SN Computer Science (2023) 4:664
https://doi.org/10.1007/s42979-023-02050-2

ORIGINAL RESEARCH

Collaborative Digital Twins: The Case of the Energy Communities

Kankam O. Adu-Kankam[1,2] · Luís M. Camarinha-Matos[1]

Received: 23 December 2022 / Accepted: 5 June 2023

Abstract

The process of urbanization is accelerating on a global scale, leading to the rapid expansion of cities and urban settlements. However, this fast-paced growth poses significant challenges in terms of sustainable development and reducing greenhouse gas emissions. As cities grow, they require more infrastructure, produce greater amounts of waste, and consume more energy. To address the energy-related challenges, renewable energy communities (RECs) have emerged as a potential solution, capturing the attention of policymakers. RECs offer a range of benefits that contribute to the sustainability of communities and cities. To further enhance their effectiveness, this work proposes the concept of "Collaborative Digital Twins" (CDT) within a collaborating ecosystem. A CDT represents a replica of a household unit within the REC environment, equipped with cognitive intelligence to make rational and autonomous decisions that promote collaborative behaviors. Thus, CDTs can be viewed as intelligent digital twins that adopt a collaborative approach to problem-solving and decision-making. To demonstrate the cognitive and collaborative capabilities of CDTs, a prototype of a "Cognitive Household Digital Twins" (CHDT) community is presented using a multimethod simulation technique. The prototype explores various collaborative scenarios, revealing the potential of CDTs as a viable decision support system for RECs and smart cities. This research highlights the positive impact that collaborative digital twins can have on scaling development while simultaneously addressing some of sustainability challenges associated with urbanization.

Keywords Renewable energy communities · Digital twins · Cognitive digital twins · IoT · Collaborative networks

Introduction

In a renewable energy community (REC), a collective of citizens and corresponding households come together motivated by a common objective, which typically involves the creation and local sharing of renewable energy. The community comprises various interdependent entities, including local residents, businesses, municipalities, small and medium-sized companies, and generation units. Cost-effective green energy management, minimizing CO_2 emissions and energy waste are central to the core objectives of such communities. The European Parliament and the Council of the European Union [1] have stated that membership in RECs should be free and optional. They are independent and governed by stakeholders. Members of RECs can produce their own energy, which can be used, stored, sold, or shared locally within the community. According to the claims of the European Commission [2], at least 2 million individuals are active in more than 7700 RECs in the European Union. These RECs have delivered about 7% of the Union's annual energy production, which is estimated at around 6.3 GW. RECs have currently received nearly 2.6 billion euros in monetary investment. In the same vein, over 5000 RECs are currently in operation in the United Kingdom. These RECs have supplied over 60 MW of energy to the country's electricity pool, with almost 23 million pounds paid into community benefit funds for the benefit of local communities.

This article is part of the topical collection "Multidisciplinary Research Perspectives for IoT Systems" guest edited by Luis Camarinha-Matos, Luis Ribeiro, Paul Havinga and Srinivas Katkoori.

✉ Kankam O. Adu-Kankam
k.adu@campus.fct.unl.pt

Luís M. Camarinha-Matos
cam@uninova.pt

1 Nova University of Lisbon, School of Science and Technology and UNINOVA-CTS, Campus de Caparica, 2829-516 Monte de Caparica, Portugal

2 School of Engineering, University of Energy and Natural Resources (UENR), P. O. Box 214, Sunyani, Ghana

Published online: 30 August 2023

Considering the ongoing digital transformation and its corresponding impact on the energy transition, it has become essential to digitalize all facets of the energy systems, including renewable energy communities. This shift has paved the way for the integration and use of artificial intelligence (AI) in the transition process. AI can play a crucial role in enhancing the integration of renewable sources into the existing energy grid and improving its overall reliability [3]. Digital transformation leverages the benefits of information and communication technologies (ICT) to enhance the functionality in both the cyber and physical dimensions of technological infrastructure. In the energy sector, digitalization is gradually blurring the boundaries between the physical energy infrastructure and its corresponding cyber components. This technological milestone has resulted in the hyperconnectivity between the physical and the virtual components of the power grid.

On one hand, the increasing levels of interconnectivity between the cyber and physical dimensions of the grid also subject it to both cyber and physical vulnerabilities. For instance, the regular occurrence of disruptive events such as human or naturally induced disasters can affect one component of the community, and this could have a cascading effect with dire consequences on other components. This effect can adversely impact the normal activities of the community due to their level of interdependence. However, while increased connectivity through digitalization does bring challenges, it also presents significant opportunities to enhance the reliability, efficiency and penetration of renewables into the power grid. The extensive data that can be collected and exchanged through the cyber-physical interface offer immense potential for advancing traditional methods of data analysis, visualization, modeling, decision-making, and problem-solving. By harnessing the power of digital technologies, including AI and big data analysis, we can optimize energy management, improve decision-making, and overcome the complexities associated with the increasing penetration of renewables, benefiting both the power grid and RECs.

With the ongoing digitalization, digital twin technology has gained considerable popularity in the area of product design and manufacturing over the last decade. This trend has expanded to other industries, including aerospace [4], automation [5], marine [6], healthcare [7], energy and others [8]. The energy sector, in particular, is beginning to explore the potential of this technology [8]. The digital twin technology promises better energy management and optimization, better servicing and maintenance, energy-efficient design, evolution of existing sites, integration with locally and regionally generated renewable energy [9], cost-effectiveness, and ease of use [10]. For instance, in Ref. [11], we can find a description of the TwinERGY project which is a typical/practical example of a digital twin application in the energy sector. In this particular case, intelligent digital twins are integrated into the energy management system of a residential buildings to help optimize energy demand response while improving the thermal comfort of the occupants. Similar use of intelligent digital twin for energy management can be found in the other recent literature. For instance in Refs. [12–14] and [15], intelligent digital twins are adopted to help improve energy consumption in different contexts. However, the majority of these applications as seen in the literature are applied on a stand-alone basis and mostly do not involve the cooperation of multiple digital twins.

As studied in the field of collaborative networks, collaboration has been identified as a process by which entities come together to share information, resources, and responsibilities to jointly plan, implement, and evaluate activities aimed at achieving some common goals [16]. Collaboration not only promotes mutual benefit but also enhances the capabilities and competences of the actors involved. It is recognized as one of the core enablers of Industry 4.0 [17], a pillar of the digital transformation [18], central to society 5.0 [19], integral to the smart grid [20], relevant in the Internet of Things [21], Cyber-Physical Systems, Digital Twins [22], etc. In the energy sector, collaboration has been suggested as a potential mechanism for facilitating efficient decision-making/choices [23] and promoting sustainable energy consumption behaviors [24]. Recognizing this background, this work proposes the concept of collaborating digital twins to be explored in the contest of RECs.

As with many emerging concepts, there is currently no clear, consistent and consolidated definition of the "digital twin" concept and what it is comprised of. Available definitions are currently sector specific [25]. However, the base idea involves three elements: (a) the real (physical) space, (b) the virtual space(s), and (c) a linking mechanism connecting the real space and the virtual space(s) [26]. From another perspective, IBM in Ref. [27] describes a digital twin as "*a virtual representation of an object or system that spans its lifecycle. It is updated from real-time data and uses simulation, machine learning, and reasoning to help decision-making*". In line with IBM, Amazon Web Services (AWS) [28] also posits that "*digital twins can be used to leverage real-time data supplied from sensing devices on a physical object to simulate behaviours and track operations throughout the object's lifecycle*". The proposers of AWS further state that many real-world objects can be replicated with digital twins, from individual factory machinery to complete installations like wind turbines and even entire cities. Using digital twin technology, it is possible to monitor the performance of an asset, spot potential problems, and make better maintenance and lifecycle decisions. Furthermore, given the increasing amounts of intelligence currently being integrated into digital twins, their potential is becoming almost endless [27]. Digital twins can continue to improve products, enhance services, and streamline operations, as they can continuously acquire new data for enhanced decision-making [27]. In this line, an Intelligent Digital Twin (IDT), according to Ref. [29], includes all the attributes of a digital twin, and is further endowed with artificial intelligence functionalities, making it an autonomous system.

Aligned with these trends, the objective of this work is twofold:

(a) To propose an architecture for a collaborating digital twin (CDT) suitable for RECs, using the IDT architecture as the base. To achieve this, we identified the key architectural attributes of IDTs from the literature, through a mini-literature review. We then extend the identified common attributes of the IDT architecture to encompass "collaborative intelligence", thus adding the capability for these digital twins to engage in collaborative endeavors. This type of digital twins can be understood as collaborative digital twins (CDT). We further suggest that a CDT in this sense is a type of IDT that takes a collaborative approach to problem-solving. The scientific field of collaborative networks [30] has contributed a repository of rich literature, that suggests how collaborative mechanisms can be useful in managing energy ecosystems. According to Ref. [31], collaboration can provide agility and mutual benefits to the ecosystem and its participants and can increase the ecosystem´s survivability and dynamic response in turbulent times. To illustrate the feasibility of the CDT concept, the case of the Cognitive Household Digital Twins is, therefore, studied.

(b) To integrate IoT technology into the Cognitive Household Digital Twin (CHDT), as introduced at the IFIP IoT 2022 conference [21]. This article in fact expands the initial paper presented at this conference.

To help pursue these objectives, the following research questions are considered:

- *What architectural framework is suitable to support the conceptualization of a collaborative digital twin (CDT)?*
- *How can the CDT concept be demonstrated and assessed in renewable energy communities?*

Subsequent sections of this article are as follows: Sect. "Related Work and Background Knowledge" focuses on related work and background knowledge. In Sect. "Related Work and Background Knowledge", a mini-literature review on IDTs is conducted and used as a baseline to propose the architectural frameworks for the CDT. The functional requirement of the CDT is also discussed in this section. In Sect. "Cognitive Household Digital Twin", the Cognitive Household Digital Twin is presented in detail. Section "Discussion of Simulation Outcomes" is devoted to the discussion of some preliminary outcomes using a prototype model. Finally, in Sect. "Limitation of the Model", we draw some conclusions, and provide some recommendations for future work.

Related Work and Background Knowledge

Although the concept of digital twin (DT) is relatively recent, several application initiatives are emerging in the energy domain. For instance, in Ref. [32], a household data-driven multi-layer digital twin that aims to mirror actual energy consumption of households is proposed. Another study described in Ref. [33] also proposed a forecasting approach in which the DT of a physical household can use data from the physical twin to forecast the energy consumption for the next day. Similarly, in Ref. [34], a DT-driven technique was adopted to improve the energy efficiency of indoor lighting based on computer vision and dynamic building information modeling (BIM). A case study reported in Ref. [35] proposed a battery energy storage system digital twin that forecasts the state of charge by applying artificial intelligence. Another novel DT-based day-ahead scheduling method is proposed in Ref. [36]. In this case, a deep neural network is trained to make statistical cost-saving scheduling by learning from both historical forecasting errors and day-ahead forecasts. Nevertheless, the combination of collaborative facets with AI mechanisms in digital twins is still in its infancy [8, 21]. Since we aim at introducing collaborative mechanisms in the energy ecosystem, a brief overview of collaborative networks follows. Some background on simulation approaches is also briefly introduced.

Collaborative Networks

The literature on collaborative networks (CNs) has witnessed significant growth over the past 2 decades [37]. This expansion can be attributed to the multitude of challenges faced by today's society in its pursuit of the "digital transformation" agenda, which aims to transition our society into a digitalized one, namely Society 5.0 [19]. This agenda seeks to infuse intelligence into all aspects of technology and foster the hyperconnectivity among millions of organizations, individuals, and things. With the convergence of virtual and physical spaces in the realm of Cyber-Physical Systems and the Internet of Things, we can anticipate future scenarios in which a vast number of networked actors, smart devices, intelligent systems, and ecosystems coexist and collaborate. To ensure the effectiveness, benefits, and reliability of this merging synergy, the involved parties must learn to collaborate in a trustworthy manner that benefits all participants. The scientific field of CNs involves the development of concepts, mechanisms, and models that support and comprehend the challenges of collaboration in such settings.

Models, mechanisms, and tools from the field of CNs emerged as promising enablers in the context of digital transformation and have subsequently been used to tackle challenges in various domains. According to Ref. [38], collaboration is inherently advantageous for all parties involved, which provides the rationale and driving force behind pursuing collaboration in a digitalized and hyperconnected society. In addition, according to Ref. [38], collaboration is a process through which a group of entities mutually enhance their capabilities. It involves collectively addressing a problem, forming an integral part of the collaborative procedure. Collaboration not only strengthens an organization's ability to compete with comparable entities but also enhances their resilience in times of turbulence.

Types of collaborative networks: Referring to Fig. 1, it is evident that numerous types of collaborative networks currently exist in various domains. This research work focuses on exploring several emerging collaborative forms that are relevant to the energy context. The following paragraphs provide a brief overview of some of these typical classes of collaborative networks [13, 21]:

- *Virtual Enterprise (VE):* which refers to a temporary alliance of enterprises that come together to share and leverage competencies and resources in order to (better) respond to business opportunities. These alliances are facilitated by computer networks, which enable seamless collaboration and information sharing among the participating entities.
- *Virtual Organization (VO)*: a network similar to a virtual enterprise, but with a broader scope that includes various types of organizations beyond for-profit companies. In this context, a Virtual Enterprise can be considered as a specific case of a Virtual Organization. Situating the CDT concept in a REC environment, a temporary VO can be constituted of CDTs which are interested to pursue or achieve some specific goal(s). These CDTs could come together and form an alliance with the objective of seizing a business opportunity or achieving a common goal. In a REC environment, business opportunities or goals may include aggregating surplus energy generated by the community and selling it to the grid. Another potential business opportunity/goal could involve grid

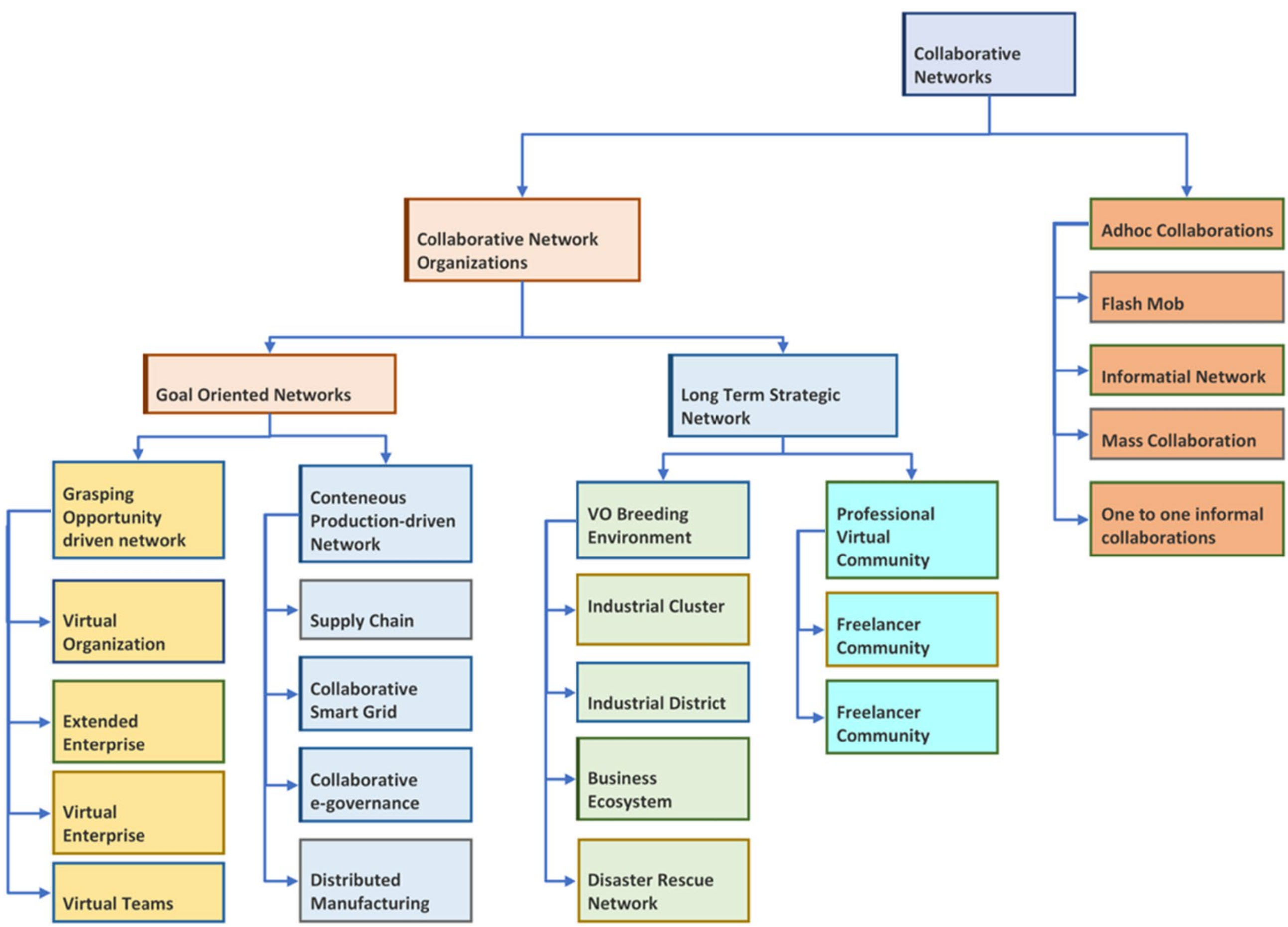


Fig. 1 Types of collaborative networks (based on [26])

management strategies, particularly during peak periods when the grid is congested and the need to shed some loads becomes necessary. In such cases, CDTs can contribute to the management strategy by deferring the use of their "deferrable loads." Deferrable loads are household appliances such as washing machines, dishwashers, and clothes dryers that can have their usage postponed to a later time without significantly affecting the service quality they provide to the user.

- *Dynamic Virtual Organization*: a sub-class of VO that is established quickly in response to a short-term business opportunity. This VO can be dissolved when the short-term objective/goal has been achieved. In the context of collaborative digital twins within a REC, the formation of VOs, as described earlier, is proposed to occur in a dynamic manner. This means that the creation of a Virtual Organization becomes necessary only when a viable business opportunity arises. These opportunities may have varying lifecycles and require prompt response times, necessitating an agile and adaptable approach. The capability of CDTs to dynamically form VOs to pursue these opportunities and having them dissolved when the opportunity/goal is achieved is key to the CDT concept.
- *VO Breeding Environment (VBE)*: a concept that represents a long-term association (also known as a cluster) of organizations and their supporting institutions, that have both the ability and the desire to cooperate through the establishment of a long-term "base cooperation agreement" and the adoption of a common or interoperable infrastructure. Jointly agreed business practices also characterize this class of network. When one member (e.g., the community manager), acting as a broker, identifies a business opportunity, some members of the VBE whose interest are in line with the opportunity can come together to form a coalition, i.e., a VE/VO to respond to that opportunity. In the energy context, a REC can be considered as a type of a VBE where the participating households have expressed their desire and agreement to cooperate and jointly pursue some common objectives/goals. Such agreement could be made between the physical households within the REC, however, decisions relating to the implementation of these goals shall be carried out by the respective CDTs on behalf of the physical households based on some level of delegation, assigned by the user. This delegation empowers the CDTs to make autonomous decisions and take actions in line with the agreed-upon objectives of the REC, while still representing the interests and preferences of the participating households.
- *Business Ecosystem*: is a class of collaborative network that falls under the sub-class of long-term strategic networks, more specifically a sub-class of VBE. It is defined in Ref. [39] as "a long-term strategic collaborative network similar to a cluster or industry district." According to the definition provided in Ref. [39], a business ecosystem draws inspiration from the mechanisms of biological ecosystems. It aims to preserve local specificities, traditions, and culture while frequently benefiting from government incentives at the local level. This type of ecosystem fosters collaboration among diverse entities and promotes synergistic relationships among different sectors to drive economic growth and development. Through the lens of collaborative networks, the organization of a REC can be viewed as a form of a business ecosystem. The REC involves the collaboration and coordination of various stakeholders, including households, businesses, local government entities, and renewable energy generation units, within a specific geographical region. Thus, we can refer to collaborative energy ecosystems. The analysis of the REC as a business ecosystem helps identify opportunities for economic growth and the establishment of sustainable energy practices within the community and the wider geographical region.

Other examples of CNs are illustrated in Fig. 1 and described in detail in Refs. [13, 21].

A Multimethod Simulation Approach

In the fourth section of this work, a simulated prototype of a CDT, namely the Cognitive Household Digital Twin is presented. The prototype is developed using a multimethod simulation approach. This simulation technique involves the integration of three simulation paradigms namely system dynamics, discrete event and agent-based simulation.

The traditional approach to simulation and modeling has often relied on single-method endeavors. However, research in the literature has revealed significant limitations to this approach, particularly when dealing with complex systems that exhibit diverse structures and dynamics. Understanding how a real-world system is structured and how it can be adequately reflected in a model is crucial for conducting effective simulations [40]. Recognizing the limitations of single-method simulations, researchers have proposed a multimethod strategy for simulation, as discussed in works such as Refs. [26, 41] and [43].

As discussed in Ref. [42], a multimethod simulation involves integrating two or more simulation techniques into one. The popularity of this approach has seen significant growth over the past 2 decades, as noted by the authors in Ref. [43]. The benefit of a seamless integration of different modeling and simulation techniques is that it allows the modeler to overcome the limitations of a single-method and capitalize on the strengths of each method in the multimethod approach. Combining diverse techniques can produce more efficient and manageable models without relying on workarounds or compromises. According to Ref. [44], three prominent simulation methods are often combined to produce a multimethod model: system dynamics, multi-agent systems, and discrete event modeling.

System Dynamics Modeling. A technique that is based on the premise that the behavior of a system is influenced by the interplay between its constituents and their interaction with the environment. This technique recognizes that these constituent elements affect each other within a dynamic and complex environment over time. This modeling technique is often used to analyze complex, non-linear processes and inter-element synergies. According to Ref. [44], system dynamics facilitates the integration of multiple perspectives of a dynamic and complex system into a software model, making it easier to analyze and explore. By adopting a modeling technique that employs a variety of modeling elements such as stocks, feedback, flows, and delays, it is possible to reduce complex problems involving numerous variables or factors to a more manageable dynamic process.

Multi-agent Systems. The area of multi-agent system (MAS) has gained considerable popularity in recent years, finding applications in numerous emerging domains, including artificial intelligence, distributed computing, software engineering, smart grid control and simulation, e-commerce, adaptive virtual environments, and social networks [5]. MAS has been successfully used to address a wide range of problems spanning numerous disciplines. According to Refs. [45] and [46], MAS can serve as the basis for a simulation technique used to model autonomous, dynamic, and adaptive systems based on three fundamental concepts: agency, dynamics, and structure. The concept of *agency* implies that agents are autonomous entities with distinct properties, behavior, and possible goal-directedness. *Dynamics* refers to the growth, transformation, and evolution of both the agents and their environment. The interaction of agents results in the formation of *structure*. Agents inhabit an environment, perceive it, and choose their actions based on the current state of the environment, their own state, and predefined decision rules. Agents may have explicit objectives of minimizing or maximizing some parameter, in addition to the ability to learn and adapt.

Discrete Event Modeling. Discrete event systems (DES) are discrete-state and event-driven systems in which the change of state depends entirely on the occurrence of discrete events over time. Examples of DES include manufacturing systems, service systems such as hospitals, transportation systems such as urban traffic networks, communication systems such as wireless networks. Discrete event modeling techniques are mainly useful for process modeling. Processes such as queueing, scheduling, prioritization, delays, seizing a resource, and releasing a resource can be modeled in an efficient way using this modeling technique.

An example of a simulation environment that combines these three modeling approaches is the AnyLogic simulation software [47], a tool that was adopted in the development of the prototype used for this study.

Proposed Architecture for the CDT

To develop the architectural framework for the CDT, we followed a three-step approach. First, we adopted the simple yet comprehensive definition of "digital twin" from the Advanced Manufacturing Research Centre (AMRC) [25]. The rationale for adopting this definition is that it is simple and can serve as the base on which a more complex definition can be proposed. Furthermore, it provides a "functional output" component which meets one of the key requirements, expected of the CDT. Second, we suggested and discussed the functional requirements of the proposed CDT based the available literature. Third, we conducted a concise literature review to identify the key architectural layers of the intelligent digital twins as recorded in the other works. Based on the outcome of these three analyses, the architectural framework for the DT is proposed.

Definition of the Digital Twin from the Perspective of AMRC

In Ref. [25], a digital twin is defined as "*a live digital coupling of the state of a physical asset or process to a virtual representation with a functional output.*" According to this definition, there are 6 functional components of the digital twin:

- *Live (data):* when state data are accessible in a time window near enough to the underlying event's timing.
- *Digital coupling (medium):* a digital carrier medium being used as the transmission mechanism between the data source(s) and the data consumption method(s).
- *State:* the specific state that the physical item or process is in at a given time.
- *Physical asset or process*: an entity that has value in terms of the economic, social, or business.
- *Virtual representation:* a description or logical model that is similar to the real asset or process it represents.
- *Functional output:* data sent to a system or human observer that can be used to produce value.

Functional Requirements and Expected Behaviors of the CDT

Insights from the domain of Requirement Engineering show that the functional requirement of a system is the concept that describes a system's requirement, purpose, aim, functionality, constraint, quality, behaviors, condition, or capability [48]. The functional requirements for the CDT are derived from some earlier studies conducted in Refs. [23] and [24]. Gleaning from these works, the requirements for the proposed CDT are expected to endow the CDT with "cognitive" intelligence and "autonomous decision-making" capabilities that could enable it to participate in collaborative ventures and endeavors within its prescribed ecosystem. Thus, the proposed functional requirements involve:

- *Cognitive intelligence*: The CDT is expected to exhibit three kinds of cognitive intelligence:
- *Cognizant of its environment*: the CDT is expected to be cognizant of (i) all community goal(s)/business opportunities in the past, present and future, and (ii) the schedule(s) associated with each business opportunity that it has accepted to participate in.
- *Cognizant of the self*: the CDT is expected to have some knowledge about itself such as (i) knowing its status as a consumer or prosumer, (ii) knowing the preferences of the user (the value system) of the physical household), (iii) being cognizant of which of the value system(s) are active and which value systems are dormant at any given time, (iv) be cognizant of its acceptance/decline to participate in a current or future coalitions, (v) have historical records of all coalitions that it has accepted, declined or participated in the past, and (vi) the capacity of installed PV/battery storage system if it is a prosumer.
- *Collaborative/intelligent algorithms*: capability enabling the CDT to execute intelligent algorithms that facilitate collaborative decision-making.
- *Autonomous decision-making*: comprising decision and actions carried out by software agents on their own, based on data, to achieve some specific goal(s). In the context of the CDT, the decision will be carried out by the CDT themselves, according to the level of delegated responsibilities. The sources of data for decision-making may include (i) the current state of the virtual representation, (ii) input from the user, and (iii) input from other sources such as the community manager. The expected objective is to participate in the formation of coalitions (i.e., VOs) that are meant to achieve some collective goal(s) or business opportunities of the community.
- *Functional output*: supporting collaborative service provision. The functional output will involve signals that can be used to control actuators or smart appliances that are located within the physical space. These control capabilities enable the CDT to control its appliances in line with collaborative endeavors.

A Brief Review of the Attributes and Number of Layers of Intelligent Digital Twins

To help in the proposition of a suitable architecture for the collaborative digital twin, we performed a succinct literature review from 8 knowledge areas to ascertain what the literature suggests about the architecture of intelligent digital twins (IDT). These different knowledge areas and domains of application enabled us to analyze the architecture of intelligent digital twins from a diversified perspective. The rationale for reviewing IDT proposals stems from the fact that our proposed CDT is expected to exhibit some level of intelligence to be able to engage in collaborative endeavors. In all considered cases, the developed digital twin is described as having some level of intelligence. The outcome of this brief review indicates that there is no widely accepted framework or architecture for the IDTs. As shown in Table 1, the number of layers that is found varied from 3 to 5. Furthermore, although most of these layers are similar in terms of their functions, the terminologies that are used to describe them differ from one application to another. However, a key finding as shown in Table 1 is that some attributes are found to be common in all the IDTs, irrespective of the number of layers or domain of application.

As shown in Table 1, column 4, there are generally 6 common attributes associated with the architecture of the IDTs: (a) physical layer, (b) data acquisition and synchronization layer, (c) database/information repository layer, (d) intelligent application/algorithm layer, (e) digital twin, and (f) service layer.

Proposed Architecture for the Collaborative Digital Twin

For the energy ecosystems, we propose a 4-layered architecture of the CDT as shown in Fig. 2. This architecture is derived from the merger of the definition of the digital twin in Sect. "Definition of the Digital Twin from the Perspective of AMRC", the functional requirement as suggested in Sect. "Functional Requirements and Expected Behaviours of the CDT", and the attributes and number of layers derived from the outcome of the literature review that is conducted in Sect. "A Brief Review of the Attributes and Number of Layers of Intelligent Digital Twins". The proposed architecture comprises the following layers:

– *Physical layer:* which refers to the real-world physical system or product which is replicated by a virtual Digital Twin. In the context of RECs, the physical layer may constitute the physical energy assets such as generation units, household appliances and energy storage systems.
– *Data collection and IoT Gateway:* the interface between the physical and cyber layers of the ecosystem. The IoT

Table 1 Outcome of a mini-literature review concerning intelligent digital twins

Domain of application and reference	Number of digital twin layers	Description of the layers	Common attributes
Intelligent search and rescue in the Maritime Industry [49]	4 Modules	Unmanned perception module	Physical asset
		Communication link module	Data acquisition and synchronization layer
		Command center module	Intelligent application/algorithm layer
		Operator's module	Service
Intelligent transportation system [50]	4 Layers	Physical layer	Physical layer
		Data layer	Database/information repository layer
		Connection layer	Data acquisition and synchronization layer
		Services layer	Intelligent application/algorithm layer
Intelligent workshop path planning [51]	3 Layers	Physical workshop	Physical asset
		Digital twin workshop	Digital twin
		Path planning	Services layer
Intelligent operation of special vehicles [52]	3 Layers	Data collection and transmission layer	Data acquisition and synchronization layer
		Data treatment layer	Database/information repository layer
		Digital twin layer	Digital twin
Intelligent diagnosis of reactor systems [53]	5 Layers	Application layer	Service
		Functional layer	Service
		Algorithm layer	Intelligent application/algorithm layer
		Database layer	Database/information repository layer
		Data layer	Data acquisition and synchronization layer
Intelligent reproduction, predicting and control of traffic [50]	5 Layers	Virtual part	Physical layer
		Services	Data acquisition and synchronization layer
		Data	Digital twin
		Physical part	Database/information repository layer
		Connections	Intelligent application/algorithm layer/ service layer
Providing guidance for developing digital twin architectures [54]	3 Layers	Physical twin	Physical asset
		Communication/integration medium	Data acquisition and synchronization layer
		Digital twin	Digital twin
Intelligent road inspection and maintenance [55]	4 Layers	Application layer	Intelligent application/algorithm layer
		Server layer	Service layer
		Database layer	Database/information repository layer
		Physical later	Physical asset

components would be responsible for collecting data from the physical asset, and the gateway would enable seamless exchange of data between the cyber and the physical spaces. IoT components may be comprised of sensors and actuators that allow the CDT to control the connected physical asset. This layer is also responsible for the synchronization of "live" data between the physical assets that are located in the physical space and the digital replica that is also located in the cyber space.

– *Information/data repository*: all the data that are collected from the physical asset are stored in dedicated databases in this layer. In the context of the CDT, three types of data can be stored:

- *Data from physical assets*: containing information that is collected form the physical asset. There can be two types of information:

- *Historical data*: a database containing historical data of the physical asset. This database can provide the CDT with historical information about past operational states or behaviors of the physical asset.
- *Live data*: This database provides the CDT information about the present operational state of the physical asset.

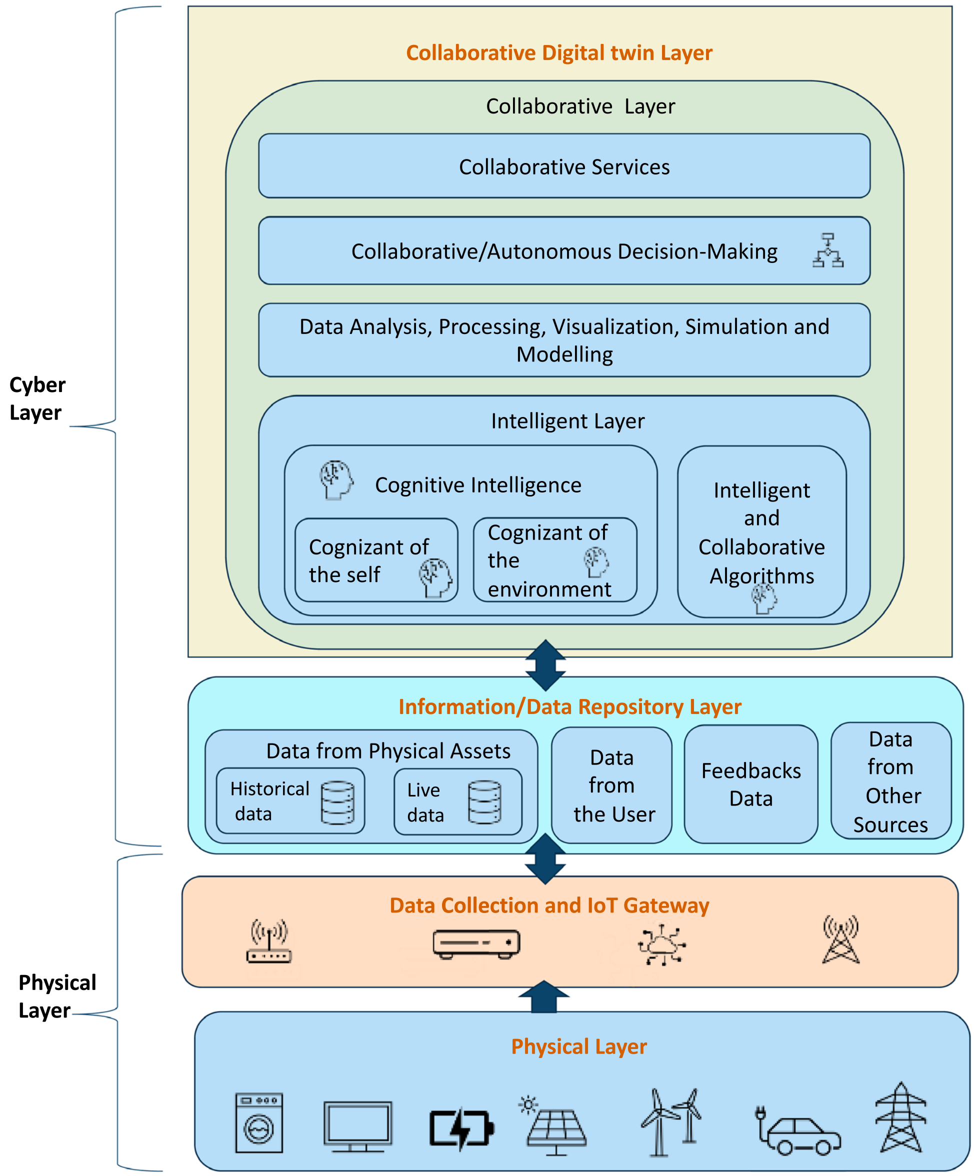


Fig. 2 A 4-layered architecture of the collaborative digital twin

- *Data from the user*: the CDT is proposed to have a user interface through which the user can provide its CDT with some information concerning preferences and priorities in relation to the types of business opportunities in which it is willing to participate, and which one is of higher or lower priority.
- *Feedback data*: every decision that is executed by the CDT would require some sort of feedback to ascertain if it was successfully carried out or not. This information gives the CDT cognizance of the outcome of its decisions and also guide it in subsequent decision-making processes.
- *Data from other sources*: as communication and information exchange are paramount aspects of every collaborative endeavor, the CDT requires access to information that is being shared across the community network. Such information may include invitations to participate in collaborative coalitions, schedules of business opportunities/goals, the availability of incentives, information about emergencies, etc.

- *Collaborative digital twin (CDT) layer*: which refers to the virtual replica of the real-world physical system or product. In the context of RECs this layer would represent the digital replicas of households in the REC environment. The key component of this layer is the collaborative layer which accommodates several sub-layers. Discussed below are the components of the CDT layer.
- *Collaborative layer*: responsible for the cognitive intelligence that facilitates the collaborative capabilities and

behaviors of the CDT. This layer is comprised of 4 key components:

- *Collaborative services*: featuring an output that would be used to provide different kind of collaborative services that are provided by the CDT. In the context of RECs such collaborative services may include participation in different coalitions that are goal specific, such as grid management and energy vending coalitions.
- *Collaborative/autonomous decision-making*: the center for decision-making. The CDT is capable of executing decisions that are motivated by collaboration. This is due to its autonomous capabilities. The cognitive intelligence enables the CDT to be autonomous, therefore, taking decision that is in the best interest of itself. However, these decisions are also made in line with the goals of the community and also in a collective manner. For instance, the decision to defer the use of certain appliances in line with the community objective of a grid management opportunity requires the CDT to autonomously switch the appliances off and on at the designated times, in line with the community schedule.
- *Data analysis, processing, visualization, emulation and simulation*

This layer provides the CDT with soft, real-time, and historical information about the physical twin. This layer can be equipped with different kinds of software, such as data analytics software for data analysis and processing, emulation software that can help model current behaviors, and simulation software that can predict future or potential behaviors. Depending on the kind of software embedded in this layer, it may also provide the CDT or user with a graphical 3D visualization of the physical twin.

- *Intelligent layer*: enables the CDT to exhibit intelligent attributes, namely:
- *Cognitive intelligence*: the capability of the CDT to have rational knowledge about itself as well as its changing environment, so that it can take decisions or actions autonomously in order to achieve its individual or collective goals. Cognitive intelligence may also help CDTs to improve their performance based on the acquired knowledge.

Cognizance of the self: the capability of the CDT to have rational knowledge about itself so that it can make autonomous decisions or actions in order to achieve its individual goals or improve its performance based on the acquired knowledge.

Cognizance of its environment: the capability of the CDT to have rational knowledge about its environment so that it can make autonomous decisions or actions in order to achieve its individual goals or the collective goals of the community. It may also improve its performance based on the acquired knowledge. As suggested earlier, collaboration could be a useful mechanism for problem-solving in the setting of a REC. In such cases, the REC members may have a problem or goal that they want to achieve collectively. For this endeavor to be successful, each CDT must be conversant with said objective/goal and be able to make autonomous and rational decisions in accordance with the common goal.

- *Intelligent and collaborative algorithms*: in general terms, an intelligent system can model certain types of human knowledge, competence, and reasoning in order to solve some specific problem(s). Any algorithm that is built on this idea and can help achieve these objectives can be considered an intelligent algorithm.

Collaborative Digital Twin Ecosystem

In this application context, it should be noted that a CDT cannot exist in isolation but rather in a collaborative environment, or ecosystem. Figure 3 illustrates a typical example of a collaborative digital twin energy ecosystem, where multiple CDTs can exist and collaborate in the same environment. This ecosystem consists of the following components: generation units, municipalities, distribution network, small/medium businesses, and local residents, which can be simple consumers or also producers (prosumers). The ecosystem is comprised of 4 layers:

- *Physical layer or grid component*: This layer is the part of the ecosystem where the physical assets of the community are located. The physical layer constitutes all the physical components of the renewable energy community.
- *Data collection and IoT gateway layer (with sensors and actuators)*: The layer is part of the architecture that lies between the physical layer and the cyber layer. It consists of sensors that collect data from the physical layer and transmit it to the corresponding CDT. These sensors are responsible for updating the CDT on the state of operation of the physical asset within the ecosystem. These sensors will have the ability to inform the CDT if the asset is malfunctioning, offline, or damaged. This layer also accommodates actuators that can be used to control the physical asset.
- *Collaborative digital twin layer*: This is the layer of the architecture where the intelligent/collaborative digital twins are hosted. This could also be known as the digital twin environment (DTE) which, according to Ref. [56], is the virtual representation of the physical environment within which the community components exist.

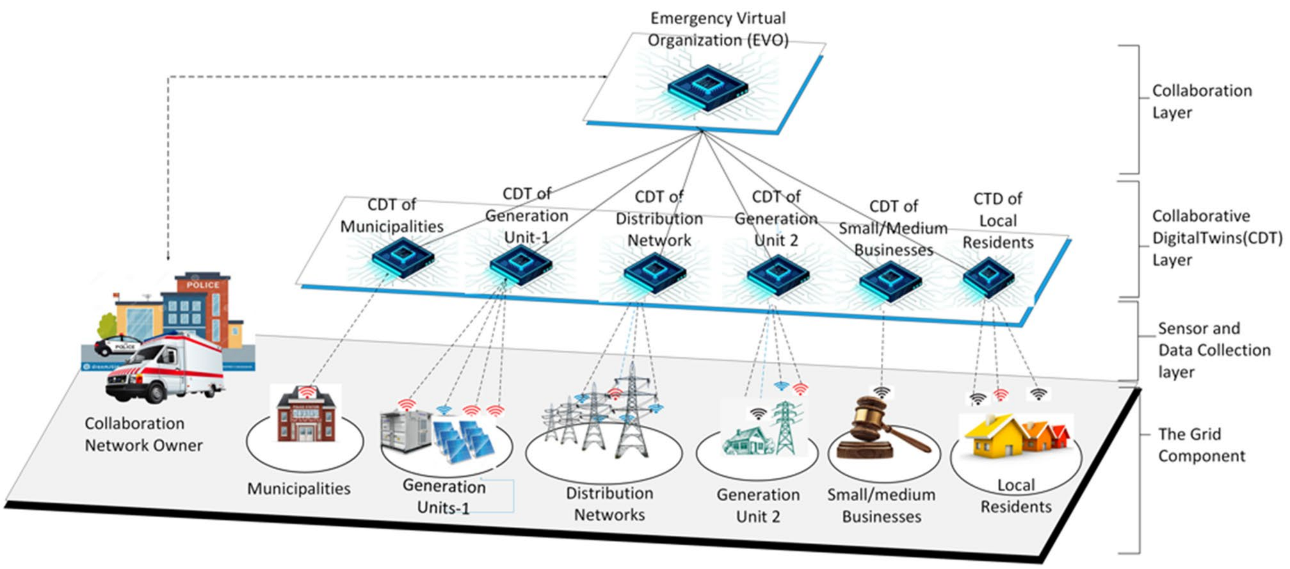


Fig. 3 Collaborative digital twin ecosystem

- *Collaborative network organization layer or collaboration layer*: This is a layer, probably in the cloud, where collaborative endeavors are pursued.

Collaborative network owner/user: This is the entity within the ecosystem that has ownership or control over the formation and dissolution of a virtual organization (VO). The VO may as well include emergency service providers, City Hall, or third-party entities that may play a relevant role in the information-gathering and collaborative processes.

Cognitive Household Digital Twin

In this section, we briefly introduce a specific type of collaborative digital twin, namely the Cognitive Household Digital Twin (CHDT). CHDTs will "inhabit" a collaborative energy ecosystem named Collaborative Virtual Power Plant Ecosystem (CVPP-E).

Concept of Collaborative Virtual Power Plant Ecosystem (CVPP-E)

The Collaborative Virtual Power Plant Ecosystem (CVPP-E) concept is the outcome of combining ideas and mechanisms from the disciplines of collaborative networks and Virtual Power Plants (VPPs). The CVPP-E, as seen from the perspective of CNs, can be perceived as a type of a business ecosystem which is constituted of prosumers who have solar panels installed on their roof-tops and are able to share, store or sell their surplus energy with other community members. The community may have common interests such as sustainability, economic, social, and technological interests. The result of this synthesis is a type of REC that uses collaborative principles and mechanisms in its operation to ensure sustainable energy consumption and exchange, while exhibiting VPP characteristics, such as the ability to aggregate excess community energy and sell it to the grid. The CVPP-E represents the community environment in our model. This ecosystem is a kind of Virtual Organizations Breeding Environment or more specifically a business ecosystem [57] in which members approach energy use and exchanges collaboratively. As a result, members engage in collaborative efforts aimed at achieving some goals that can be shared by the entire community. A CVPP-E in the proposed formulation includes: (a) the community manager who promotes collaborative activities and behaviors. This manager also has access to external entities such as weather forecasting stations, the energy market, regulatory bodies, and distribution services operators (DSOs); (b) multiple user actors that may include prosumers and consumers; and finally, (c) a common community-owned energy storage system.

Notion of Cognitive Household Digital Twin

In the developed prototype, each CVPP-E actor is modeled as a software agent (implementation of digital twin) that mimics the traits and actions of the real actor. These software agents are designed to live in and interact with each other within a digital REC environment, namely the CVPP-E. A Cognitive Household Digital Twin (CHDT) represents a household unit in this environment. CHDTs are modeled to possess cognitive and collaborative intelligence, as described in the case of the collaborative digital twins in Sect. "Proposed Architecture for the CDT". CHDTs can make logical and independent judgments on behalf of their owners (owners of the physical households). Thus, we mimic the population of households in a typical community by aggregating several CHDTs. Using agent-based techniques, we simulate the uniqueness of each household as an autonomous software agent possessing distinct behaviors. Thus, the replica of a community having overall stochastic behaviors is modeled. In the implemented prototype, the decisions of CHDTs are based on the users' preferences, which are captured as their digital profile. The digital profile of a CHDT consists of (a) their value system, and (b) their delegated autonomy.

Value system: The value system represents the preferences, choices, and options of the physical twin that have been modeled in the CHDT. This informs the kinds of choices and decisions that the CHDT can make. Technically, the value system of individuals may constitute a spectrum of needs that may differ from one person to another, so the notion of value system allows the collective objective of the community to be achieved without compromising the individual user's preferences and expectations. Some examples of values systems discussed in previous studies such as Refs. [24] and [21] include:

a) *100% renewable sources*: For this type of value system, the owner's preference is to consume energy from renewable sources only. Any other source of energy that is not renewable is prohibited to this actor.
b) *Mixed energy sources*: For this case, the user considers the use of energy from mixed sources, which may include a mix of renewable and non-renewable sources. It may be possible for the owner to specify the preferred ratio of renewable to non-renewable sources.
c) *Free rider*: Technically, this is not a value system, rather it represents an instance where the owner is unable to define a value system.
d) *Cost savings*: This represents users whose priority is to reduce costs and, therefore, prefer to use certain appliances at times when tariffs are the lowest.
e) *Revenue or income*: This represents homeowners who want to engage in activities such as demand response actions to earn revenue or sell energy from their roof-mounted photovoltaic system (PV system) to earn additional income.
f) *Load management*: This value system represents owners who are willing to have some appliances (interruptible loads) able to be interrupted for grid load management purposes.

Delegated autonomy: The notion of delegated autonomy represents the specific instructions that a homeowner assigns to his/her CHDT to be followed in carrying out or executing his/her value system. In the prototype model, delegated autonomy is carried out using deferrable loads. These are appliances whose use can be deferred to a later time without affecting the quality of service (QoS) the appliance offers to the user. Three types of appliances can be delegated in the prototype: a washing machine, a dishwasher, and a clothes' dryer. Delegation can be accomplished by deferring (a) any one of the three appliances, (b) any two appliances, or (c) all three appliances.

CHDT decision-making process: Fig. 4 shows a BPMN diagram illustrating how decisions are made by the CHDTs. These decisions are based on several inputs from sources such as the community goal, the digital profile, data from the physical twin, and sources of influence. A source of influence in this sense can be perceived as exogenous or endogenous factors that can influence or alter the decisions of the CHDT. In a practical sense, this could be a form of incentive or reward that promotes pro-sustainable behaviors.

Testing the Control Capabilities of CHDTs

To illustrate the control capabilities of the CHDTs, we consider a scenario where a CHDT sends a series of control signals to switch appliances between the "on" and "off" states. Three appliances, namely a washing machine, a dishwasher, and a tumble dryer are controlled. Table 2 shows the time at which the control signals are transmitted and the corresponding control action that the signal is expected to achieve. Figure 5 shows the usage behavior of the three appliances without the control signals. In Fig. 6, we illustrate the usage behavior of the three appliances when the control signals are received by these appliances. The period between each "on" and "off" cycle is 10 h.

To further illustrate the decision-making and control capabilities of these CHDTs, we discuss in Sect. "Discussion of Simulation Outcomes" some outcomes from previous studies, which were conducted using two different scenarios. However, to better understand these case studies, it may be relevant to provide some insight into the prototype model that was used for the study. First, the prototype model is constituted of several sub-models that are integrated to function as a single model. This technique allows the modeling of different actors and systems that interact to enable the CVPP-E to realize its intended functionalities. Some of the sub-models are as follows:

(a) The PV and local storage sub-model (Fig. 7) which is used to model the embedded PV systems for prosumers.
(b) The embedded household appliances model (Fig. 8), which is used to model all embedded appliances. Nine appliances were considered in the model.

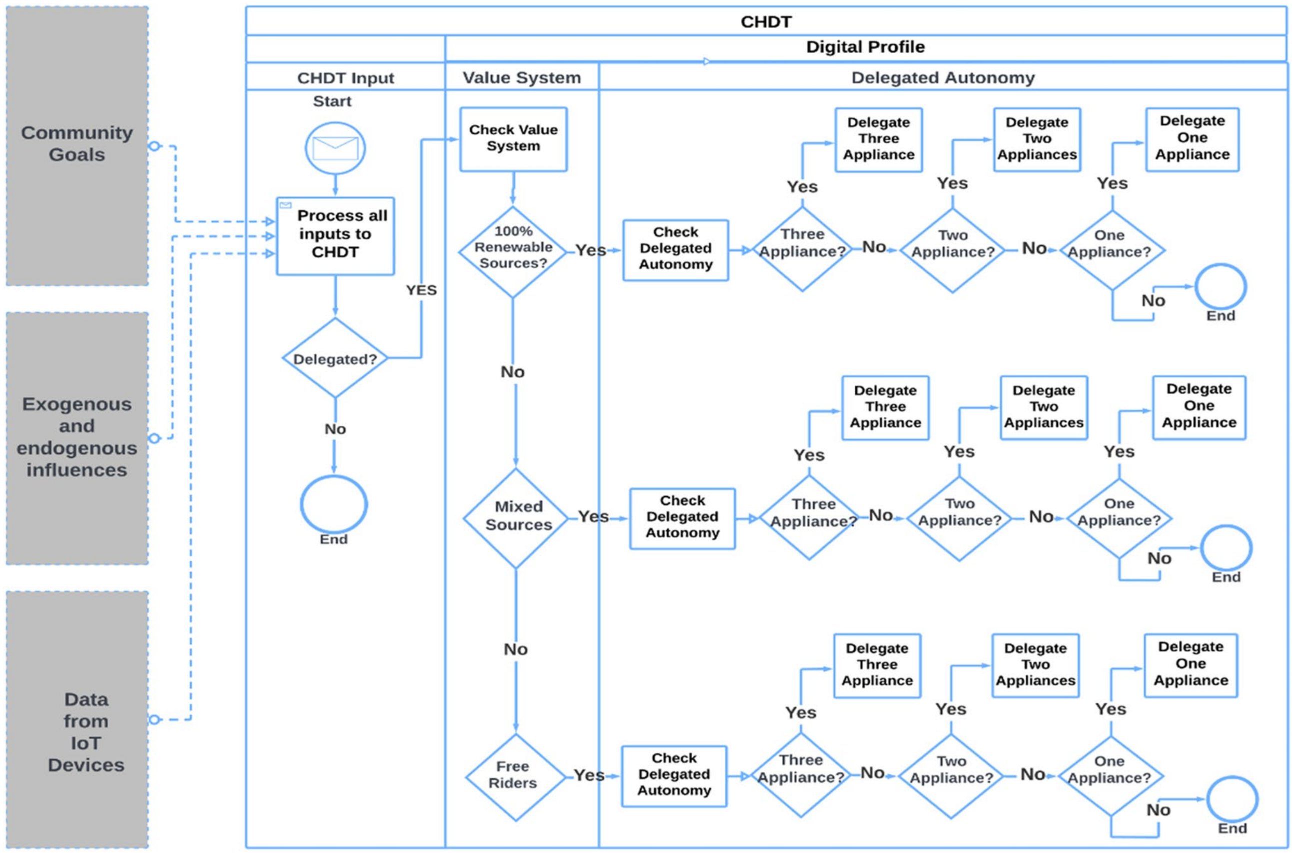


Fig. 4 A BPMN representation of the decision-making process of a CHDT

Table 2 Periodic control signals to test the control capabilities of CHDTs

	Time (hours)									
	20	30	50	60	80	90	110	120	140	150
Control action	Off	On	Off	On	Off	On	Off	On	Off	On

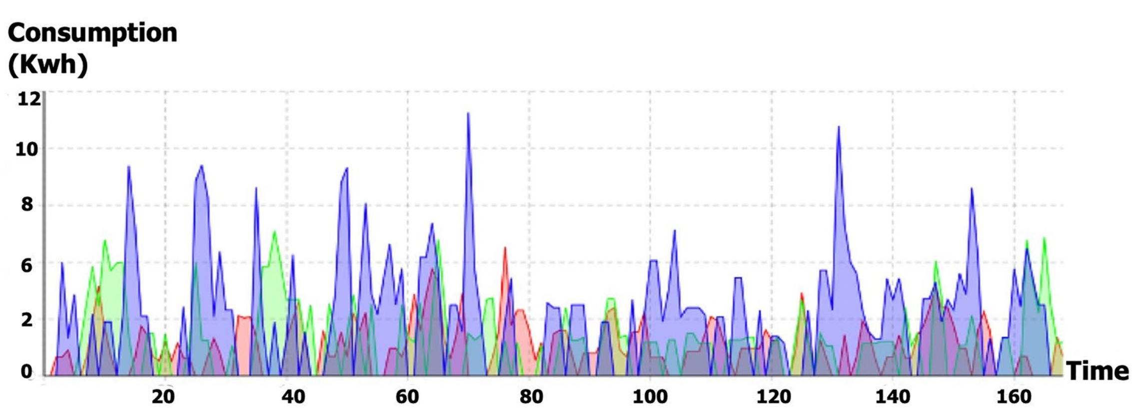


Fig. 5 Profile of three appliances without control signals

(c) The prosumer model (Fig. 9), which is used to model prosumers.
(d) The consumer model (Fig. 10), which is used to model consumers.

Depending on the intended use, a sub-model in AnyLogic [47] can be created using one of three modeling strategies. For example, all models that display dynamic behaviors, with continually changing parameters, are simulated using system dynamics modeling techniques. The photovoltaic system (PV system) and local storage sub-model, as well as the embedded household appliances sub-models, are examples of system dynamics models. The multi-agent system approach was also used to model the changing states (active and inactive states) of prosumer and consumer CHDTS. Finally, all aspects of the model that required the formation of an entity endowed with autonomous qualities were also modeled using agent-based modeling techniques.

Although the prototype model consists of several other sub-models, those shown in Fig. 13 to 14 form the core of the prototype. Discussed in the next section are the outcomes of some simulation studies.

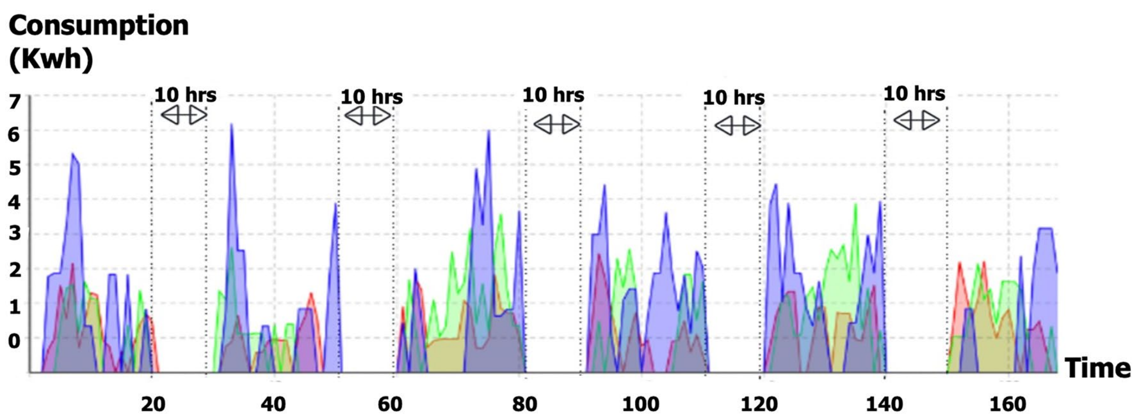
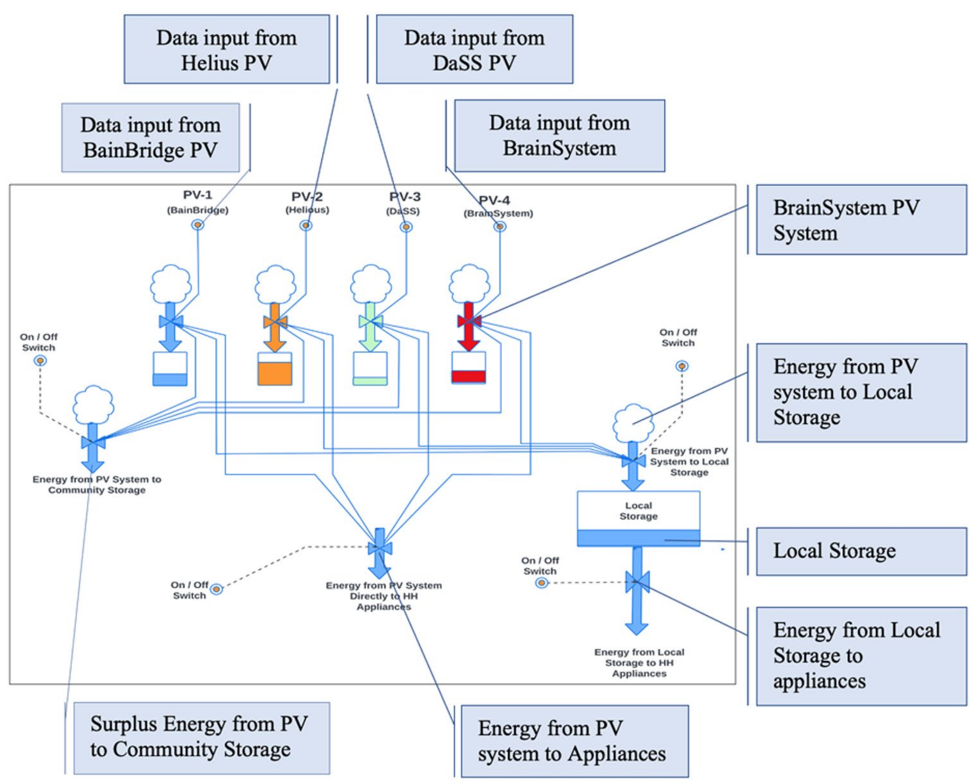


Fig. 6 Profile of three appliances with "On" and "Off "control signals

Fig. 7 An example model of a four PV-based system and a local storage



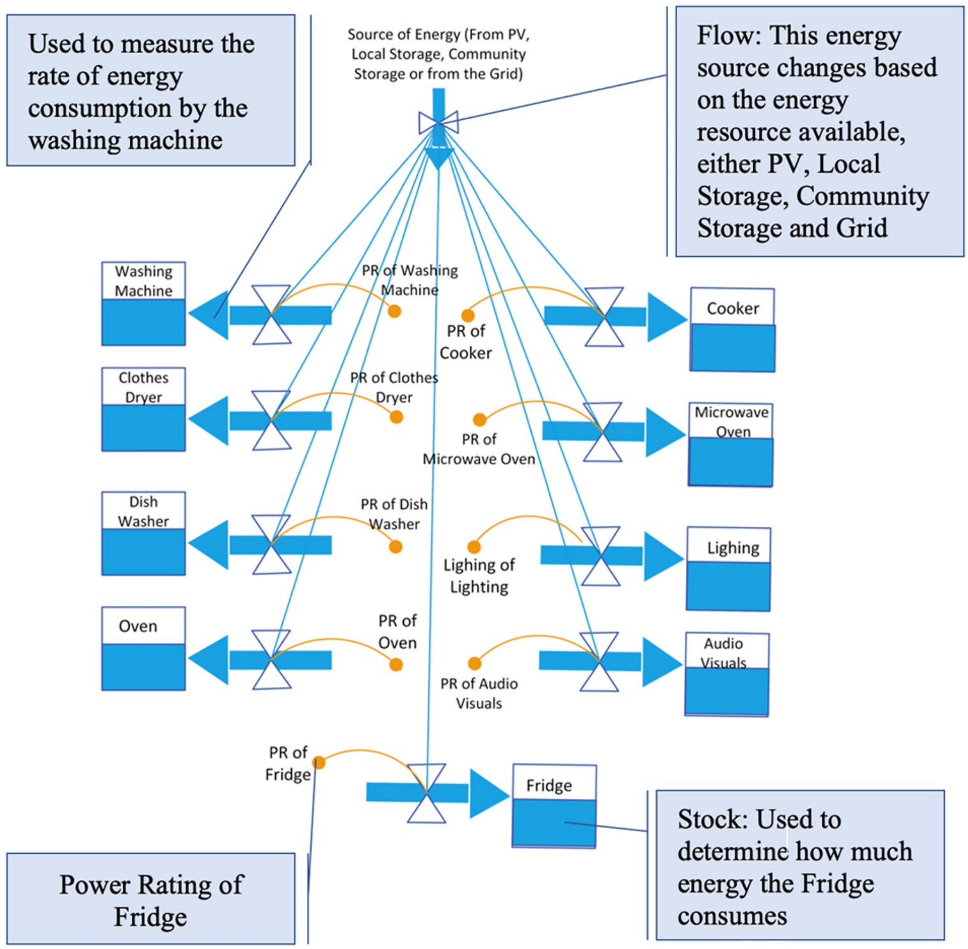


Fig. 8 A system dynamics model of the embedded household appliances

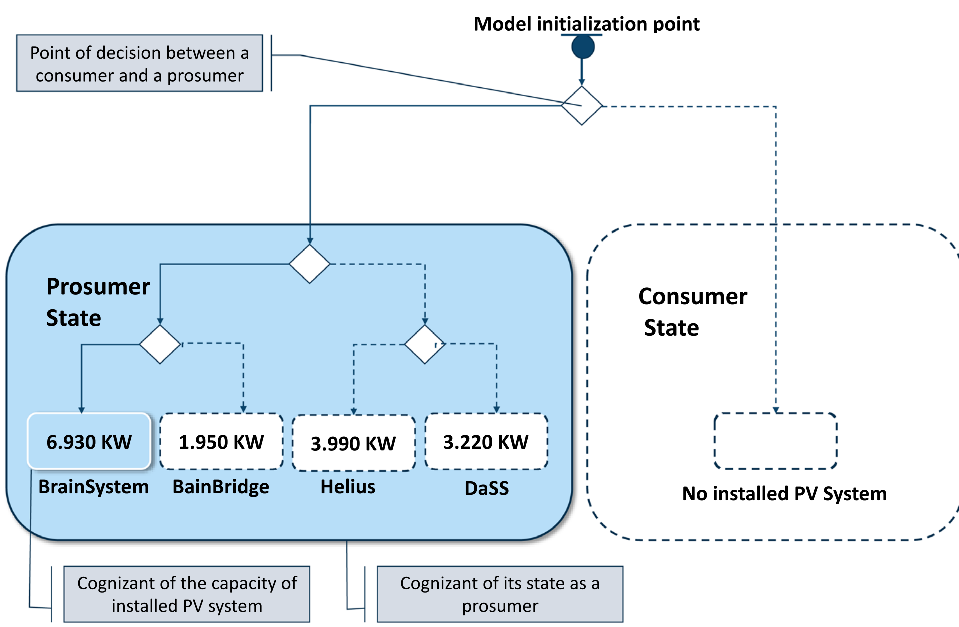


Fig. 9 An agent-based model of an active prosumer CHDT with an active 3.99 kW PV system

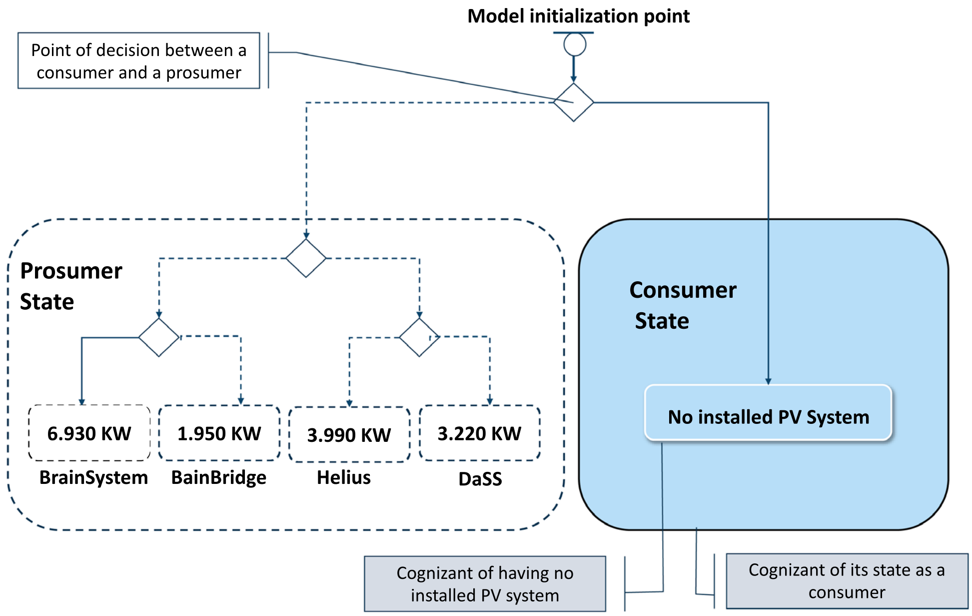


Fig. 10 An agent-based model of an active consumer with no installed PV system

Table 3 Parameters used to model the various household appliances [58]

Type of appliance	Annual power (kwh)			Peak periods		Number of wash cycles year
	Min	Average	Max	P1	P2	
Washing machine	15.00	178	700	5 am–4 pm	5 pm–2 am	284
Tumble dryer	64.25	497	1600	5 am–12 pm	6 pm–11 pm	280
Dishwasher	33.32	315	608	5 am–3 am	6 pm–2 am	270

Table 4 The population size of the various HH in the sample scenario

Scenarios		Degree of delegation	Number of delegated appliances	Percentage of CHDT population (%)	
				Delegated	Undelegated
1	High population of delegated CHDTs	Full	3	100	0
2	Low population of delegated CHDTs	Full	3	10	90
3	High population of delegated CHDTs	Full	3	90	10
4	High population of delegated CHDTs	Partial	2	90	10
5	High population of delegated CHDTs	Partial	1	90	10

Discussion of Simulation Outcomes

In this section, we present the outcome of some preliminary results obtained using the prototype model to study some selected scenarios. For this discussion, we consider two illustrative examples, namely modeling delegated autonomy and modeling mutual influences.

Case 1: Modeling Delegated Autonomy

In Tables 3 and 4, we show some selected scenarios that were used to test the CVPP-E prototype. The data shown in Table 3 were obtained from Ref. [58]. For demonstration purposes, Table 3 shows data from only three out of the nine household appliances that were embedded in each CHDT.

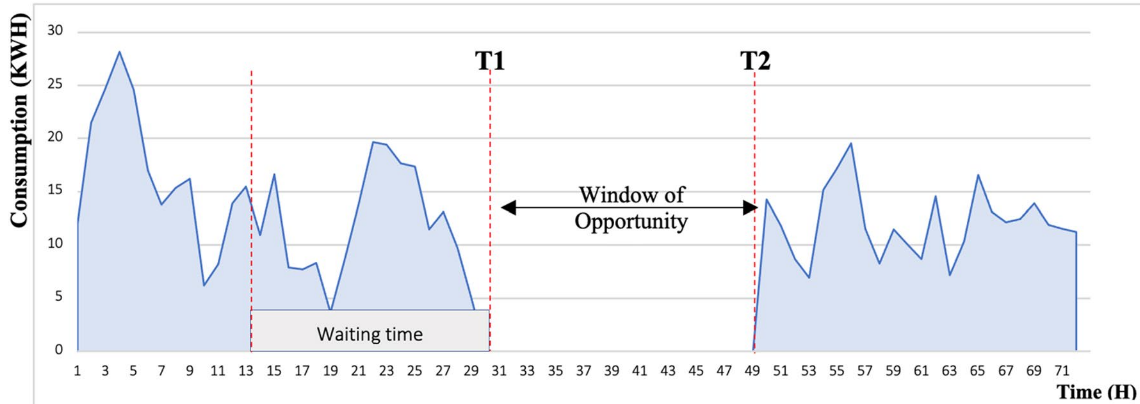


Fig. 11 The outcome of collective action behaviors for case 1 (Table 3)

These parameters were used to model the usage behavior of each of the appliances. Furthermore, in Table 4, we consider different scenarios of varying prosumer and consumer populations. For each scenario, we tested different degrees of delegated autonomy. Delegation in this sense means that the CHDT has been authorized by its owner to make some rational decisions on his/her behalf. In this example, the goal is to minimize community consumption within a certain period, namely the "window of opportunity" (Fig. 11) to reduce grid congestion. We tested different delegated autonomy options, i.e., delegating 1, 2, or 3 from any of the appliances mentioned in Table 3. In Fig. 11, we show the outcome of one scenario, i.e., scenario 1 from Table 4. This result shows that, within the window of opportunity, the CHDTs executed the control instruction (delegated autonomy) that consists of deferring the use of these appliances within the defined period (window of opportunity), thus resulting in zero consumption within the window.

Case 2: Modeling Mutual Influence of CHDTs

As initially reported in Ref. [59], the concept of mutual influence was explored. Under this scenario, the following parameters are assumed: (a) Positive influence: Uniform distribution (0, 2), (b) Negative influence: Uniform distribution (− 2, 0), (c) Frequency of transmission: Uniform distribution (0, 3) times per week, (d) Impact: Uniform distribution (0, 5) hours from the time the influence is received, (e) Decision constant ($\propto$) = 50. Details of other relevant parameters such as duration of use, appliance power rating, and frequency of use can be found in Ref. [59].

Table 5 describes two different cases, with different population sizes, that were considered. In these cases, the influencer CHDTs try to influence the "influencee" CHDTs to use the loads mentioned in Table 3 only when the available energy is from renewable sources, thus directly from PV sources, local storage, or community storage, to avoid using energy from the grid. A total population of 50 CHDTs was used. Two scenarios were considered, as shown in Ref. Table 5.

In a practical context, an influence could be a kind of incentive. Positive influence could be a positive incentive that is offered to reward participants for making specific choices or taking certain pro-sustainable actions or decisions. For example, deferring deferrable loads, participating in coalitions to pursue sustainable goals, consuming energy from the grid only during periods of low tariffs, or consuming energy from renewable sources Negative incentives, on the other hand, could involve nudges or punitive actions for making specific choices or taking certain actions that are anti-sustainable and contrary to the interests of the community. Some examples may include "free-rider" behaviors, consumption from the grid when other renewable sources are available, etc.

At the end of the model run (128 simulated hours), Fig. 12a, b shows the characteristics of the modeled

Table 5 Two cases with varying population sizes are used to test collective decision-making

Cases	Population (%)					
	Influencer population "A"	Influencee population	Positive influencer population	Negative influencer population	Prosumer population	Consumer population
Case-1a	90%	10%	90%	10%	20%	80%
Case-1b	90%	10%	10%	90%	20%	80%

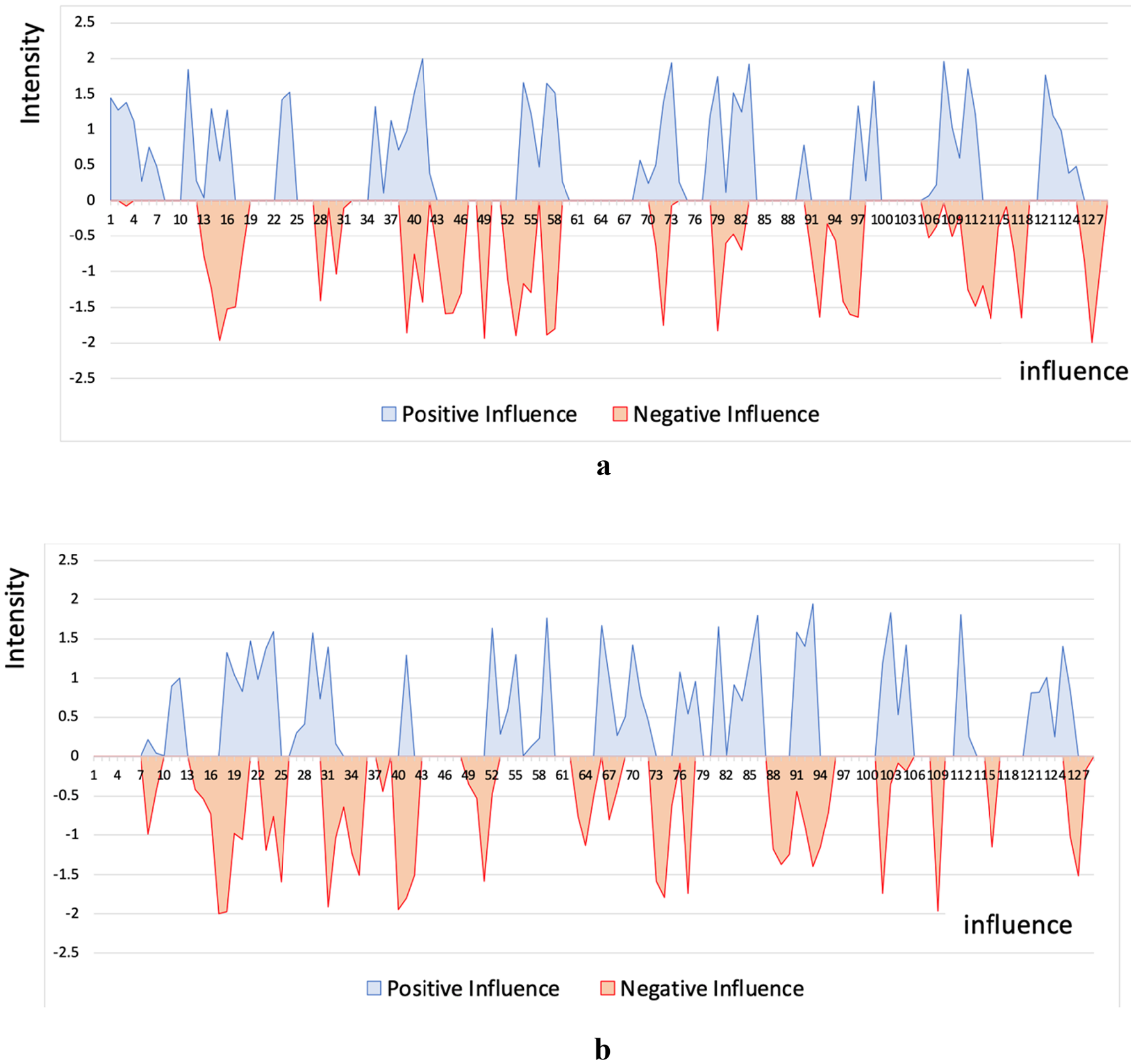


Fig. 12 **a** Influences received by CHDT-1. **b** Influences received by CHDT-2

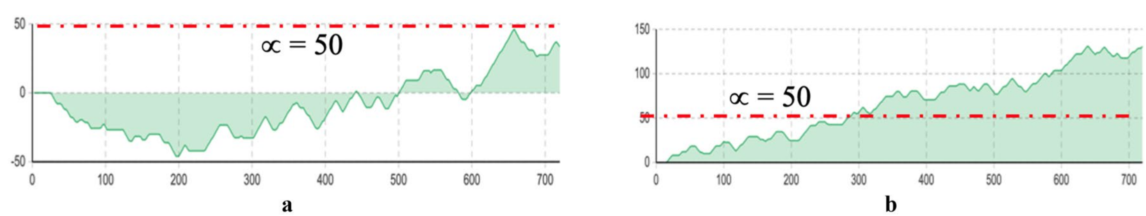


Fig. 13 **a** CHDT-3**b** CHDT-4

influence that was received by two different CHDTs, i.e., CHDT-1 and CHDT-2. The pulses appearing below the X-axis represent negative influences while those above the X-axis are positive influences.

In Fig. 13a, b, we show how the aggregation of influences over time can be used to determine the global behavior of a CHDT. We also illustrate how the global behavior can be used in decision-making. For instance, in Fig. 13a, b, we show CHDTs 3&4. Initially, CHDT 3 was negatively influenced, however, the general behavior turned into a positive behavior after 500 h. This CHDT could not decide because its behavior (the aggregation of influence) over time could not cross the threshold "∝". In Fig. 13b, CHDT-4 was positively influenced from the beginning of

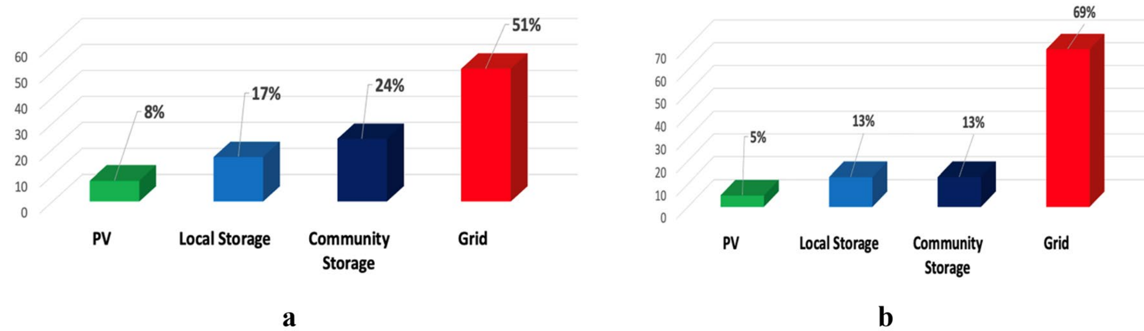


Fig. 14 **a** Case-1a. 90% positive influencers. **b** Case-1b. 10% positive influencers

the model run until its end. CHDT-4 was able to make a decision at 300 h.

By comparing the outcome of case-1a and case-1b (Fig. 14a, b), the model result shows that when the population of positive influencers is high (90% in case-1a vs. 10% in case-1b) most CHDTs were positively influenced, therefore, most were able to make the decision to switch consumption from the grid to renewable sources, hence consumption from the grid was about 51% as compared to 69% in case-1b) where the number of positive influencers is low (10%). In addition, the consumption from community storage, local storage and PV appreciated significantly in case-1a more than in case-1b. This can also be attributed to the difference in the population of positive influencers.

Limitation of the Model

Despite the promising outcomes, there are several limitations with the current prototype. In future studies, these limitations will be addressed. Some of the observed limitations include:

Limited goal conditions: We restricted the number of goal conditions in this simulation model to three. However, before a goal can be established in a typical real-life scenario, there may be a number of factors that need to be taken into account. As an illustration, the formulation of a goal that makes it easier to sell energy to the grid may require several criteria or conditions that relate to power quality (frequency and voltage), tariffs, and other contractual terms that may be found between the grid operators, the energy market, and the community.

Condition for VO formation: For the current implementation, the only prerequisite for the formation of a VO is the threshold technique. However, in a real-world situation, the sheer volume of accepted invitations might not be enough to justify the formation of a VO. There may be other technical considerations. The contribution from each member may be just as important as the number of invitations accepted, for example, in the case of exporting electricity to the grid. For instance, the community manager's projected predictions must be met by the total contribution anticipated from everyone who accepted an invitation. As a result, in addition to the number of accepted invitations, other technical information may also be relevant and necessary to take into consideration.

Limited value system: In the current implementation, each CHDT is thought to have two value systems. In practical terms, the number of value systems may be higher than the suggested number.

Overrides: The prototype presupposes that CHDTs would adhere to their judgments following acceptance of invitations. However, it is feasible that some users may change their minds a while after acceptance and may prefer to override the system and go against their earlier preferences. As a result, CHDTs are unable to alter their initial decisions in this simulation model because such provisions were not taken into account.

Current development was focused on simulation-based prototyping. In order to move to physical implementation some additional steps are necessary, e.g.,

Sensors and actuators: Some market survey in order to determine the most appropriate and compatible sensors that can support data collection from household appliances. Additionally, actuators that facilitate remote control of these appliances need to be identified. Even though the market is full of such products, for implementing a physical prototype, a careful study needs to be conducted first. Concerning smart appliances, it is necessary to assess how their built-in smart capabilities can be utilized to support the CHDT concepts.

Digital twin platform provider: It is necessary to identify, evaluate, and procure a qualified "digital twin as a service provider." The digital twin environment (DTE), which will house the digital twins, may be provided by this source provider. It may be necessary to investigate further if the integration of collaborative and intelligent algorithms can be supported in their DTE. Currently, Ansis Twin Builder, Bosch IoT Suite, IBM's Digital Twin Builder, and Azure

Digital Twins are a few of the potential service providers that have been identified.

Smart home portals: Other smart home portals that are currently available may also be explored to determine if they could provide DTE services. Some examples include: openHAB, Home Assist, ioBroker, Ago Control, OpenMotics, and Domoticz.

Conclusion and Future Works

Renewable energy communities are gradually becoming an integral part of the power grid infrastructure. These communities are usually comprised of multiple entities that are united by a common objective and purpose. The current trends reveal that the number of these communities is growing rapidly within the European Union and beyond. Furthermore, considering the ongoing digital transformation and its impact on the energy transition, the use of novel technologies, such as intelligent digital twins, for problem-solving and decision-making within the energy landscape is gradually becoming feasible. Therefore, the first part of this work aimed at extending the idea of Intelligent Digital Twin (IDT) with collaborative facets, leading to the notion of collaborative digital twin (CDT). The architecture of both the IDT and the proposed CDT are presented and described.

In the second part of the article, a prototype model of the collaborating digital twin namely the Collaborative Household Digital Twin is also introduced and discussed. Some partial results from the prototype model are also shown. The outcome of the study has proven that the idea of collaborative digital twins is a feasible one. The simulation results also helped in revealing how the collaborative capacities of these digital twins can be harnessed as a management mechanism or technique within the framework of a renewable energy community.

Furthermore, such collaborative actions can help to facilitate sustainable energy consumption within the ecosystem. In this sense, surplus energy from generating units could be aggregated into a VO, which is similar to a virtual power plant (VPP) and can be used to inject some renewable energy into the grid. This technique can help to maximize consumption from renewable sources and minimize consumption from the grid within the ecosystem. The CDTs can also collaborate with, say, a distribution service operator to help provide grid management services such as shifting loads from peak to off-peak periods, relying on the technique of "delegated autonomy."

In future works, the usefulness and applicability of these concepts shall be explored further. For instance, in the event of a disruptive event, or catastrophic failure of any aspect of the grid infrastructure, several potential Emergency Virtual Organizations (EVO) can be formed to assist emergency response teams in planning and executing appropriate disaster response actions. In the occasion where these CDTs are endowed with cognitive intelligence, and autonomous decision-making capabilities, they could autonomously collaborate among themselves to determine which aspects of the grid infrastructure stand the risk of experiencing cascading failure. The CDTs can then take proactive measures, such as autonomously isolating certain critical infrastructure, to protect the grid or prevent subsequent damage to property and the lives of citizens.

In addition to disaster management, the capabilities of CDTs to aggregate surplus energy to support the grid will also be investigated in detail. The proposed CDT ecosystem could also be a useful base to explore novel concepts like "antifragility" and how it can help improve the resilience and agility of the power grid.

The main contribution of this work is the proposition and development of an architectural framework for the collaborating digital twin concept. This contribution is perceived as relevant and timely, particularly in this time and era of digitalization. Another contribution is that this work brings the attention of the research community to the fact that CDTs could be useful in promoting sustainable energy consumption within RECs.

Acknowledgements We acknowledge the Portuguese FCT program UIDB/00066/2020 for providing partial financial support for this work. We also acknowledge the University of Energy and Natural Resources and UNINOVA CTS (Center of Technology and Systems) for supporting this work with their research facilities and resources.

Data availability The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors have no conflict of interest to declare. All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. we certify that the submission is original work is not under review at any other publication.

References

1. European Parliament, Regulation (EU) 2018/1999 of the European Parliament and of the Council of 11 December 2018, Off J Eur Union 328(1):1–77, 2018, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018R1999&from=EN.
2. European Commission, State of the Energy Union 2021—Contributing to the European Green Deal and the Union's recovery, 2021. [Online]. https://iea.blob.core.windows.net/assets/beceb956-0dcf-4d73-89fe-1310e3046d68/NetZeroby2050-.
3. Behara RK, Saha AK. Artificial intelligence methodologies in smart grid-integrated doubly fed induction generator design optimization and reliability assessment: a review. Energies. 2022;15(19):7164. https://doi.org/10.3390/en15197164.

4. Li L, Aslam S, Wileman A, Perinpanayagam S. Digital twin in aerospace industry: a gentle introduction. IEEE Access. 2022;10:9543–62. https://doi.org/10.1109/ACCESS.2021.3136458.
5. Locklin A, Muller M, Jung T, Jazdi N, White D, Weyrich M (2020) Digital twin for verification and validation of industrial automation systems—a survey. In: 2020 25th IEEE International conference on emerging technologies and factory automation (ETFA), 2020, 2020-Septe: 851–858, https://doi.org/10.1109/ETFA46521.2020.9212051.
6. Zhang X, Liu Z, Han B. Toward digital twins based marine SCADA system. IEEE Int Conf Artif Intell Comput Appl (ICAICA). 2020;2020:1049–53. https://doi.org/10.1109/ICAICA50127.2020.9182549.
7. Erol T, Mendi AF, Dogan D The Digital Twin Revolution in Healthcare. In: 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), 2020, no. January 2021; pp 1–7, https://doi.org/10.1109/ISMSIT50672.2020.9255249.
8. Adu-Kankam KO, Camarinha-Matos LM Modelling 'Cognitive Households Digital Twins' in an Energy Community. In: The Proceedings of the International Conference on Electrical Systems & Automation, 2022, pp 67–79, https://doi.org/10.1007/978-981-19-0039-6_6.
9. Yu W, Patros P, Young B, Klinac E, Walmsley TG Energy digital twin technology for industrial energy management: Classification, challenges and future. Renew Sustain Energy Rev. 161(November 2021):112407; 2022, https://doi.org/10.1016/j.rser.2022.112407.
10. Why Digital Twin Is an Essential Tool For Smart Cities. [Online]. https://www.challenge.org/insights/digital-twins-and-smart-cities/. Accessed: 14 Nov 2022.
11. TwinErgy, TwinERGY system, 2020. [Online]. https://www.twinergy.eu/twinergy-system. Accessed: 07 Oct 2022.
12. Xiong T, Cheng Q, Yang C, Yang X, Lin S. Application of digital twin technology in intelligent building energy efficiency management system. Int Conf E-Commerce E-Management (ICECEM). 2021;2021:393–6. https://doi.org/10.1109/ICECEM54757.2021.00083.
13. Yu G, Ye X, Xia X, Chen Y Towards Cognitive EV Charging Stations Enabled by Digital Twin and Parallel Intelligence. In: 2021 IEEE 1st International conference on digital twins and parallel intelligence (DTPI), 2021, pp 290–293, https://doi.org/10.1109/DTPI52967.2021.9540103.
14. Gu J Data vertical decoupling digital twin aggregation technology in the energy efficiency internet of things in small and micro parks. In: 2022 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA), 2022, pp 761–765, doi: https://doi.org/10.1109/AEECA55500.2022.9918862
15. Kannari L, Piira K, Bistrom H, Vainio T Energy-data-related digital twin for office building and data centre complex. In: 2022 37th Conference on Design of Circuits and Integrated Circuits (DCIS), 2022, pp 01–05, https://doi.org/10.1109/DCIS55711.2022.9970040.
16. Adu-Kankam KO, Camarinha-Matos LM Renewable energy communities or ecosystems: An analysis of selected cases. Heliyon, 8(12): e12617, 2022, https://doi.org/10.1016/j.heliyon.2022.e12617.
17. Camarinha-Matos LM, Fornasiero R, Afsarmanesh H Society. In: Collaboration in a Data-Rich World. PRO-VE 2017. IFIP Advances in Information and Communication Technology, 2017, 507: 3–17, doi: https://doi.org/10.1007/978-3-319-65151-4_1.
18. Camarinha-Matos LM, Fornasiero R, Ramezani J, Ferrada F. Collaborative networks: a pillar of digital transformation. Appl Sci. 2019;9(5431):1–33. https://doi.org/10.3390/app9245431.
19. Camarinha-Matos LM, Ortiz A, Boucher X, Osório AL Collaborative Networks in Digitalization and Society 5.0: Proceedings of PRO-VE 2022, 662. Cham: Springer International Publishing, 2022.
20. Camarinha-Matos LM. Collaborative smart grids—a survey on trends. Renew Sustain Energy Rev. 2016;65:283–94. https://doi.org/10.1016/j.rser.2016.06.093.
21. Adu-Kankam KO, Camarinha-Matos LM A Framework for the Integration of IoT Components into the Household Digital Twins for Energy Communities. In: IFIP Advances in Information and Communication Technology, vol. 665 IFIP, L. Camarinha-Matos, L.M., Ribeiro, L., Strous, Ed. Amstadam: Springer, chem, 2022, pp. 197–216.
22. Nazarenko AA, Camarinha-Matos LM The role of digital twins in collaborative cyber-physical systems. In; Technological innovation for life improvement, DoCEIS 2020, 2020, 577: 191–205, https://doi.org/10.1007/978-3-030-45124-0_18.
23. Adu-Kankam KO, Camarinha-matos L Delegating Autonomy on Digital Twins in Energy Ecosystems. Int. J. SMART GRID, 6(4); 2022, https://doi.org/10.20508/ijsmartgrid.v6i4.257.g253.
24. Adu-Kankam KO, Camarinha-Matos LM. Modeling collaborative behaviors in energy ecosystems. Computers. 2023;12(2):39. https://doi.org/10.3390/computers12020039.
25. AMRC-The University of Sheffield Untangling the requirements of a Digital Twin. Advanced Manufacturing Research Centre, 2020. [Online]. https://www.amrc.co.uk/files/document/404/1604658922_AMRC_Digital_Twin_AW.pdf. Accessed 16 May 2023.
26. Grieves MW. Product lifecycle management: the new paradigm for enterprises. Int J Prod Dev. 2005;2(1–2):71–84. https://doi.org/10.1504/ijpd.2005.006669.
27. IBM, "What is a digital twin?" [Online]. https://www.ibm.com/topics/what-is-a-digital-twin. Accessed 30 Jun 2022.
28. Amazon Web Services. What is Digital Twin Technology?—Digital Twin Technology Explained—AWS, 2022. [Online]. https://aws.amazon.com/what-is/digital-twin/. Accessed 16 Dec 2022.
29. Ashtari Talkhestani B et al. An architecture of an Intelligent Digital Twin in a Cyber-Physical Production System. Autom 67(9): 762–782; 2019. https://doi.org/10.1515/auto-2019-0039.
30. Camarinha-Matos LM, Afsrmanesh H. Collaborative networks: a new scientific discipline. J Intell Manuf. 2005;16:439–52.
31. Romero D, Molina A. Collaborative networked organisations and customer communities: value co-creation and co-innovation in the networking era. Prod Plan Control. 2011;22(5–6):447–72. https://doi.org/10.1080/09537287.2010.536619.
32. Fathy Y, Jaber M, Nadeem Z. Digital Twin-Driven Decision Making and Planning for Energy Consumption. J Sens Actuator Networks. 2021;10(37):1–33. https://doi.org/10.3390/jsan10020037.
33. Henzel J, Wróbel Ł, Fice M, Sikora M. Energy consumption forecasting for the digital-twin model of the building. Energies. 2022;15(12):4318. https://doi.org/10.3390/en15124318.
34. Tan Y, Cheng P, Shou W, Sadick A-M Digital Twin-driven approach to improving energy efficiency of indoor lighting based on computer vision and dynamic BIM. Energy Build. 270: 112271, 2022. https://doi.org/10.1016/j.enbuild.2022.112271.
35. Kharlamova N, Traholt C, Hashemi S A Digital Twin of Battery Energy Storage Systems Providing Frequency Regulation. In: SysCon 2022 - 16th Annual IEEE International Systems Conference, Proceedings, 2022. https://doi.org/10.1109/SysCon53536.2022.9773919.
36. You M, Wang Q, Sun H, Castro I, Jiang J Digital twins based day-ahead integrated energy system scheduling under load and renewable energy uncertainties. Appl. Energy, 305(April 2021): 117899, 2022. https://doi.org/10.1016/j.apenergy.2021.117899.

37. Camarinha-Matos LM, Afsarmanesh H The Evolution Path to Collaborative Networks 4.0. In: IFIP Advances in Information and Communication Technology, vol. 600, Springer, Cham, 2021, pp 170–193. https://doi.org/10.1007/978-3-030-81701-5_7
38. Camarinha-Matos LM, Afsarmanesh H, Galeano N, Molina A. Collaborative networked organizations—Concepts and practice in manufacturing enterprises. Comput Ind Eng. 2009;57(1):46–60. https://doi.org/10.1016/j.cie.2008.11.024.
39. Camarinha-Matos LM, Afsarmanesh H Collaborative networks: reference modeling. L. M. Camarinha-Matos and H. Afsarmanesh, Ed. New York: Springer Science+Business Media, LLC, 2008, pp. 1–334.
40. Anylogic, Multimethod Modeling Modelling for business, *Whitepaper*. [Online]. https://www.scribd.com/document/428707576/Multimethod-Simulation-Modeling-for-Business-Applications. Accessed 15 Apr 2023.
41. Borshchev A Multi-method modelling. In: Proceedings of the 2013 Winter Simulation Conference, 2013. [Online]. https://informs-sim.org/wsc13papers/includes/files/410.pdf. Accessed 10 Apr 2023.
42. Brailsford SC, Eldabi T, Kunc M, Mustafee N, Osorio AF. Hybrid simulation modelling in operational research: a state-of-the-art review. Eur J Oper Res. 2019;278(3):721–37. https://doi.org/10.1016/j.ejor.2018.10.025.
43. Nguyen LKN, Howick S, Megiddo I A Hybrid Simulation Modelling Framework for Combining System Dynamics and Agent-Based Models. In: Proceedings of SW21 The OR Society Simulation Workshop, 2021, no. March, pp 385–394, https://doi.org/10.36819/SW21.042.
44. Multimethod Modeling—AnyLogic Simulation Software. [Online]. https://www.anylogic.com/use-of-simulation/multimethod-modeling/. Accessed 02 Sept 2022.
45. Borshchev A, Filippov A From System dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. In: 22nd International Conference of the System Dynamics Society, 2004, 66(11): 1–23.
46. Gunal MM. A guide for building hospital simulation models. Heal Syst. 2012;1(1):17–25. https://doi.org/10.1057/hs.2012.8.
47. AnyLogic, “AnyLogic: Simulation Modeling Software Tools & Solutions for Business,” 2018. [Online]. https://www.anylogic.com/. Accessed 27 Apr 2020.
48. Jureta I, Mylopoulos J, Faulkner S Revisiting the core ontology and problem in requirements engineering. In: 2008 16th IEEE International Requirements Engineering Conference, 2008, pp 71–80, https://doi.org/10.1109/RE.2008.13.
49. Guo Z-Z, Wang K, Qin J-Y, Li X-B, Ran D-C, Shen Y An Intelligent Maritime Scene Frame Prediction Based on Digital Twins Technology. In: 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), 2021, pp 25–28, https://doi.org/10.1109/DTPI52967.2021.9540188.
50. Liu Q, Qi X, Liu S, Cheng X, Ke X, Wang F. Application of lightweight digital twin system in intelligent transportation. IEEE J Radio Freq Identif. 2022;6:729–32. https://doi.org/10.1109/JRFID.2022.3212169.
51. Wang S, Fu T, Luo P, Wang A Multi AGV simulation system of intelligent workshop based on Digital Twin. In: 2021 4th World Conference on Mechanical Engineering and Intelligent Manufacturing (WCMEIM), 2021, pp 325–329, https://doi.org/10.1109/WCMEIM54377.2021.00073.
52. Nie Z, Fang W, Yu L L, Hong J, Shi J, Hong D The Data treatment process for intelligent operation of Special Vehicles in Digital Twin Space. In: 2022 Global Reliability and Prognostics and Health Management (PHM-Yantai), 2022, pp 1–5, https://doi.org/10.1109/PHM-Yantai55411.2022.9941908.
53. Su Z, Wang Y, Zhang T, Zhang G Research on digital twin architecture of rule-based intelligent diagnosis of reactor system. In: 2022 Global Reliability and Prognostics and Health Management Conference, PHM-Yantai 2022, 2022, pp 1–5, https://doi.org/10.1109/PHM-Yantai55411.2022.9941852
54. Nwogu C, Lugaresi G, Anagnostou A, Matta A, Taylor SJE. Towards a Requirement-driven digital twin architecture. Procedia CIRP. 2022;107(March):758–63. https://doi.org/10.1016/j.procir.2022.05.058.
55. Consilvio A, et al. Towards a digital twin-based intelligent decision support for road maintenance. Transp Res Procedia. 2023;69:791–8. https://doi.org/10.1016/j.trpro.2023.02.237.
56. Jones D, Snider C, Nassehi A, Yon J, Hicks B. Characterising the digital twin: a systematic literature review. CIRP J Manuf Sci Technol. 2020;29:36–52. https://doi.org/10.1016/j.cirpj.2020.02.002.
57. Adu-Kankam KO, Camarinha-Matos LM. Towards collaborative virtual power plants: trends and convergence. Sustain Energy, Grids Networks. 2018;16:217–30. https://doi.org/10.1016/j.segan.2018.08.003.
58. Zimmermann L, Evans J-P, Griggs M, King J, Harding N, Oberts C, Penelope. Evans, Household Electricity Survey: A study of domestic electrical product usage, Intertek Report R66141, 2012. [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/208097/10043_R66141HouseholdElectricitySurveyFinalReportissue4.pdf. Accessed 05 Sept 2021.
59. Adu-Kankam KO, Camarinha-Matos LM Modelling Mutual Influence Towards Sustainable Energy Consumption. In: Technological Innovation for Digitalization and Virtualization, Luis M. Camarinha-Matos, Ed. Lisbon, Portugal,: Springer, Cham, 2022, pp. 3–15. https://doi.org/10.1007/978-3-031-07520-9_1