multiple stakeholders often also requires the introduction of common operational norms, rules and objectives. The DT needs to be aware of those rules that reflect the priorities, policies and other terms of collaboration among stakeholders.

All factors considered, [10] provide a methodology on the steps taken to set-up an urban logistics DT for an LSP. The 6-step procedure starts at data collection. The data types collected should be dictated by the availability of data and interests of LSP using the DT. in Step 2, and after the data has been collected, it has to be suitably processed for a particular purpose such as devising diagnostic statistics that prescribe the operational context and can then bed fed to a mathematical model. For the latter purpose in Step 3, a mathematical optimization model could be set up by which decisions are made. The planning then has to be verified by means of a simulation in Step 4 in a more representative setting where the behavior of the city is better captured than in a simplified optimization model. 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 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.

The design proposed in [10] is specific to an LSP in a developing city. A DT of a smart city should be utilized by different stakeholders including policy-makers and consumers in line with the Living Lab approach presented above. We expect that the steps in the approach of [10] may be very similar with the differences appearing in the detail of each step. For instance, different data types could be collected depending on the requirements of consumers in Step 1, such as total encountered delay, to compute relevant statistics in Step 2 such as expected arrival time. This induces slight differences in the design of the twin used by consumers compared to the one used by LSPs. [31] states that “One object can have more than one twin, with different models created for different users and use cases”.

4 Conceptual Model

In this section, we present our own conceptual model of DTs based on AI methodology. Our model is identified by three components, namely a knowledge base, machine learning and mathematical optimization.

Using the characterization in Section 2 and the set-up methodology of [10] in Section 3.4, we are able to devise an ontology expressed by means of a knowledge graph. This ontology is similar to the one used in [2] in terms of knowledge and relation representation and is shown in Figure 2.

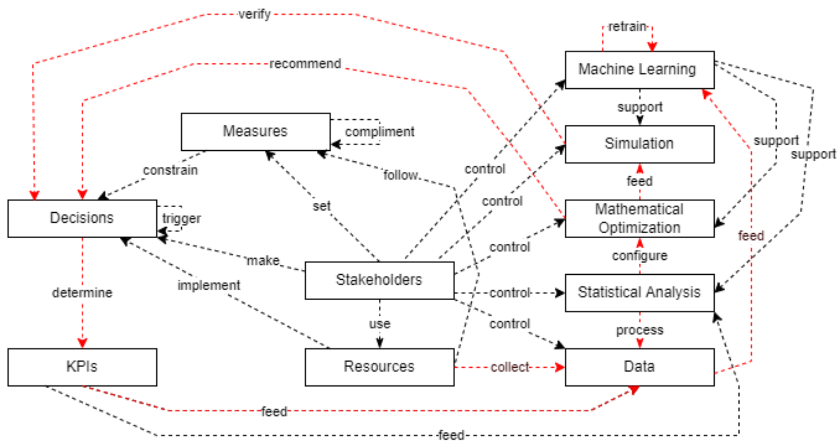

Fig. 2. Our proposed urban logistics DT ontology

The real-time aspect of a DT not only ensures that the DT models the current - and correct - state of the physical system but also that its models are up-to-date. This occurs by means of a learning mechanism.

Let $P(t)$ be a high-dimensional vector representing the parameters of the DT at continuous time t. 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 evolution with the physical system can be characterized by the following relationship:

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

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. Human controllers can define the functions in $f(.)$ and the interval Δ where 'better' choices lead to better models. For Δ, it is crucial to have a high data-updating frequency while taking latency into account [20].

For more details on this learning methodology, we refer to [39]. This update technique can be applied to all the quantitative model parameters in the DT. Since this training mechanism involves constant interaction with the environment, it resembles reinforcement learning. The feedback loop due to the bidirectional data exchange that characterizes this learning process is marked by the red arcs in Figure 2.

Lastly, we discuss optimization. Mathematical optimization models such as the VRP begin with specifying a mathematical program of the following structure:

$$\{\min c(x) | A(x) \leq b, x \in \mathcal{R}\}$$

where x is a vector in some subspace $\mathcal{R}$ representing decisions and $c(.)$ and $A(.)$ being the objective and constraint functions. Such programs are normally very difficult to solve with standard commercial solvers such as the ones mentioned in [3]. Therefore, we may resort to meta-heuristics such as search heuristics and all their variants. In principle, these heuristics are configured by a set of parameters which affect their performance. finding the right set of parameters corresponds to solving the following problem:

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

where $\Omega(\mu) = \{\min c(x) | A(x) \leq b, x \in \mathcal{S}(\mu)\}$, with μ being a vector of parameters of the heuristic in subspace $\mathcal{M}$ and $\mathcal{S}(\mu)$ being the search space created by calibrating the heuristic with parameters μ. Observe that $\mu \in P(t)$. Further details on this optimization methodology can be found in [21] and [16]. Other optimization techniques exist that could be suitably coupled with the DT such as Simulation Optimization [1], Bayesian Optimization [34], expert decision-making based on statistical analysis, or data-driven optimization methods [41].

Furthermore, it is useful to develop ontology that represents important parameters and relations for specific optimization problems. This enables integration of reasoning, learning, and optimization.

5 Future Research

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, [5] cite data security concerns and communication network-related obstacles. Additionally, the set-up costs of the technology-intensive DT are not negligible. [31] 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 [19], which is a virtual replica of cities in the Netherlands, is one such example. In Atlas, the transfer of data is unidirectional – from the physical to the virtual system only, in contrast to definition from Section 3.1. [20] 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. [20] 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 about the usefulness of the virtual model.

There are other challenges associated with building a DT. [20] 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 correctness of a fully functional DT may be too slow to realize any convincing gains in the short-term.

Furthermore, [20] 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 to so that changes in relationships and knowledge are incorporated on time, otherwise its added value may be questionable.

On the other hand, with past data, DTs can explain the possible underlying causes of encountered phenomena. This real-time management and control of situations aids with the integration of short-term decision making with long-term strategies as [25] suggests. Therefore, the DT would provide a more suitable framework to achieve the sustainability goals than other contemporary methodologies. That said, we aspire that future research expands on the ontology we proposed.

References

1. Amaran, S., Sahinidis, N.V., Sharda, B., Bury, S.J.: Simulation optimization: a review of algorithms and applications. Annals of Operations Research **240**(1), 351–380 (2016)
2. Anand, N., Yang, M., van Duin, J.R., Tavasszy, L.: Genclon: An ontology for city logistics. Expert Systems with Applications **39**(15), 11944–11960 (2012)
3. Barykin, S.Y., Bochkarev, A.A., Kalinina, O.V., Yadykin, V.K.: Concept for a supply chain digital twin. International Journal of Mathematical, Engineering and Management Sciences **5**(6), 1498 (2020)
4. Belfadel, A., Hörl, S., Tapia, R.J., Puchinger, J.: Towards a digital twin framework for adaptive last mile city logistics. In: 2021 6th International Conference on Smart and Sustainable Technologies (SpliTech). pp. 1–6. IEEE (2021)
5. Botín-Sanabria, D.M., Mihaita, A.S., Peimbert-García, R.E., Ramírez-Moreno, M.A., Ramírez-Mendoza, R.A., Lozoya-Santos, J.d.J.: Digital twin technology challenges and applications: A comprehensive review. Remote Sensing **14**(6), 1335 (2022)
6. Büyüközkan, G., Ilıcak, Ö.: Smart urban logistics: Literature review and future directions. Socio-Economic Planning Sciences p. 101197 (2021)
7. Cardenas, I., Borbon-Galvez, Y., Verlinden, T., Van de Voorde, E., Vanelslander, T., Dewulf, W.: City logistics, urban goods distribution and last mile delivery and collection. Competition and regulation in network industries **18**(1-2), 22–43 (2017)

8. Griffis, S.E., Goldsby, T.J., Cooper, M., Closs, D.J.: Aligning logistics performance measures to the information needs of the firm. Journal of business logistics **28**(2), 35–56 (2007)
9. Gunasekaran, A., Kobu, B.: 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 (2007)
10. Gutierrez-Franco, E., Mejia-Argueta, C., Rabelo, L.: Data-driven methodology to support long-lasting logistics and decision making for urban last-mile operations. Sustainability **13**(11), 6230 (2021)
11. Haße, H., Li, B., Weißenberg, N., Cirullies, J., Otto, B.: 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 (2019)
12. van Heeswijk, W.J., Mes, M.R., Schutten, J., Zijm, W.: Evaluating urban logistics schemes using agent-based simulation. Transportation science **54**(3), 651–675 (2020)
13. Ivanov, S., Nikolskaya, K., Radchenko, G., Sokolinsky, L., Zymbler, M.: Digital twin of city: Concept overview. In: 2020 Global Smart Industry Conference (GloSIC). pp. 178–186. IEEE (2020)
14. Jucha, P.: Use of artificial intelligence in last mile delivery. In: SHS Web of Conferences. vol. 92, p. 04011. EDP Sciences (2021)
15. Kalaboukas, K., Rožanec, J., Košmerlj, A., Kiritsis, D., Arampatzis, G.: Implementation of cognitive digital twins in connected and agile supply networks—an operational model. Applied Sciences **11**(9), 4103 (2021)
16. Khalil, E., Dai, H., Zhang, Y., Dilkina, B., Song, L.: Learning combinatorial optimization algorithms over graphs. Advances in neural information processing systems **30** (2017)
17. Lagorio, A., Pinto, R., Golini, R.: Research in urban logistics: a systematic literature review. International Journal of Physical Distribution & Logistics Management (2016)
18. Lagorio, A., Pinto, R., Golini, R.: Urban logistics ecosystem: A system of system framework for stakeholders in urban freight transport projects. IFAC-PapersOnLine **50**(1), 7284–7289 (2017)
19. LCB: Leefbare stad (2022), https://www.lcb.nu/themas/details/?id=2722a341-a017-eb11-a813-000d3abaccb2, accessed: 27-07-2022
20. Marcucci, E., Gatta, V., Le Pira, M., Hansson, L., Bråthen, S.: Digital twins: A critical discussion on their potential for supporting policy-making and planning in urban logistics. Sustainability **12**(24), 10623 (2020)
21. Mazyavkina, N., Sviridov, S., Ivanov, S., Burnaev, E.: Reinforcement learning for combinatorial optimization: A survey. Computers & Operations Research **134**, 105400 (2021)
22. Morana, J., Gonzalez-Feliu, J.: A sustainable urban logistics dashboard from the perspective of a group of operational managers. Management Research Review (2015)
23. Moshood, T.D., Nawanir, G., Sorooshian, S., Okfalisa, O.: Digital twins driven supply chain visibility within logistics: a new paradigm for future logistics. Applied System Innovation **4**(2), 29 (2021)
24. Muñuzuri, J., Larrañeta, J., Onieva, L., Cortés, P.: Solutions applicable by local administrations for urban logistics improvement. Cities **22**(1), 15–28 (2005)

25. Nochta, T., Badstuber, N., Wahby, N.: On the governance of city digital twins-insights from the cambridge case study (2019)
26. Pan, S., Zhou, W., Piramuthu, S., Giannikas, V., Chen, C.: Smart city for sustainable urban freight logistics (2021)
27. Rosen, R., Von Wichert, G., Lo, G., Bettenhausen, K.D.: About the importance of autonomy and digital twins for the future of manufacturing. Ifac-papersonline **48**(3), 567–572 (2015)
28. Russo, F., Comi, A.: A classification of city logistics measures and connected impacts. Procedia-Social and behavioral sciences **2**(3), 6355–6365 (2010)
29. Sarraj, R., Ballot, E., Pan, S., Hakimi, D., Montreuil, B.: Interconnected logistic networks and protocols: simulation-based efficiency assessment. International Journal of Production Research **52**(11), 3185–3208 (2014)
30. Savelsbergh, M., Van Woensel, T.: 50th anniversary invited article—city logistics: Challenges and opportunities. Transportation Science **50**(2), 579–590 (2016)
31. Schislyaeva, E.R., Kovalenko, E.A.: Innovations in logistics networks on the basis of the digital twin. Academy of Strategic Management Journal **20**, 1–17 (2021)
32. Semanjski, I., Gautama, S.: A collaborative stakeholder decision-making approach for sustainable urban logistics. Sustainability **11**(1), 234 (2019)
33. Semeraro, C., Lezoche, M., Panetto, H., Dassisti, M.: Digital twin paradigm: A systematic literature review. Computers in Industry **130**, 103469 (2021)
34. Shahriari, B., Swersky, K., Wang, Z., Adams, R.P., De Freitas, N.: Taking the human out of the loop: A review of bayesian optimization. Proceedings of the IEEE **104**(1), 148–175 (2015)
35. Shi, H., Sun, L., Teng, Y., Hu, X.: An online intelligent vehicle routing and scheduling approach for b2c e-commerce urban logistics distribution. Procedia Computer Science **159**, 2533–2542 (2019)
36. Sonneberg, M.O., Leyerer, M., Kleinschmidt, A., Knigge, F., Breitner, M.H.: Autonomous unmanned ground vehicles for urban logistics: Optimization of last mile delivery operations. In: Proceedings of the 52nd hawaii international conference on system sciences (2019)
37. Szmelter-Jarosz, A., Rześny-Cieplińska, J., Jezierski, A.: Assessing resources management for sharing economy in urban logistics. Resources **9**(9), 113 (2020)
38. Tao, F., Qi, Q., Wang, L., Nee, A.: Digital twins and cyber–physical systems toward smart manufacturing and industry 4.0: Correlation and comparison. Engineering **5**(4), 653–661 (2019)
39. Wang, R., Zhou, X., Dong, L., Wen, Y., Tan, R., Chen, L., Wang, G., Zeng, F.: Kalibre: Knowledge-based neural 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 (2020)
40. White, G., Zink, A., Codecá, L., Clarke, S.: A digital twin smart city for citizen feedback. Cities **110**, 103064 (2021)
41. Zhang, J., Wang, F.Y., Wang, K., Lin, W.H., Xu, X., Chen, C.: Data-driven intelligent transportation systems: A survey. IEEE Transactions on Intelligent Transportation Systems **12**(4), 1624–1639 (2011)