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Digital twins for performance management in the built environment

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ABSTRACT

Recent events worldwide of climate and geological origins highlight the vulnerability of our infrastructures and stress the often dramatic consequences on our environment. Accurate digital models are needed to understand how climate change and associated risks affect buildings, while informing on ways of enhancing their adaptability and resilience. This requires a paradigm shift in design and engineering interventions as the potential for adaptation and resilience should be embedded into initial brief formulation, design, engineering, construction and facility maintenance methods. This paper argues the need for smarter and digital interventions for buildings and infrastructures and their underpinning data systems that factor in topology (including geometry), mereology, and behavioural (dynamic) considerations. Digital models can be used as a basis to understand the complex interplay between environmental variables and performance, and explore real-time response strategies (including control and actuation) to known and uncertain solicitations enabled by a new generation of technologies. The paper proposes a digital twin model for the construction and industrial assets that paves the way to a new generation of buildings and infrastructures that (a) address lifetime requirements, (b) are capable of performing optimally within the constraints of unknown future scenarios, and (c) achieve acceptable levels of adaptability, efficiency and resilience.

1. Introduction

The built environment plays a significant role in anthropogenic climate change, with over 45% of global energy consumption, one-third of greenhouse gas emissions, and about half of all non-renewable resources [1]. The current rate of resource consumption is unsustainable for the earth, and the effects will be seen for many generations into a future of unreliable resources, pollution, and uncertain climatic conditions [2]. Therefore, the construction industry offers a significant chance to advance in reducing energy use, increasing efficiency, and cutting carbon emissions. Emergency response strategies in buildings are mainly based on experience, heuristics, and assumptions as opposed to real-time knowledge (i.e. data) about the facility's state. Recently, the use of new technologies has become prevalent for many scenarios related to climate change, extreme weather and natural hazards to mitigate the risks, ensure human safety and reduce infrastructure costs [3–5].

Buildings should have the capability to collaboratively respond to these adverse events through a "modulated response" [6]. This response is embedded within the design and manufacturing process, and the "modulation" is achieved through embedded sensing capabilities that continually establish the state of the building [7]. The latter can be defined at the stimuli, and adaptation can be optimised based on the present building status established by real-time data and information. Referring back to the Fukushima plant disaster, damages in the pool would be sensed and a notification of the risks incurred should be sent to decision factors. Ideally, self-corrective and repairing measures using materials with self-healing properties would have been triggered almost immediately and monitored in real-time to ascertain their effectiveness.

Current approaches to building management require that buildings meet several serviceability performance criteria related to each of their constituent systems. A set of performance functions can describe the physical state of a structure accounting for the specified serviceability requirements. Each performance function corresponds to one requirement. It is constructed on the basis of mathematical models describing the building physical phenomenon [8]. Serviceability requirements are formulated in range values (upper and lower limit) to be satisfied. When serviceability requirements are outside the range of these specified values, undesired conditions can be induced, which can cause stress and potential harm to the building and its occupants.

However, many model parameters vary and change over the projected building lifecycle. The complex interplay between the variables underpinning building systems behaviour precludes a simple set of rules

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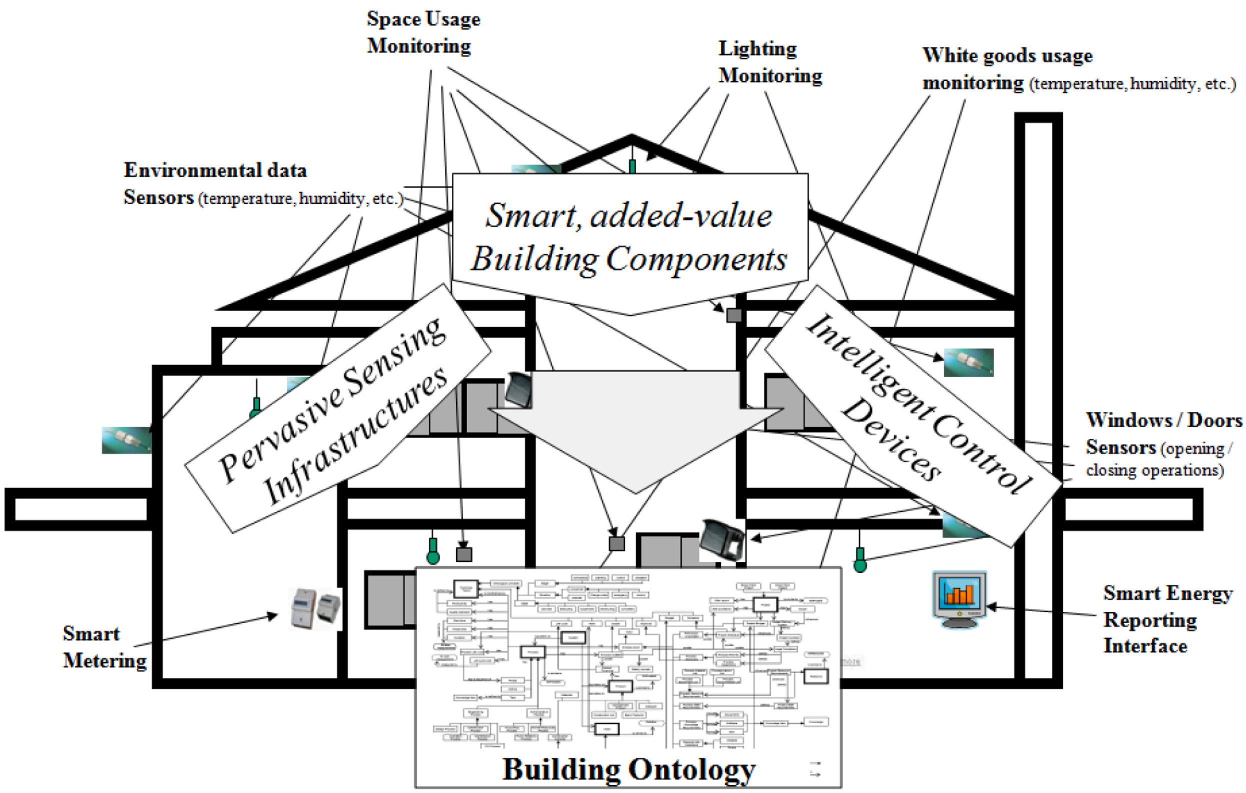

Fig. 1. Smart Building Model: Components and associated variables for the digital twin model (i) sensing devices, (ii) controlling devices and (ii) smart devices.

or guidelines. It necessitates the development of more complex data-rich models which (a) better inform designers about the lifecycle tradeoffs that can be made between different systems of a building and (b) devise appropriate response strategies to unexpected solicitations [9]. It provides a foundation for building systems modelling (such as Building Information Modelling) necessary to understand how the different components within a building interact, the involved variables, their dependencies, and the dynamic forces that affect their performance. The core to this approach is delivering higher-order data and knowledge structures that exploit a new generation of smart materials that provide condition feedback and embed shape memory, energy sensitivity, and self-healing properties (enabled by self-triggering biological or other processes). These materials can exploit real-time building information with a view of delivering lifelong building adaptability and resilience.

To comply with these requirements, “smart” buildings can dramatically reduce the effort to add new functions and applications related to building optimisation, greatly supporting communications and control capabilities facilitating control for groups of buildings which can, for instance, cooperatively exchange data and resources [10]. Smartainability is a concept referring to the level sustainability and smartness of the building assets as a result of smart technology adoption. Smartainability has emerged as a concept relating both to the "Smartness" and "Sustainability" of building assets and subsequent computer methods that can assist stakeholder with the process of decision making [11].

The paper discusses and proposes a vision, technical architecture and research directions for delivering adaptable and resilient infrastructures. We develop such vision using the concept of digital twins in the attempt to address a number of requirements that may appear in construction and industrial applications related to energy efficient practises and sustainable interventions. To improve efficiency and enable more active monitoring of buildings, advanced controls are required such as motion sensors and other wireless sensors that allow more detailed monitoring to be carried out with a higher frequency of data capture. We present a digital twin model with an adaptable architecture formed of several layers that can interact to deliver informed management in an industrial building scenario.

The reminder of this paper is as follows: In Section 2 we present the related works in the field of building sustainability and digital twins. In Section 3, we conduct an analysis of the complexity identified in buildings and associated interventions followed by the digital twin architecture presented in Section 4. Section 5 provides the implementation details. Section 6 presents the validation of the digital twin model in an application scenario. We conclude and discuss future work in Section 7.

2. Related work

Recent technological developments have made it possible to integrate sensor networks as decentralised distributed systems where sensor-based applications [12] can use a Cloud infrastructure to carry out data analytics and decision support. Such “Sensor-Cloud” enable users to collect, access, process, visualise, archive, share and search large amounts of sensor data from different applications. Sensor-cloud also facilitate the sharing of sensor resources by various users and applications in flexible usage scenarios while monitoring sensors assets/-resources and to control sensors via the use of a Web-based interface [13].

A more direct integration of the physical world into computer-based systems is made possible by the use of digital twins. Digital twins rely on a variety of edge and IoT networks formed by physical objects and items embedded with electronics, software, sensors, actuators, and connectivity that allow these devices to interact and exchange data [14]. This requires precise assessment of the indoor building conditions, particularly in pilots where the ambiance is not uniform and a substantial horizontal gradient may also exist in addition to the usual vertical stratification [15]. In facilities, where building orientation, solar radiation, and the amount of glazed surface play a crucial role in the thermal loads and temperature distribution in the environment, the position of sensors to determine the ideal value of environmental related variables becomes crucial. The instrumentation of sensors based on proximity analysis and positioning can enhance the accuracy of the interventions and pave the way to the development of smart digital twins [16].

With such a sensor based environment, several interactions between the different sensors, actuators, and controllers are facilitated, leading to the creation of smarter building ecosystems. A smart building involves embedded monitoring and control equipment with the potential to reduce energy use along with operations and maintenance expenses. For achieving an equilibrium in terms of consumption and comfort, these systems typically necessitate the deployment of a wide range of sensors (e.g., temperature, CO2, zone airflow, daylight levels, occupancy levels, etc.). These sensors are integrated through an Energy Management Control System (EMCS) and an array of electronic actuators, terminal unit controllers to process sensor outputs, and control setpoints. In particular, sensor systems can enable building energy simulations – enabling users to optimise various associated aspects of building use over time [17]. An example is the energy optimization with real time use of sensor data, where a number of parameters need to be optimised based on a particular building representation often modelled via BIM and IFC (Industry Foundation Classes) [18,19]. Based on such real-time readings from sensors it has become possible for facility managers to take decisions in order to reduce energy consumption and improve the process operation. As sensors can provide readings within an interval of 15–30 min, it is necessary for any simulation/ optimization to also be carried out over a similar interval to facilitate timely interventions.

Digital twins have emerged as applications that provide digital duplicates of physical objects for buildings and industrial processes. Digital twins aggregate numerous layers of information, greatly modelling behaviours and generating intelligence for physical artefacts. The development of digital twins based on edge capabilities identifies several challenges around resource availability and performance required for conducting near real-time analytics [20]. When deploying digital twin applications using edge devices several potential benefits are identified with the proximity of data and better contextualization [21]. However, data management at the edge requires specific adaptation of the analytics methods as data can have fluctuating attributes. A method for ensuring edge supported data processing is the use of machine learning and the subsequent approximation methods to ensure compatibility of data workflow and edge resources [22].

An increased number of industries are now embracing such automation and control systems in areas such as Building Management Systems, appliance management, HVAC, health and safety, Telecommunications, white goods, utility services (e.g. energy), as illustrated in Fig. 1.

The components of a smart building model can be classified into: (a) Pervasive sensing infrastructure, (b) intelligent sensing, control and actuation devices, and (c) smart building services. This fundamental change in material design philosophy facilitates the creation of a wide range of 'smart' materials and intelligent structures, including both autogenous and autonomic self-healing materials, and adaptable, self-repairing structures that can positively react to environmental changes. Given the dynamic conditions described above, buildings need to continually adjust their performance to various stimuli. This vision raises a number of challenges forming the scope of this paper:

- Ø How to conciliate, interpret, and make sense of the diverse, dynamic, uncertain, and complex data of various sources related to a building, the external environment (climate, operation, surrounding natural and built environment), and internal occupancy and related processes to address the constraints of present and unknown future scenarios?
- Ø How to conceptualise these diverse sources of data into a dynamic and multi-aspect building ontology that factors in environmental and building physical phenomena as well as human behaviours resulting from their interactions with buildings?
- Ø How to inform stakeholders in the delivery, maintenance and operation of buildings centered on dynamic building conceptualisations, by drawing on complex systems theory, material sciences, human behaviour, and other related areas?

The ultimate aim is to exploit the fundamentals of complex systems applied to the construction industry to deliver more autonomous buildings and infrastructures that (a) address lifetime requirements and (b) are capable of performing optimally within the constraints of unknown future scenarios.

Several well-established digital twin solutions exist, all leveraging on deep and machine learning to manage HVAC systems [23,24] and optimise load for renewable energy in various industrial energy management applications [25,26]. Digital twin models are proposed in the field of smart maintenance systems [27] alongside functional architectures with applicability for industrial case studies [28]. Commercial examples include digital twin platforms from PTC [29], IBM [30] and GE [31] that provide advance analytics and machine learning for cost optimization [32]. The current research contributes to the creation and deployment of digital twins in the built environment by proposing a) a reference architecture; b) a software platform; c) semantic models; d) machine learning techniques & AI; e) cost analysis and business models for digital twins.

3. Buildings as complex systems for digital twins

Complexity in construction can be explained by (a) the resources employed to design and construct a building, (b) the natural and physical environment that surrounds the building, (c) the stringent requirements and increasing level of technology involved in building design and engineering, (d) the resulting coupled building systems and their components, and (e) the various forms of occupancy and overall "environment-building-occupants" interactions taking place over the facility lifecycle. In fact, buildings involve complex interacting systems that exhibit dynamic and non-linear behaviour in a continuously changing and uncertain environment [33].

Digital models need to be underpinned by a socio-technical representation of a built or infrastructure facility (including energy, water, land, ICT and health) to enable holistic system reasoning and analytics. Such analytics can contribute to cross-discipline evaluation of changes to building design, configuration, costing, and management of associated sub-systems during the Construction and operation stage [34].

A building becomes a complex system formed of many components which may interact with each other [35]. Sensitive to initial conditions, number of interacting components is large, multiple possible pathways to evolve and dynamic - attributes and variables related to energy, water, heating, storage, etc. Therefore, buildings need to have the capacity to react and adapt to changes by self-adaptability and autonomics but also to behave in a system of systems i.e. district level. Digital twin can be useful instruments for achieving building automation and reaction to factors such as weather conditions, events related to internal conditions and to ensure real-time controlling/actuation techniques. Therefore, the scope of building systems is quite large, it includes the systems that underpin the building (load bearing structure, the various technical services and installations, and their controls), the internal environment in terms of building usage and occupants, and the external environment in terms of site geology, climate, and physical structure of the surrounding built environment. In fact, recent thinking stresses the importance of the notion of the human (i.e. building occupant) being an integral part of the system, as opposed to being considered outside of the system [36].

A systems philosophy demands that an uncoordinated approach is replaced by a framework in which the identities of the separate parts are subsumed by the identity of the total system. Furthermore, a building systems thinking approach is necessary to understand how the different components within a building interact, the involved variables, and the dynamic forces that affect their collective performance. Digital twins can leverage on model-driven data derived from model based system engineering (MBSE) techniques including engineering simulation models, building information modelling (BIM), and wider (CityGML) models in relation with the construction project and the surrounding site / local environment [37]. A digital twin uses data, domain and engineering models to represent, at any time, a true reflection of the physical asset (i.e. twin) maintained through a persistent communication between the digital and physical twins.

This is in-line with the systems thinking which can be summarised as follows [38]:

Ø Viewing the situation holistically, as opposed to reductionistically, as a set of diverse interacting elements within an environment.
Ø Recognising that the relationships or interactions between elements are more important than the elements themselves in determining the behaviour of the system.
Ø Recognising a hierarchy of levels of systems and the consequent ideas of properties emerging at different levels, and mutual causality both within and between levels.
Ø Accepting, especially in social systems, that people will act in accordance with differing purposes or rationalities.

As such, a digital twin leverages on data, domain, and engineering models including native software and proprietary underpinning data structures. Such data models inform the development of machine learning which is required to help address predictable but also predict unforeseen situations thus conferring a pro-reactive and reactive capacity for buildings. Machine learning also provides the digital twin with proactive and preventative capabilities, with the ability to save costs, delivery times, and hazards while upholding the building complexity principles. Such informed interventions lead to more ecologically friendly construction-stage solutions that significantly reduce carbon footprint.

4. Digital twins architecture

The proposed digital twin framework uses a four-layered architecture applicable to performance management of energy applications in buildings to support on-demand, self-adaptability and autonomy of interventions and operations in the built environment.

Layer 0: (User layer) represents a visual interface where the data produced by the twin layer is displayed to the user. At this layer, various use-cases can be executed in order to enable the user to take informed decisions. Users are provided with access to knowledge representations where they can observe the status of the pilot and visualise various scenarios analytics using devices such as PCs, laptops or smart-phones.

Layer 1: (Digital twin layer) represents the location where complex optimisation techniques are developed and decisions are produced in relation to predefined objectives. The components on the digital twin layer include (a) Semantics and ontologies module (L1SO), (b) Simulation module (L1SE), (c) Prediction module (L1P) and (d) Optimisation module (L1O). These constituent modules support operations related to energy simulations, building physics measurements or machine learning algorithms including operations such as artificial neural networks (ANN), genetic algorithms, etc. This layer is usually hosted on a cloud system that provides the infrastructure required to run real-time building simulation and optimisation using software packages but can be also used as a mean to store data from the building sensors. The cloud has also a coordination role of the various processes that can happen in the pilot. Operations at this layer can include complex optimization, data mining, ANN training, process coordination.

Layer 2: **(**Software layer) identifies edge devices such as regular PCs, servers, routers, switches, and other devices with limited computing capabilities. These devices are often linked to controlling elements of the building. This layer represents the first stage where preliminary decisions can be developed and implemented into the pilot. Software layer operations include optimization, simulation, edge based machine-learning, data analytics, control /actuation operations.

Layer 3: (Data capture layer) manages data from sensors deployed within the building and transfers it to the devices layer. The data is retrieved at predefined time intervals specified according to the logic of the building element. There are two main data streams: a) sensed (from sensors) - data retrieved from sensors for analysis such as temperature, humidity, CO2 emissions, etc. and b) actuated (to actuators): set-points implemented for controlling states at the device level. Sensor operations can include operations such as average, summation, frequency change.

5. Implementation of the digital twin

The digital twin model is applied to an industrial building running fish processing operations with the objective to reduce the operation costs and the carbon footprint. The Polar site is a large industrial building situated in Ireland that integrates an entire supply chain of the fish processing involving fish storage, processing and delivery to various market locations around world. The Polar site is formed of a two cold storage units with capacity of 1500 tonnes. The operation temperature is between −19 to −23 °C and the unit has five led lighting system with power capacity 100 Watt each. There are three cooling fans with installed temperature sensors and a heating system installed under the basement of the unit. The second cold storage unit has a capacity of 2500 tonnes with an operation temperature between −19 to −23 °C, six led lighting system with power capacity 100 Watt each and three cooling fans. There are three compressors with total power capacity of 355 kWh each. The production line identifies several processing stages including scheduling and operation of energy intensive appliances with human interactions for the coordination. The overall goal is to link all the appliances and to optimise the energy consumption.

The pilot presents also flexible loads that relates to electrical sources that can be controlled to dynamically manage the amount of electricity being used or supplied. These can include cold stores and ice making machines. The primary objective is to minimise the cost of operation through an effective control schedule over a pre-defined planning period given a set of temporally varying operational parameters such as energy consumption, renewable and energy pricing. To address the above requirement, we propose a digital twin model that relies on the conceptual modelling of the industrial process and includes:

(i) Ontology for capturing the semantic knowledge and make such knowledge machine understandable for the optimisation of the buildings pilot,
(ii) Simulation capability in the form of a digital replica of the pilot that is calibrated with real site data which facilitates simulation of “what-if” scenarios and
(iii) Forecasting and optimisation capability using machine learning to determine in advance process behaviours and trends used to optimise various aspects of the pilot.

Semantics, in general, and ontology in particular, play a determinant role in conceptualizing and contextualising complex artefacts, domains and scenarios, such as the built environment and its associated stressors (including climate change). Semantics provide context to sensory data acquired through sensor networks and the wider IoT, but also uncover intricate interdependencies between the variables involved in any given scenario. This understanding can also help comprehend the complex variables involved and inform the process of reducing the dimensionality of a scenario by relying on adapted machine learning algorithms, such as PCA (Principle Component Analysis), as demonstrated by the authors in [47]. These algorithms will therefore rely on variables that are rooted in the semantic models (i.e., ontologies) describing the domain they address and can thus exploit effectively time series data sourced from sensors, and the wider IoT. This ultimately helps improve on a continuous basis the fitness for purpose and accuracy of the prediction and optimization algorithms addressing the scenario(s) at hand.

5.1. Ontology model

The semantics and ontology module (L1SO) underpinning the digital twin model is composed of different parts as shown in Fig. 3. The ontology has been developed using Computer Aided Process Engineering (OntoCAPE) [39] with models concepts, entities and relationships as identified in the industrial site.

The structure of the ontology is composed of the following modules as follows:

- Mereology: the mereology module defines part-whole relationships of two types, aggregation and composition.
- Topology: the topology module defines connectedness models, node and edge concepts.
- System: the system module provides conceptualisations of systems, kinds of systems and taxonomical semantics for hierarchical systems of systems.
- Time: emergent properties of systems are path-dependent; the sequence of past decisions influences the current behaviour. The time module defines a specific coordinate system for time-dependent data that goes beyond the built-in XML time constructs.
- Physical dimension: the physical dimension module allows the representation of physical quantities, dimensions and units, that are required to describe physical and economic properties of the district energy system components.
- Socio-technical system: it allows the representation of real or abstract networks both at a technical level (involving physical elements) and social aspects (involving decision making entities).
- Domain ontologies: all the modules above are domain independent, but the pilot ontology also relies on domain specific ontologies. Some reused ontology modules are derived from standardised information models.

The ontology model in the semantics module (L1SO) is formed by physical and social nodes that are horizontally linked by physical edges and social edges (see Fig. 4). All the classes are also linked vertically by cross-domain connections. Physical nodes are building, energy system, storage system and energy networks whereas the social nodes are the stakeholders and users of the site.

The ontological models enables the digital twin to orchestrate the interaction of the energy system with other systems as social, economic and technical systems and coordinates the dynamic local data from many devices and systems including sensors, smart meters, actuators, BMS (Building Management System), EMS (Energy Management System). In the ontology, devices and systems are configured to share a common model and protocols facilitating the distribution and the allocation of energy loads within the site. The ontology uses a common vocabulary which will be used by the local BMS and EMS and supports real time knowledge querying of data and knowledge required in the digital twin.

For the industrial site, the ontology uses entities for modelling electrical appliances and electrical boats as consumption units followed by production units and battery systems for the industrial site. A communication with the grid is added to enable exchange of electricity. The external dispatcher is connected to an internal building dispatcher connected with the appliances existing in the building. The energy controller can coordinate dispatchers to send the electricity to a building and to the appliances. The social structure is composed of stakeholders that can lead businesses in an industrial site, all linked by contracts. These contracts allow them to sell and buy energy and to interact with the electricity supplier

5.2. Simulation capability

The simulation model forming the digital twin simulation module (L1SE) was developed using an energy audit process based on (i) a visit of the site, and (ii) a questionnaire and interview with energy staff at the site. The audit has captured the requirements and processes of the site for the energy use with identification of sensitive areas of the sit energy consumption. For the development of the energy model, an analysis of interviews and questionnaires was followed by an analysis of utility bills for 12 months. Data of local energy appliances was collected with an emphasis of the efficiency and operation time of the appliances. Based on “what-if” scenarios determined using the simulation model, recommendations can be obtained to reduce costs with energy consumption and carbon emissions. The simulation model has been generated using DesignBuilder [40] and has capabilities to reproduce energy consumption profiles using EnergyPlus [41] at each stage of production process (Fig. 5).

The energy simulation model is then used to identify strategies and scenarios for minimising energy consumption with a direct impact on the energy cost. The simulation model can optimise energy use in the industrial building by identifying the sensitive parameters that effect the overall energy use. At a higher level, the energy simulation is used to evaluate the impact of various policies and regulations to help the decision makers to design new business strategies and explore business opportunities based on different projections. A digital twin with simulation capability facilitates advanced monitoring and estimating the actual energy use in the industrial buildings including detection and diagnoses of faults in the system.

Fig. 6 presents daily energy consumption of the Polar. Fig. 7 illustrates the monthly energy consumption of Polar site reflecting an increase of consumption in the winter season when energy consumption is influenced by the fishing time.

5.3. Machine learning for energy forecasting and optimisation

The method employed to achieve optimization of the flexible energy load has incorporated the following steps:

1. define a model of the flexible load system being controlled with a set of influencing parameters.
2. collect a training set of data to determine the impact different operational parameters have in the operation of the flexible load.
3. prepare a directed graph representing the set of possible operation states the flexible load system can take at any planning interval.
4. invoke a search algorithm to determine the optimal operating schedule over a pre-determined time interval for optimal operation at the minimal cost given the set of temporally varying parameters over the planning period.

5.3.1. Forecasting capability

A forecasting model for the digital twin prediction module (L1P) was developed to optimise energy usage and reduce energy costs based on scenarios identified in the Polar site. A short-term forecasting model was developed using a Multilayer Perceptron Neural network (MLP) [42] to predict power and temperature in two cold rooms at thirty-minute intervals.

A Genetic Algorithm (GA) is used to optimise the ANN function with Simulated Annealing algorithms [43,44]. The model then maps the relationships between future temperature and power and the system variables affecting them. These relationships were established through testing with real-world data sets to assess the accuracy of the proposed method. The model aimed to determine the accurate prediction of power and temperature and seamless integration with an optimiser to achieve optimal energy costs in the Polar site. The optimisation model uses sensitivity analysis to determine the variable’s degree of importance

Table 1
The accuracy of DNN approaches expressed in terms of the statistical measures.

Algorithms	Temp MAPE (%)	RMSE	MAE	Power MAPE (%)	RMSE	MAE
Proposed Model	1.695	0.514	0.348	63.643	19.954	12.448
LSTM	1.857	0.623	0.386	66.065	24.459	15.634
peephole-LSTM	1.835	0.633	0.380	65.959	24.991	15.519
GRU	1.827	0.612	0.376	64.680	20.766	13.046

concerning the stipulated objectives.

After extensive data cleaning and modelling from the site, each variable's weighting in the model was determined. A hyperbolic tangent activation function was used. The mean square error of the MLP model was used as criteria for the performance of the model. The training of the neural network involved setting the most suitable weights on the input of each unit. The total number of instances is 2229. The instance splitting method was random, and the percentage of training instances was set to 60.1% whereas the number of selection instances was set to 20% and the number of testing instances set to 20%. The quasi-Newton method was used here for training with an initial value of the selection loss is 3.84683, and the final value after 509 iterations is 0.118187.

The results of the experiments indicate that the proposed MLP model performs with higher accuracy than the Long Short-term Memory, as an artificial Recurrent Neural Network architecture, peephole-LSTM, and the Gated Recurrent Unit. The presented MLP was chosen based on a comparison with the following methods: LSTM, peephole-LSTM and GRU. Most techniques used in predicting power demand include recurrent neural network (RNN)-based LSTMs using time series data, and natural language processing. RNN is used to assign missing values and to accommodate for the nonlinearity of meteorological time-series data. However, the training of standard RNNs to successfully solve problems that require learning long-term temporal dependencies is challenging. LSTM implements gate and memory cells in each hidden layer. One problem with the LSTM is that the gates cannot access information from the memory cell output when the output gate is closed.

Furthermore, the Long short-term memory (LSTM) as an AI recurrent neural; peephole-LTSM and gated recurrent unit (GRU) methods were compared to MLP. MAPE, RMSE and MAE evaluate how the forecasting models perform and their results are presented in Table 1.

Among the ML approaches compared, the proposed model and GRU showed significantly lower error measures compared with LSTM and peephole-LSTM. GRU performed better across predictions of temperature and power than LSTM and peephole-LSTM. The proposed model scored 1.695% for MAPE compared to the 1.827% for GRU. Similarly, scores of 0.514 and 0.348 in RMSE and MAE, respectively, suggested the proposed model produced the least error compared to other models used for comparison. Similarly, in the prediction of power usage, the proposed model had a MAPE of 63.643%, superior to the GRU measure of 64.680%.

In conclusion, the accuracy of and the MLP capabilities of utilising tabular data make it the preferred approach for the application of this paper.

Fig. 8 illustrates the fluctuations for data measuring real power usage across one day and compares this with the DNN approaches' predictions. When the set-point is set to zero (shown by a vertical drop in real power towards zero), power consumption is followed most closely by predicting the proposed model. At the time when the set-point changes to zero, the most significant forecasting errors occur. Interestingly, peephole-LSTM shows the most variation compared to real data.

The results in one site demonstrate energy cost savings in the range of 15–18% after applying the forecast-optimiser approach. The forecasting of temperature and power in the Polar site was done by observing the interaction between real-time energy optimisation and the cost of the power based on pricing schemes and power demand. The energy management system was then assessed to reduce cost and power usage. The optimisation strategy proposed is shown in Fig. 9.

5.3.2. Optimisation capability

The optimisation model in the digital twin optimisation module (L1O) was developed to address the dynamics of the energy management system. The objective is to minimise the energy usage and match the peak times of usage with the most cost-effective times concerning the power grid. In this application, the optimiser is making a one-hour prediction using two predictions of thirty-minute intervals. The output of the first prediction is used as the second's input to produce a one-hour prediction of temperature. The use of a multi-stage prediction is expected to make a cumulative error. However, the model performs within the 0.5 °C accuracy threshold required for this application. The optimiser then assesses the real-time energy cost and adjusts the combination of set-points for the next one-hour. The prediction model's ability to stay within the 0.5 °C degree error limit while experiencing cumulative error is reflective of the accuracy of the proposed model.

In general, the digital twin operates with a set of settings and algorithms that separate the objectives into those that are calculated directly from the model output of a simulation and prediction and those that are indirectly calculated as supplied by the end-user (e.g., energy tariff in energy cost minimization scenarios). After formulating the optimization problem, the system communicates data for the variables in the optimisation scenario with corresponding timestamps to determine the adequate optimisation setting.

The economic efficiency and the results show a significant reduction in cost after applying the forecast-optimiser system. Furthermore, carbon dioxide emissions were also reduced. It was then concluded that the MLP can enhance the modelling of the energy profile of this fishery site and could be successfully integrated into an optimiser platform.

One key question was how the cold rooms would behave when set to different set-points with different capacities and ambient temperatures. The impact of ramping up and down between these set-points was carefully measured. The graphs in Fig. 10 demonstrate the model's ability to stay within 0.5 ° of actual temperatures for a day in March 2020. This model is currently in full-time use for the optimiser.

The optimiser runs hourly and takes a live temperature reading from the site as a starting point. It then assesses the current load profile in use at the cold rooms and acquires data from the wholesale market to get energy prices for the upcoming period. With this information, a directed graph of various possibilities is formed. The algorithm is run against this graph, and the optimal path with the least cost to the system is found. With this path, the optimal set-point schedule for the next hour is selected to give the most value for energy cost.

The cold store example below explains how machine learning has been integrated within the digital twin. Steps 1 and 2 of this process consist of the prediction modelling outlined in the previous sections. The selected influencing factors that impact the operation of the cold store are ambient temperature which is driven by the season and capacity. For example, a higher outside ambient temperature requires more energy to cool the room. A higher capacity within the room requires less energy to maintain a cold temperature as the product temperature is less volatile and helps maintain a cooler temperature, thus using less energy on an ongoing basis. The control parameter is the set-points at which the room can operate. 0, −22 and −25 have been selected here.

The minimum of −18 ° and the maximum of −25 has been set as the boundaries of operation. Once the prediction model has been trained to understand how maintaining a control value and switching between control values impacts the electrical load over a given period, it can then be queried. A multidimensional table can be built with the electrical load values and resulting finish temperature for each control parameter from the resulting queries. The transition from each control parameter to another for the different influencing variables and within the upper and lower bounds of the acceptable operating temperatures is also

Table 2
Multidimensional table used for querying the optimiser.

StartTemp (°C)	Set-Point −25 FinishTemp (°C)	EnergyUsed (kWh)	Set-Point −22 FinishTemp (°C)	EnergyUsed (kWh)	Set-Point 0 (off) FinishTemp (°C)	EnergyUsed (kWh)
−18	−20.1	51.1	−19.4	38.7	Not allowed here as it would fall outside operating params	
−18.1	−20.3	50.7	−19.6	39.5		
−18.2	−20.4	50.6	−19.7	39.5		
…	…	…	…	…	…	…
…	…	…	…	…	…	…
−20	−22.8	54	−21.6	39.7	−18.9	4
−20.1	−22.9	53.7	−21.6	39.4	−18.7	4
…	…	…	…	…	…	…
…	…	…	…	…	…	…
−25	−24.8	58	−21.8	39.1	−19.7	4

Table 3
Measured consumption and savings obtained with the digital twin intervention.

Period	Number of cold stores and Capacity engaged	Before retrofit Energy Consumption [kWh]	After retrofit Energy Consumption [kWh]	Energy savings [kWh]	Cost avoided [€]	CO2 emissions avoided [kg]
First baseline	One-%75	67,291	62,253	4037	237,193	1716
Second baseline	Two-%100	133,436	126,712	6224	320,081	2645

incorporated in this process. An example of one such table for a set of influencing factors such as 75% capacity during the summer season can be seen in Table 2.

Once the system model data is collected, a directed graph is created to represent the possible states the control parameter can take along with the resulting impact on the electrical load. Each node of the chart will represent a control parameter setting. Each transition will represent a unit of electrical load per planning period. For instance, taking an example from the table above at −18.1(°C) and using the control set-point −25, the transition will have an edge to −20.3. It will cost 50.7 kWH over the planning period of 30 min. When the graph is created, a depth-first search is executed to a maximum number of steps required for the total planning period, which is 24 h.

At each planning interval, the cost of the transition step is calculated, which is based on all influencing parameters at that planning interval for the flexible load unit and results in the cost of the operation. When the maximum number of iterations has been reached, the historical set of nodes and edges traversed will constitute a planned schedule for the flexible load. This schedule will have a total cost associated with it based on some factors that were considered at each step. The objective of the depth-first search is to find the optimal combination of iterations through the constructed graph that minimises the cost of operation of the flexible load unit.

5.4. A scenario using the components of the digital twin

The scenario considers that a building component detects via its sensing node a stimulus reflected by an environmental change condition. The component attempts to use its inherent knowledge and intelligence to interpret the stimulus and informs / sends a request to the control and actuation layer to analyse localised and overall impact assessment. With a view of characterizing and establishing the resulting state of the building, the control and actuation layer queries the building ontology, which updates itself by querying / retrieving real-time parameters across systems.

An up-to-date state of the building is sent back to the control and actuation layer, which then invokes the building knowledge base to accurately characterise the stimulus (see Fig. 11). The building knowledge base may invoke the data mining module to confirm or investigate further building new status interpretation by inferring new data and identifying potential useful patterns. The knowledge base passes the inferred stimulus characterisation to the control and actuation layer which in turn invokes the optimiser to devise a response plan. The optimiser requests a dependency simulation modelling to understand key dependencies across variables and systems supported by a sensitivity analysis to determine sensitive variables against the scenario. Various simulations are run to determine optimal plan and inform back the control and actuation layer. Building systems are informed by optimised response plans and triggering / actuating messages are sent to specific building components.

6. Validation and digital twin analytics

In this section, we validate the digital twin model by testing its efficiency in a real-world scenario. For undertaking the validation, we use the Polar site trial to demonstrate deployment and efficiency for the digital twin model in an energy management scenario for an industrial building.

The provided energy application represents a demonstration of the proposed digital twin involving interaction of an ensemble of loosely coupled components, including the semantic module ontology, simulation, prediction and optimisation components. As such, the digital twin uses data analytics and machine learning capabilities augmented with a semantic models and provides an interface between the above data sources (IoT layer) and the services (Digital twin layer) to be made at the disposal of the energy application and associated value chain.

6.1. Pilot description

Data captured at the pilot site was used for the assessment of the digital twin model. The site is a stand-alone fish cold store, operating at around −21 °C. The fish are stored in two cold rooms controlled by one refrigeration unit. For collection of the granular data necessary, temperature sensors and energy monitors were installed and connected to the refrigeration control system. By default, energy sustainability was not a motivating factor on this site and cold rooms were operated at a set temperature of −23 °C, the refrigeration system controlled and maintained the cold rooms with little deviation to the set temperature. A variety of factors such as quantity of traffic in and out of the cold rooms, seasonality, capacity of rooms etc. all play a part in how well the set temperature is maintained. The digital twin system aims was to track and analyse the predicted temperature and energy based on changing

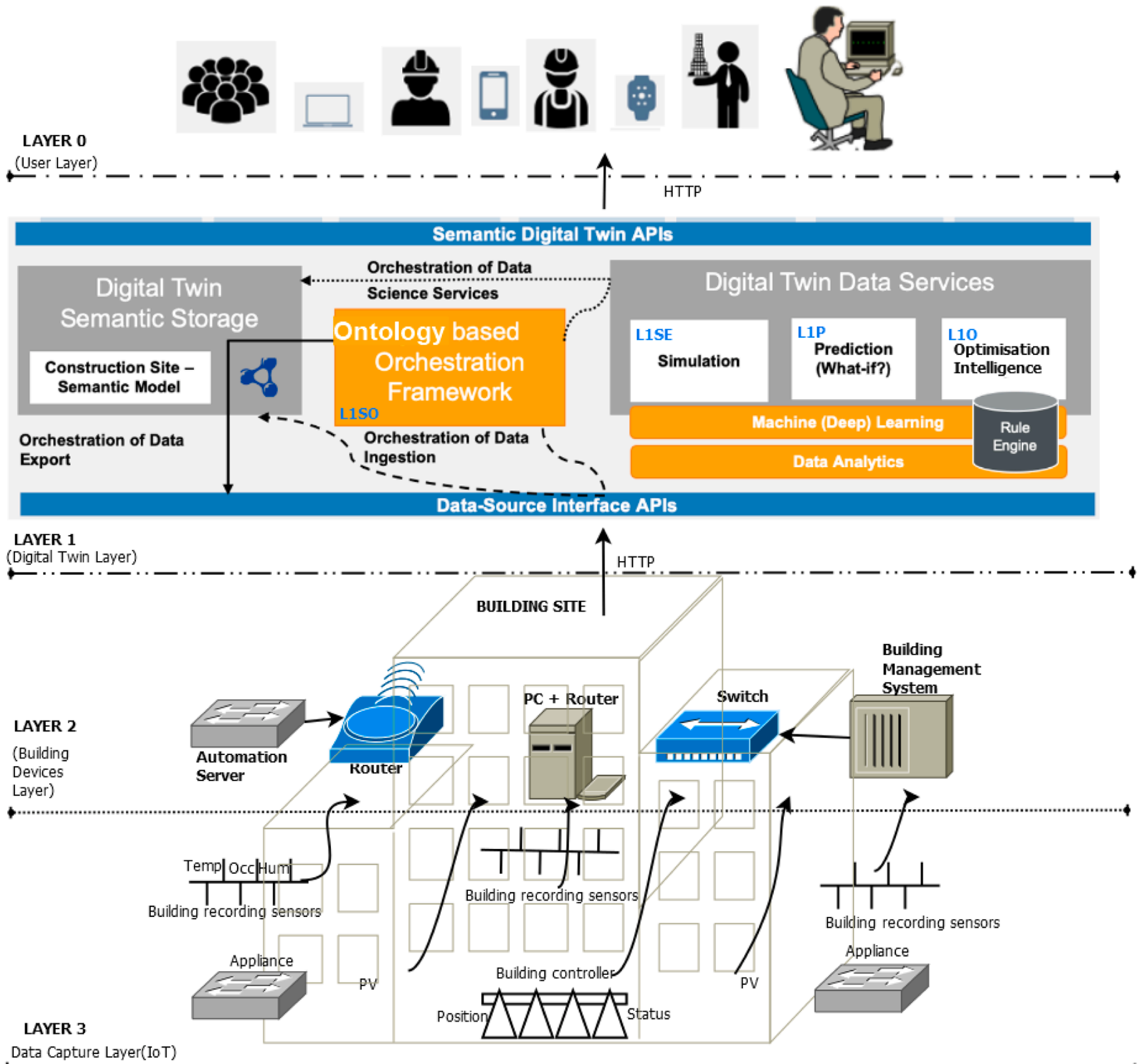

Fig. 2. The digital twin architecture and constituent digital twin modules.

the rooms set point and then compare it to what happens. Each cold store had two defrost cycles per day. This was required to prevent ice build-up on the rear of the units, affecting its performance. The process involved using heating coils to melt any built-up ice and was performed twice a day to all coolers. This is an example of a double loss as the energy is consumed to introduce heat to the coolers, also increasing room temperature, which must later be recovered via refrigeration after the defrost schedule completes. The defrost schedule is reduced from twice a day to once without impacting the coolers. By default, the schedule was timed at relatively expensive times of the day as they were spaced twelve hours apart. Aftermarket data was analysed, the schedule for a single defrost was changed to coincide with the cheapest time of day on average, providing further savings. The defrost cycles are run at 2am in Cold Store 1, and 3am in Cold Store 2. These times were selected as they were consistently the cheapest time of the day for energy cost.

6.2. Digital twin deployment and analysis

For the analysis, we record energy consumption over one week period to measure the baseline energy consumption. Real energy data was used as recorded from the pilot sensors and meters to serve as a basis on comparison for the analysis. The data is interpreted by the various modules and actionable insights are computed by the digital twin platform (see Fig. 12) interfaced through a Cesium [45] web interface.

The objective of the evaluation is to compare the digital twin intervention, as identified in this paper, with manual intervention as traditionally identified in the pilot. A manual intervention refers to operations that pilot personnel are adopting for reducing energy which are manually applied (e.g., switching off the appliance, adjust temperature, the lighting system, etc.). A digital twin intervention, on the other hand, is obtained through a seamlessly data interaction between ontology, simulation, forecasting and optimisation modules applied to a set of input parameters. The digital twin calculates optimum actuation set-points that are implemented in the building pilot into the cold-rooms at 15 min intervals.

Our measurement and verification (M&V) plan [46] includes the following metrics:

- KPIs (Key performance indicators): expected energy.
- Factors affecting energy consumption: season and capacity.
- Baseline performance metrics: power and time.

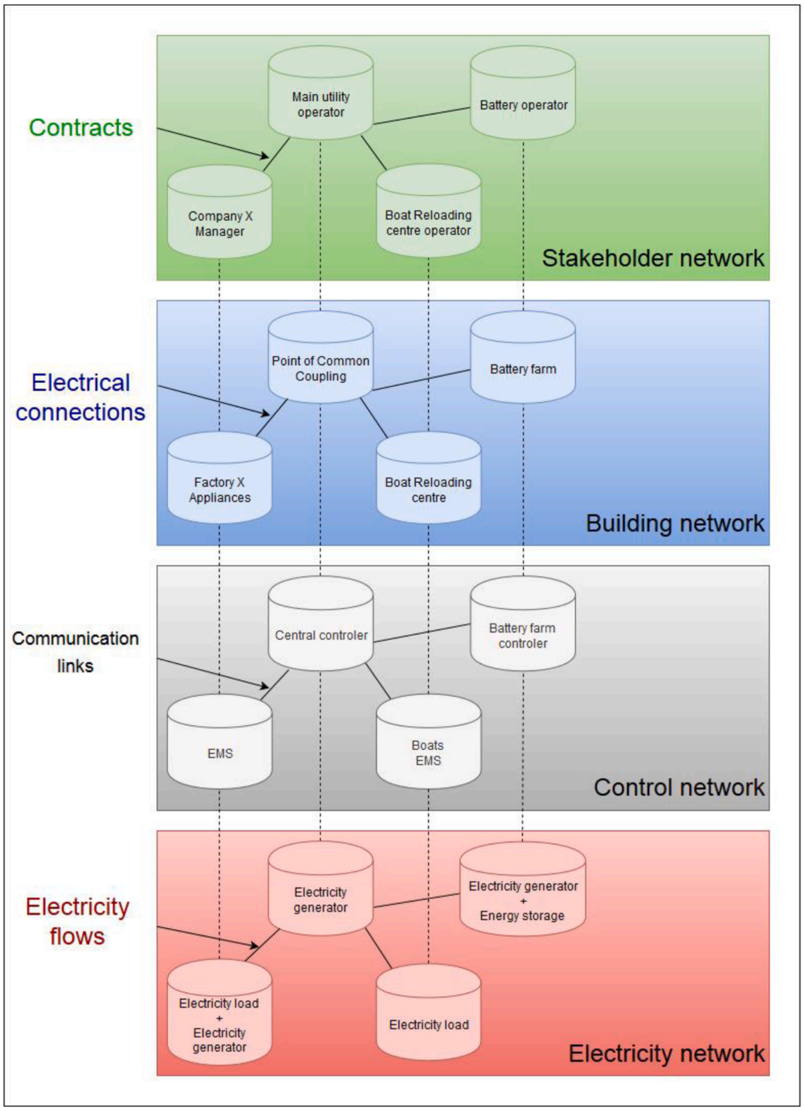

Fig. 3. Concepts and relationship in the ontology.

The outputs of temperature and energy from the prediction model are used as inputs for the optimisation system, guiding it to choose the optimal set point for each hour of run-time. Despite the system predicting outputs for 24 h in advance to visualise upcoming peaks and troughs in the trends, the optimisation model checks all parameters hourly and recalculates and actuates the optimal decisions for the system. Consequently, the system is self-checking and makes certain that decisions are made using only the most up-to-date information available. The system analyses the cost of energy at each given hourly period and finds the optimal trend of temperatures and set-points such that the cost of energy is reduced across the whole of the 24 h. It repeats this process every hour while knowing the grid's cost fluctuations for the whole day.

For measurement and verification of results, energy usage and operating data are gathered to compute energy savings. The energy consumptions and capacities of the cold rooms are considered. Calibration is achieved by verifying that the simulation model reasonably predicts the temperature and power use by comparing model results to a set of calibration data. Calibration of building simulations is usually done once hourly. The accumulated effect of the calibration was a significant impact on the system's efficiency outside of the savings from the optimisation. To compare the energy usage before and after the digital twin intervention, a baseline model recording the consumption before implementing the measures was developed. The baseline model allows for the isolation of the effects of the pilot of the impact of other parameters that can simultaneously affect the energy consumption, therefore reducing the uncertainty with which savings are estimated. The baseline is established thanks to the data collected by the measurement infrastructure already on site.

6.3. Results

For the analysis, option B, the Retrofit Isolation option from IPMVP is selected. Here the savings are calculated by field measurements of important parameters to measure system performance. This option is considered optimal for the proposed methodology used. It was important to keep the conditions in the facility as consistent as possible for before and after implementation measurement periods. The savings calculation can be made using the simplified equation as any calibration error would equally affect the baseline and post-implementation periods.

$$\begin{aligned} ExpectedsavingskWh &= ExpectedoldenergyusekWh \\ &\quad - -ExpectednewenergyusekWh \end{aligned} \tag{1}$$

The Polar site pays for energy per kWh based on the base market

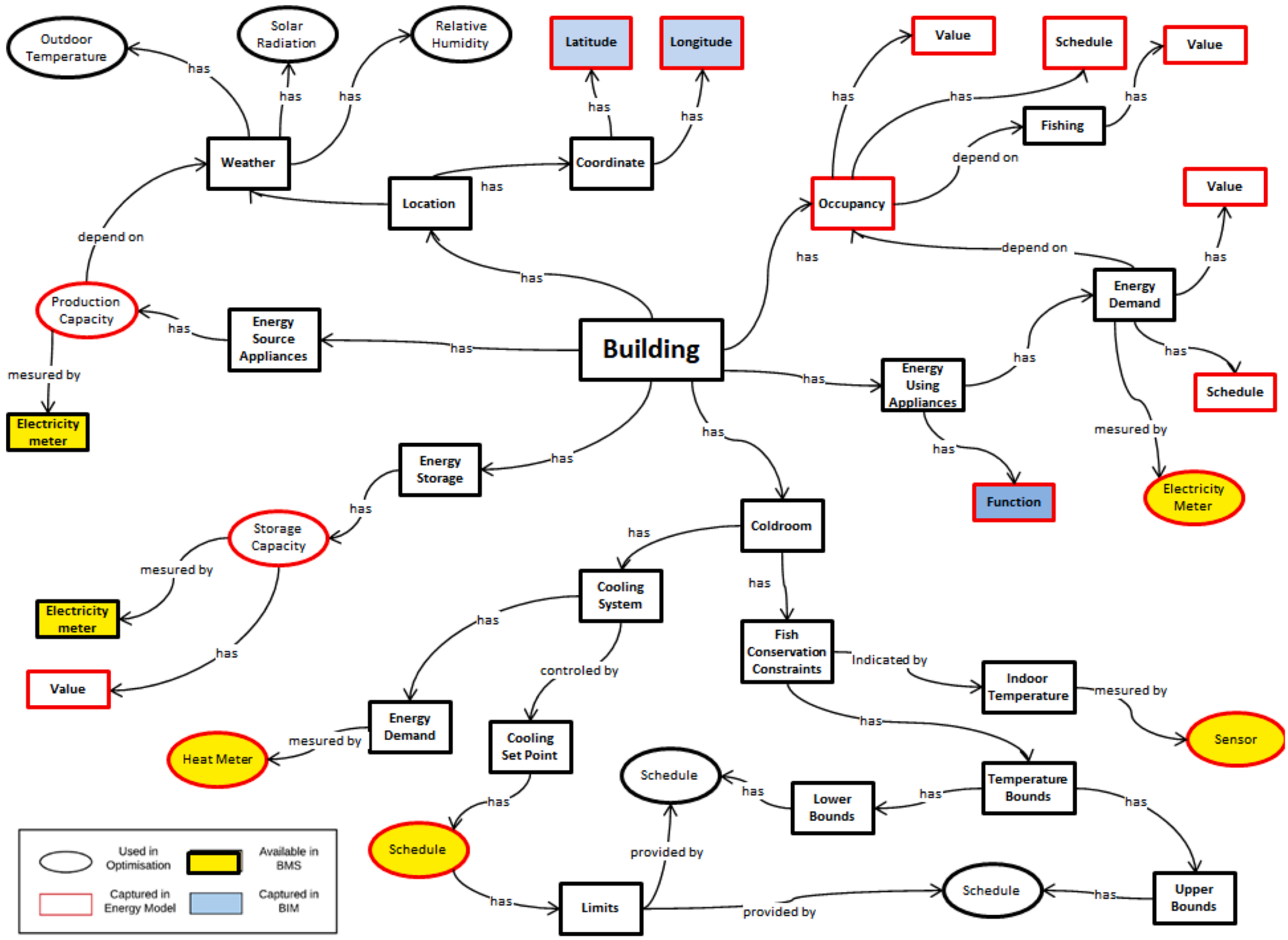

Fig. 4. Industrial building ontology.

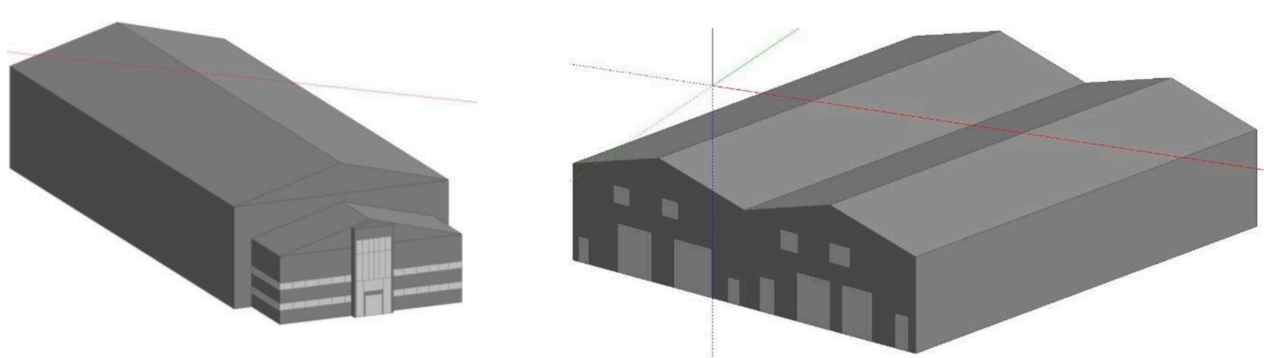

Fig. 5. 3D simulation model of the Polar site.

value, and all the extra charges are: Distribution Use of System (Duos), Time of Use (ToU) and Distribution Loss Adjustments Factors (DLAF) charges that Polar pay due to their Maximum Import Capacity (MIC). Calculating how much is paid per hour has been precalculated.

$$TotalhourlyCost = \left(kWh^{'}s * kWh\_price\right) + time\_price. \tag{2}$$

This is the breakdown of all the Open Market Wholesale charges used for the Polar site based on:

$$\begin{aligned} &PolarMIC : 190kVA \\ &Duos : DG6 \\ &Tuos : DTS - D2non - LEU \end{aligned} \tag{3}$$

Figs. 13 and 14 illustrate the compared energy consumption and energy costs for one week (one and two cold stores) where baseline is compared with digital twin optimisation results. Two baseline periods were considered. The first period was from 1st September to 31st October 2019. For one store with 75% of capacity engaged, the hourly average energy saving is 2.77 kWh, and the hourly average cost saving is €162.6. The daily average energy-saving and cost-saving are 66.4 kWh

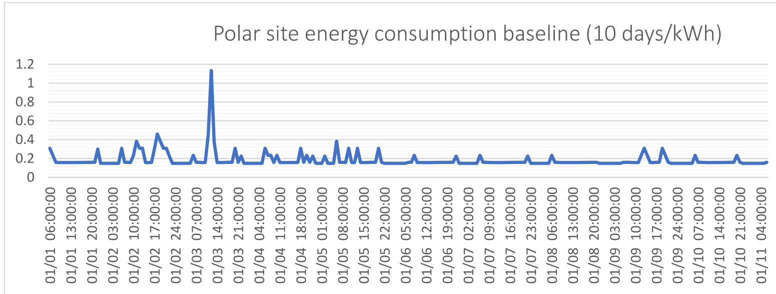

Fig. 6. Daily energy consumption of the Polar site.

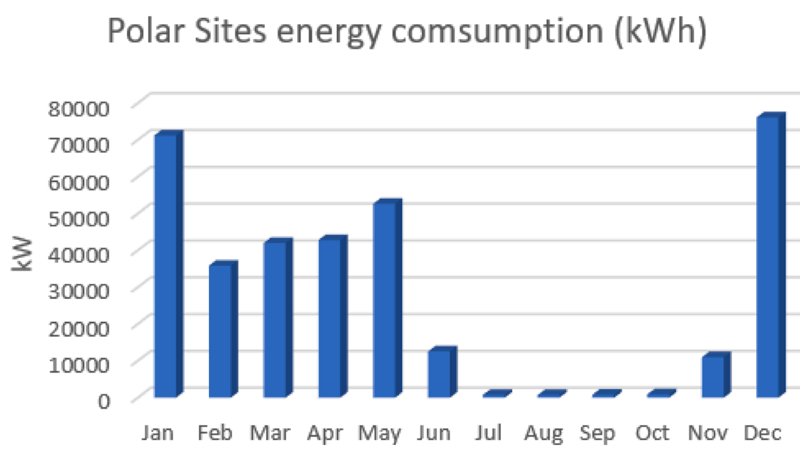

Fig. 7. Monthly energy consumption of polar site cold storages.

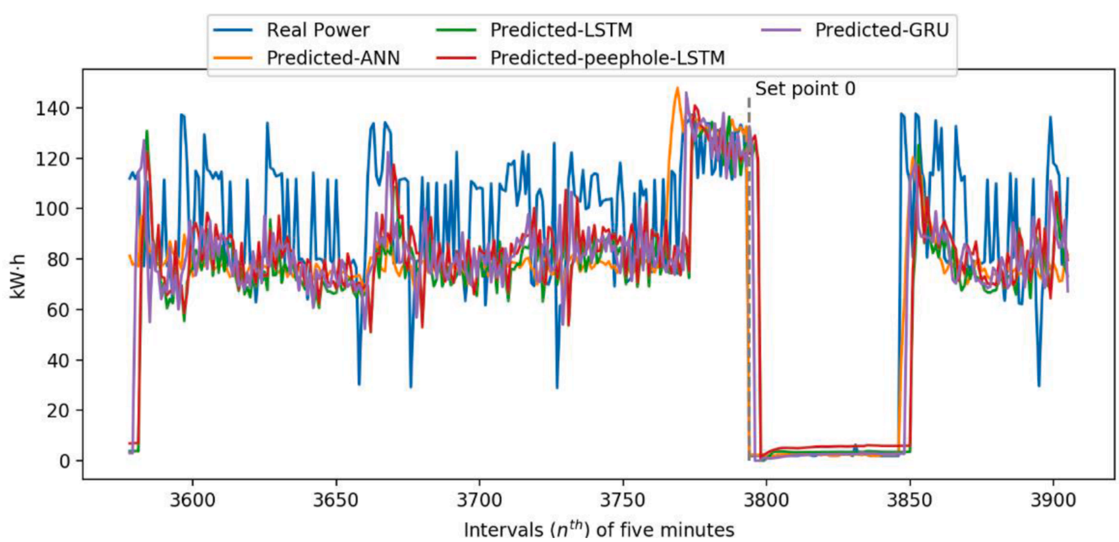

Fig. 8. Power-forecasting performances.

and €3901.7. This equates for the first baseline period as energy saving and cost saving of 4038 kWh and €237,193 respectively.

The second period was from 20th April to 30th June. For two stores with 100% capacity engaged, the hourly average energy saving is 4 kWh per hour, and the hourly average cost saving is €187.4. The daily average energy-saving and cost-saving are 94.5 kWh and €4497.6. This equates for the first baseline period as energy saving and cost saving of 4038 kWh and €237,193 respectively. The CO2 emission intensity (kg CO2/kWh) is calculated as the ratio of CO2 emissions from electricity production. CO2 emission avoided during the baselines is obtained using the conversion rate for Ireland (0.425 kg CO2 per kWh, source: The European Environment Agency - 2016). Table 3 shows the average power usage for both periods and the savings calculated.

7. Conclusions

The paper argues that the industry needs to move from the application interoperability and data sharing problematic to embrace a system engineering approach that embeds adaptability and resilience to the challenges faced by our built and industrial environments, including

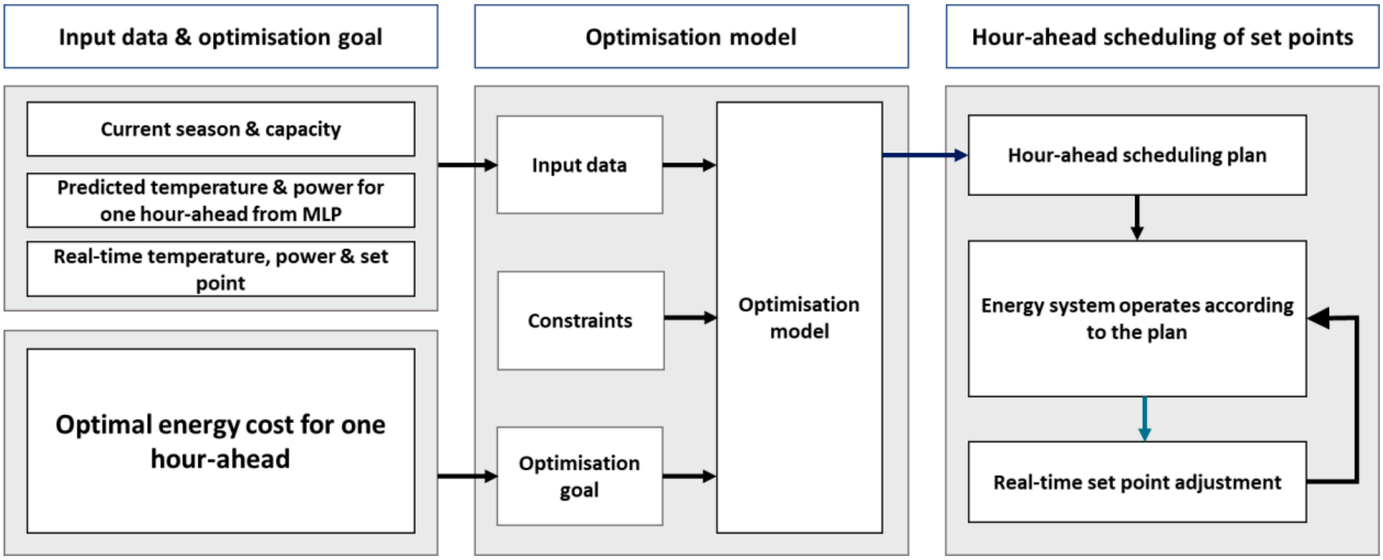

Fig. 9. The architecture of the optimisation strategy.

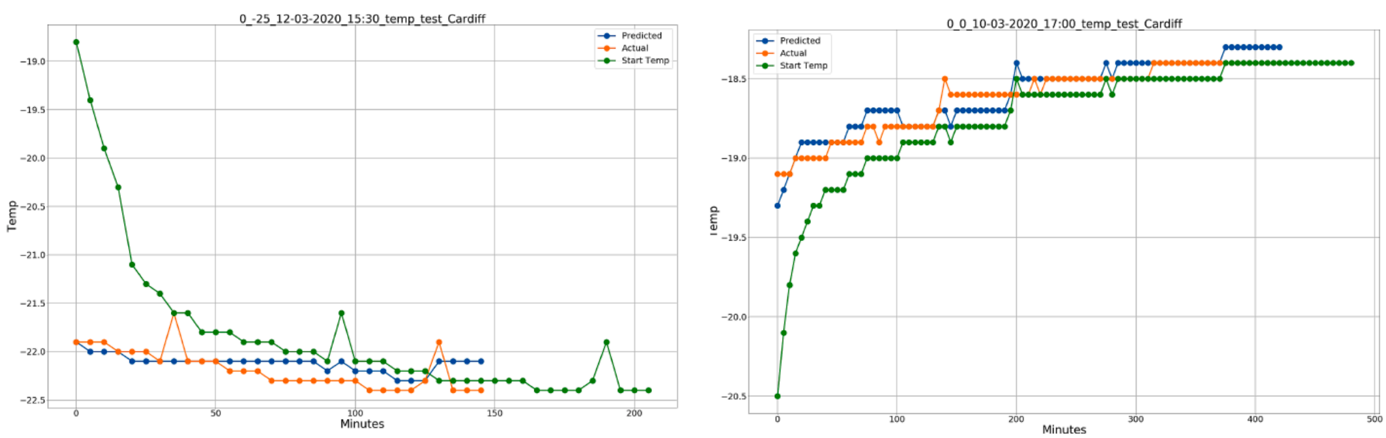

Fig. 10. Graphed results from the testing of the proposed model's temperature predictions against real-time across some different set-point changes.

climate change. We present a performance management application for industrial buildings to demonstrate the use of the digital twin into the built environment with a cost analysis approach to evidence the expected impacts of energy savings.

We believe that our research contributes to the ongoing efforts to decarbonise our built environment and provides valuable insights for a number of challenges for the construction and industrial research community in a number of areas including:

- Ø Smart materials: There is a need to rethink construction materials and exploit recent development in material sciences to promote the wide adoption in buildings of a new generation of materials that provide condition feedback and embed shape memory, energy sensitivity, and self-healing properties (enabled by self-triggering biological or other processes).
- Ø Smart components: there is a need to develop a new generation of smart (parametric, modular, inter-operable, and context-aware) building and industrial components including appliances with embedded intelligence that enable buildings and industrial sites to be assembled from, or refurbished / retrofitted with smarter engineered products and systems, while providing greater flexibility to satisfy larger customer choices and changing regulatory requirements.
- Ø Asset intelligence: There is a need to enhance current IFCs and BIM efforts and develop dynamic and total lifecycle conceptualizations of a building that provide forward and backward compatibility and regulatory compliance checking, real-time performance accounts, simulates future adaptability requirements, ensures optimum resiliency, and fitness for purpose.
- Ø Performance Characterization: there is a need to move from single-aspect to multiple aspect building performance characterisation.
- Ø Data and Process Governance: the Construction industry needs more robust and scalable software / hardware infrastructures with the right data governance model in terms of ownership, rights, and security that ensure data consistency and availability anytime / anywhere.

We have used a measurement and verification plan to perform a study on energy saving using data and models from a real industrial building. Reliable data from direct measurement evaluated the results and monitoring and two baseline metrics have been investigated. The results demonstrate that industrial buildings appliances can be managed efficiently and economically without the compromise of the products' quality. Digital twins have the capability of optimising the industrial ecosystem in accordance to a number of requirements and timing constraints. In data-intensive scenarios, executing optimisation in a distributed way can lead to significant benefits. We show how digital twins exploit the benefits of modern independent and wireless sensor technologies allowing deeper monitoring with increased frequency and

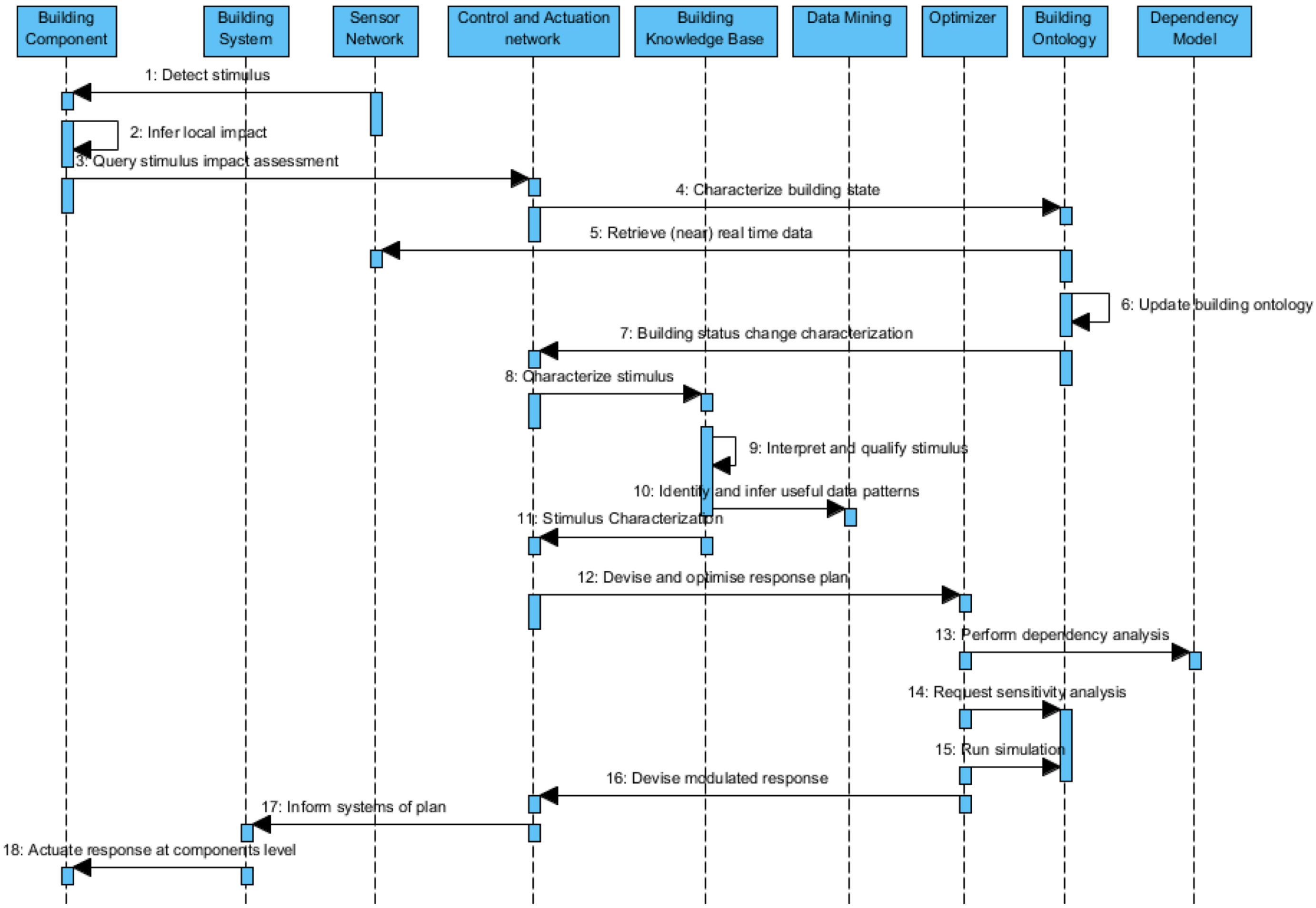

Fig. 11. Digital twin scenario illustration.

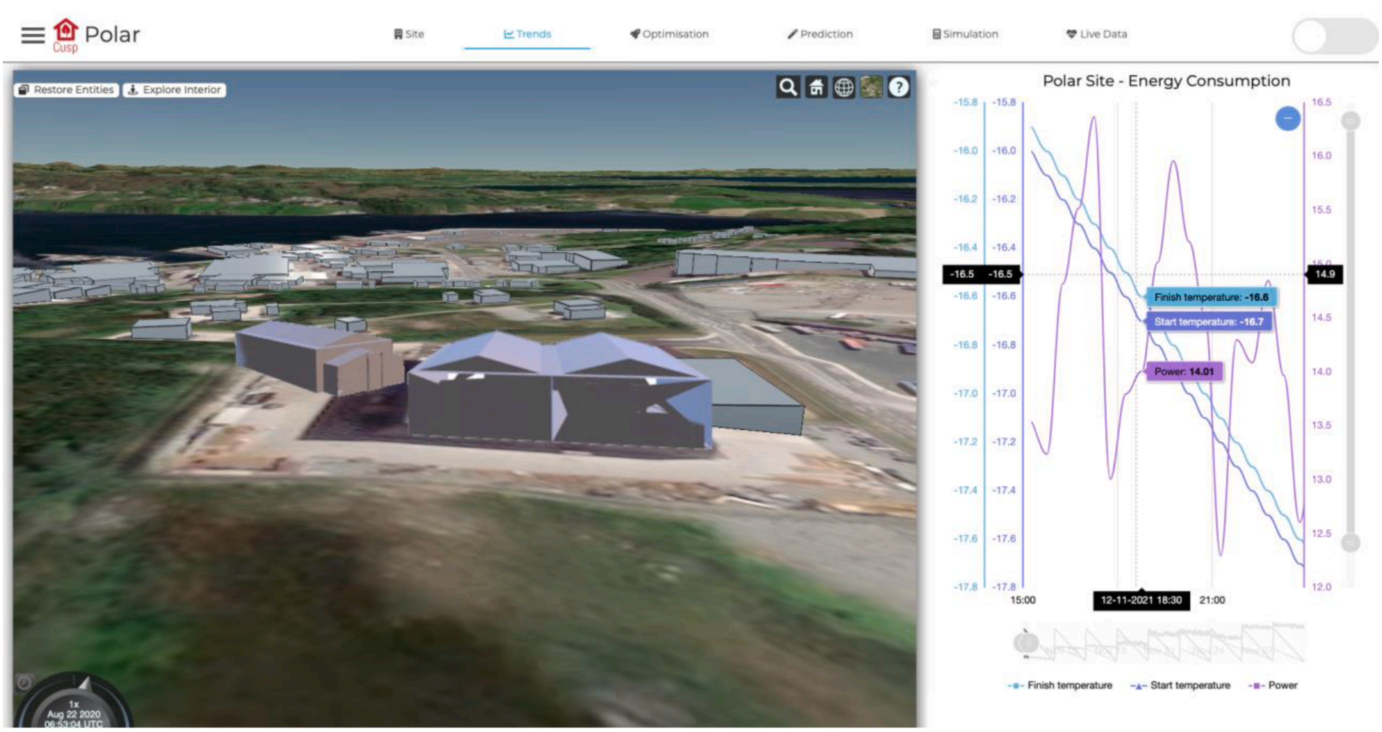

Fig. 12. Digital twin illustration of the Polar Site.

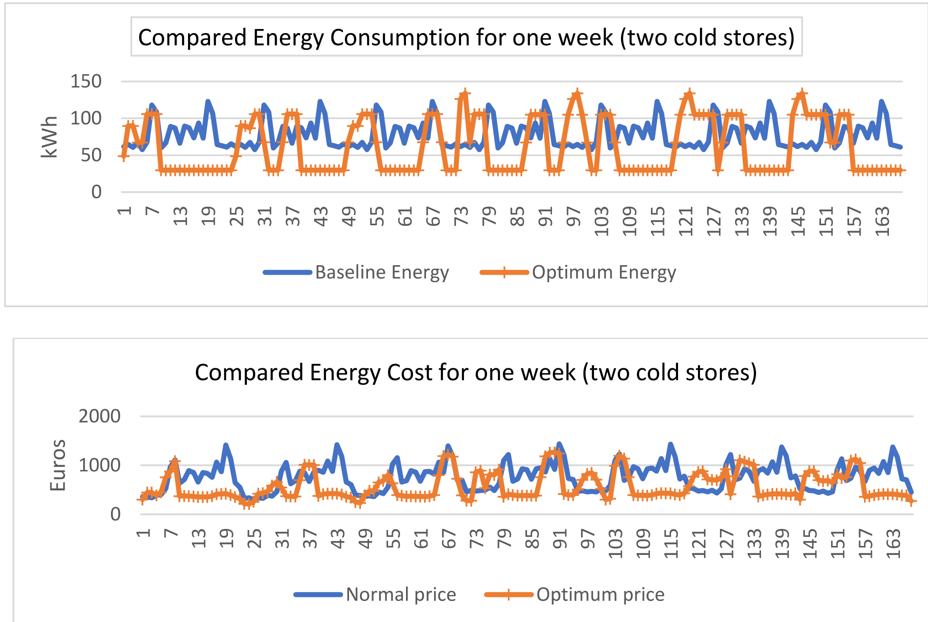

Fig. 13. The compared energy consumption and energy costs for one week (two cold stores).

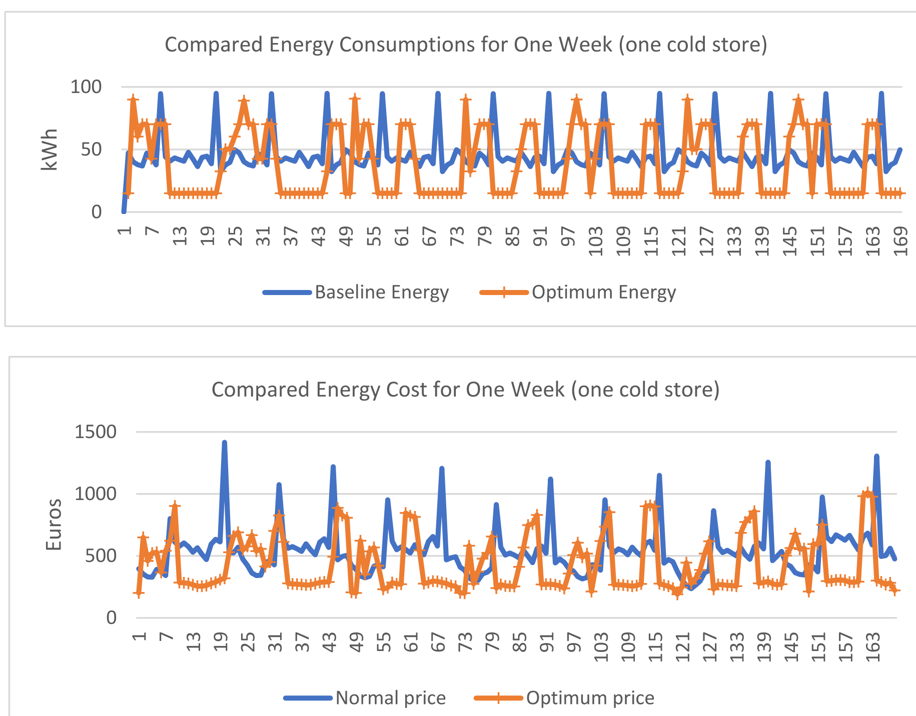

Fig. 14. The compared energy consumption and energy costs for one week (one cold store).

to enable an automatic and instant distribution of receiver tailored and pre-processed information (raw data, consumption trends, deviation alarms, etc.).

The business implications of digital twins need to be considered in relation to economic models with a focus on consumption and production factors for small and medium enterprises. A Digital twin should be underpinned by a well-elaborated business model for the investors to assess the value of their investment in digital assets whilst facilitating flexibility and innovation strategies. Digital twins also open up new opportunities of a total lifecycle philosophy where all actors of Construction and product manufacturing chain can be integrated under a digital construction framework that can support the operation and collaboration needs of the entire supply chain (Fig. 2).

CRediT authorship contribution statement

Ioan Petri: Conceptualization, Methodology, Supervision, Writing – review & editing. **Yacine Rezgui:** Conceptualization, Investigation, Supervision, Writing – review & editing. **Ali Ghoroghi:** Data curation, Formal analysis, Software. **Ateyah Alzahrani:** Data curation, Software.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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