A Knowledge-enhanced Digital Twin Modeling Method for Zero-Energy Building Operations: Semantic Integration of BIM, IoT, and Domain Knowledge with a Zero-Carbon House Case Study

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Abstract: Zero-energy buildings require operation and maintenance workflows that can continuously interpret heterogeneous building data, track equipment and environmental states, and connect sensed conditions with expert rules and control logic. Conventional building digital twins often emphasize geometric visualization and data streaming but provide limited support for semantic reasoning and knowledge-driven operation. This study proposes a knowledge-enhanced digital twin modeling method for zero-energy building operations by integrating Building Information Modeling (BIM), Internet of Things (IoT) time-series data, and ontology-based domain knowledge within a unified operational framework. The proposed method comprises a seven-layer architecture, a closed-loop construction process of data collection-modeling-simulation-verification, a multi-source fusion mechanism for static, dynamic, and knowledge data, and a composite model consisting of geometric, physical, behavioral, and semantic sub-models. A zero-carbon house at Beijing University of Technology is used to demonstrate the method. The case integrates a Revit-based BIM model, a Grasshopper/Ladybug/Honeybee energy model, an IoT sensing network with InfluxDB, and a Unity-based interactive twin. The implementation shows that the proposed model can synchronize building objects, operation states, and rule knowledge; support real-time indoor environmental quality monitoring; and enable rule-based comfort-oriented equipment control. The work contributes a practical modeling route for moving from data-centric digital twins toward knowledge-enhanced operation support in zero-energy buildings.

Keywords: Digital Twin; Zero-Energy Building; Building Operation; BIM; IoT; Knowledge Graph; Indoor Environmental Quality

1. Introduction

Buildings account for a large share of operational energy use and carbon emissions, which makes the operation phase a critical target for decarbonization and performance improvement. At the same time, building operation must maintain indoor environmental quality (IEQ), occupant comfort, and equipment reliability rather than pursuing energy reduction in isolation [1-3]. For zero-energy and near-zero-energy buildings, these requirements are even more stringent because renewable generation, envelope performance, occupant behavior, and system control interact dynamically during daily operation [2,13,14].

Digital twin research has rapidly expanded across the architecture, engineering, construction, operation, and facility management (AECO-FM) domain. Recent reviews in the Journal of Building Engineering show that digital twins are increasingly applied to facility monitoring, energy and environment management, predictive maintenance, and intelligent operation support, but most implementations still face gaps in interoperability, semantics, automation, and decision support [4-9]. Existing studies have demonstrated valuable capabilities for real-time indoor environment visualization [8], platform-oriented predictive maintenance [26], and digital twin system deployment for central air-conditioning [25]. However, fragmented data pipelines and insufficient semantic integration remain major barriers to building-level operational intelligence [4-12].

A recurring limitation in the literature is that BIM-based twins and IoT-driven operation platforms often remain predominantly data-centric. They can describe geometry, display sensor values, and sometimes trigger analytics, yet they usually struggle to formalize expert knowledge, operation rules, comfort criteria, equipment constraints, and causal relations among building objects and events [10-12,15,16]. This limitation is critical for zero-energy building operation, where an operator must not only know what is happening but also interpret why a state is problematic, which thresholds matter, and what response is appropriate under energy, comfort, and equipment constraints.

Recent work has started to address this gap through semantic construction digital twins [10], knowledge graph-based integration [11], dynamic knowledge graph applications [12], ontology-enabled intelligent twins [15], and ontology-driven energy modeling workflows [16]. These studies collectively suggest that the next step for building digital twins is to move beyond geometry-plus-data integration toward knowledge-enhanced models that can support explanation, traceability, and action. Yet a clear operational modeling pathway for zero-energy buildings is still insufficiently articulated, especially one that links BIM, time-series sensing, domain knowledge, and operation-oriented control logic in an implementable case.

From the perspective of zero-energy building operation, the inadequacy of purely data-centric twins is not a minor technical inconvenience but a structural limitation. A zero-energy building is evaluated not only by annual energy balance, but also by whether it can maintain acceptable indoor environmental quality, operational stability, and user satisfaction under varying weather conditions, intermittent renewable energy supply, and changing occupancy schedules. In practice, building operators need to interpret the relationship among envelope performance, equipment states, sensed IEQ indicators, control thresholds, and renewable-energy-related operating decisions. Such interpretation requires a model that can connect physical entities and streaming data with rules, semantics, and domain constraints rather than merely displaying values in a dashboard [2,3,13,14].

Another important issue is the difference between design-stage optimization and operation-stage intelligence. Many high-performance buildings achieve favorable simulation outcomes during design, yet their operational performance later diverges due to commissioning problems, equipment degradation, altered occupancy patterns, manual overrides, or insufficiently contextualized controls. The operation phase therefore demands a digital representation that remains responsive to real-time evidence while preserving the engineering meaning of that evidence. Recent literature in the Journal of Building Engineering shows that digital twins are increasingly adopted to support monitoring, maintenance, and performance management, but their maturity still depends on how effectively geometry, sensing, analytics, and operational knowledge are orchestrated into an actionable system [4-9].

The literature further suggests that semantic technologies can play a decisive role in overcoming fragmentation. Semantic construction twins, knowledge graphs, and ontology-enabled agents can formalize building entities, states, dependencies, and rules, thereby improving interoperability, explainability, and automated reasoning [10-12,15,16]. However, existing studies often focus on either conceptual architecture, data models, or isolated analytical tasks. Fewer studies provide an end-to-end operational modeling route that starts from a building information model, incorporates IoT sensing and simulation, encodes rule knowledge, and demonstrates how these components jointly support zero-energy operation in a concrete building case. This gap is particularly evident for small-to-medium demonstrator buildings, where research prototypes can reveal implementation logic but are often reported in a fragmented manner.

Based on the above review, four research gaps are identified. First, many operational twins still lack an explicit object-state-rule chain, meaning that building components, sensor streams, thresholds, and control responses are not systematically linked. Second, static data, dynamic data, and expert knowledge are often treated as parallel resources rather than as mutually constrained layers of a single twin. Third, existing implementations frequently emphasize either visual monitoring or predictive analytics, while the semantic basis for reasoned decision support remains underdeveloped. Fourth, validation in the literature often concentrates on one technical module, such as sensing, simulation, or maintenance, without showing how a knowledge-enhanced twin can be assembled and iteratively refined for a zero-energy operation scenario.

Accordingly, the present study makes four main contributions. First, it proposes a seven-layer knowledge-enhanced digital twin architecture tailored to zero-energy building operation, explicitly distinguishing model, data, semantic, agent, application, and connection roles. Second, it formulates a closed-loop construction process in which multi-source data collection, model building, simulation analysis, and verification are iteratively connected. Third, it develops a composite twin model composed of geometric, physical, behavioral, and semantic knowledge sub-models, thereby clarifying how a building can be represented simultaneously as a spatial object, a thermophysical system, a time-varying operational process, and a knowledge-bearing entity. Fourth, it demonstrates the method through a zero-carbon house case integrating Revit, Grasshopper/Ladybug/Honeybee, IoT sensing, InfluxDB, and Unity, showing how knowledge-enhanced modeling can support IEQ-oriented monitoring and rule-based control assistance.

The remainder of this paper is organized as follows. Section 2 presents the proposed methodology, including the architecture, construction loop, multi-source fusion strategy, and composite model logic. Section 3 introduces the case building and implementation workflow. Section 4 discusses the integrated results, operational implications, limitations, and research significance. Section 5 concludes the paper and outlines future research directions for scalable and increasingly autonomous digital twins in zero-energy building operation.

This study addresses that need by transforming a thesis chapter on knowledge-enhanced digital twin construction into a journal-style research article suitable for the Journal of Building Engineering. The study proposes a knowledge-enhanced digital twin modeling method for zero-energy building operations with three objectives: (1) to establish a multi-layer operational architecture that unifies physical assets, virtual models, data, semantics, analytics, and applications; (2) to develop a multi-source fusion method that integrates static BIM data, dynamic IoT data, and domain knowledge into a composite digital twin; and (3) to demonstrate the method through a zero-carbon house case involving energy modeling, IEQ monitoring, and comfort-oriented automated control.

2. Methodology

2.1 Overall Architecture of the Knowledge-enhanced Digital Twin

The proposed digital twin is organized as a seven-layer architecture composed of the physical layer, model layer, data layer, semantic layer, agent layer, application layer, and connection layer, as illustrated in Figure 1. Unlike a conventional BIM-IoT stack, the framework explicitly introduces a semantic layer to formalize object meaning, operating logic, evaluation criteria, and response rules, thereby enabling the twin to evolve from state representation toward interpretable operation support [5,6,8,10,15].

The physical layer contains the actual zero-energy building entity and its operating context, including spaces, envelope elements, HVAC equipment, renewable energy systems, sensor nodes, and indoor-outdoor environments. The model layer provides high-fidelity virtual representations of building spaces, envelope components, MEP systems, and topology through BIM and energy simulation models. The data layer aggregates static model data, real-time sensor data, and historical operation records, while the semantic layer organizes entities, attributes, rules, thresholds, and relationships through ontology and knowledge graph techniques [11,12].

On top of these layers, the agent layer executes analytics such as state perception, trend interpretation, anomaly indication, and control rule evaluation; the application layer delivers monitoring, visualization, warning, and operation-support functions to users; and the connection layer ensures bidirectional communication among the physical and virtual spaces. This layered arrangement is intended to support zero-energy building operation as a coordinated cyber-physical-knowledge system rather than a stand-alone visualization environment.

The architecture was guided by four design principles. The first is operational completeness: the twin should represent not only geometry and telemetry, but also the decision context of building operation. This means that static design attributes, real-time states, control thresholds, and response rules must coexist in a coordinated structure. The second is semantic traceability: every relevant sensor stream and analytical result should be traceable back to a building object, spatial unit, or system entity with explicit engineering meaning. The third is iterative updatability: model parameters, semantic relations, and operational rules should be revisable as new evidence emerges. The fourth is controllability: the twin should be designed so that analysis can inform practical operation support, whether through visualization, alerts, or supervised control execution.

These principles are especially important for zero-energy buildings because operational decisions are multi-objective by nature. A seemingly simple control action, such as lowering indoor temperature in summer, may influence comfort, equipment runtime, electricity consumption, and the use of locally generated renewable energy. Likewise, an indoor illuminance threshold is not only a lighting issue; it may interact with occupancy schedules, daylight availability, plug loads, and occupant satisfaction. The proposed architecture therefore separates layers according to their dominant functions while ensuring that information can move across layers in a governed manner. In other words, the architecture is modular in implementation but integrated in logic.

Within this layered view, the semantic layer acts as the pivotal mechanism for transforming a digital building model into an operational knowledge system. It mediates between data and action by expressing which parameter belongs to which object, which state is considered acceptable, which conditions define an event, and which responses are allowed or recommended. The agent layer can then evaluate conditions in a machine-readable way instead of relying on ad hoc scripts tightly coupled to individual sensors. This separation improves the reusability of analytics and reduces the risk that the twin becomes a brittle, one-off integration project. As a result, the proposed architecture is intended not only as a case-specific implementation, but also as a transferable modeling blueprint for similar high-performance building operation scenarios.

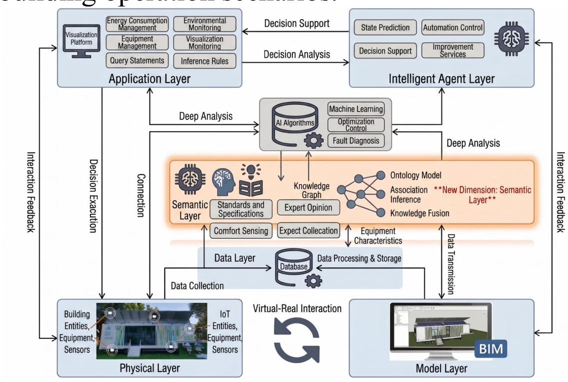

Figure 1. Overall Architecture of the Knowledge-enhanced Digital Twin for Zero-energy Building Operation.

Table 1. Seven-layer Architecture and Operational Roles of the Proposed Digital Twin

Layer	Core contents	Operational role
Physical layer	Building spaces, envelope, HVAC, renewable systems, sensors, indoor/outdoor environment	Provides the real operating entity and data source
Model layer	BIM geometry, physical properties, topology, energy model	Creates the virtual carrier for mapping and simulation
Data layer	Static BIM data, IoT time-series data, historical records	Aggregates and manages heterogeneous building data
Semantic layer	Ontology, knowledge graph, rules, thresholds, object relations	Connects geometry, data, and knowledge for reasoning
Agent layer	State perception, prediction, diagnosis, optimization logic	Supports analytics and decision generation
Application layer	Visualization, alarms, dashboards, assisted control	Delivers user-facing operation services
Connection layer	Protocols, APIs, communication interfaces, feedback links	Maintains bidirectional synchronization and interoperability

2.2 Closed-Loop Model Construction Process

To ensure that the digital twin remains operationally relevant, model construction is treated as a closed-loop process rather than a one-time modeling exercise, as illustrated in Figure 2. The workflow includes four stages: data collection, model development, simulation and analysis, and verification and iterative updating. Static data, dynamic data, and domain knowledge are first acquired; geometric, physical, behavioral, and semantic models are then established; simulation and operational analysis are subsequently performed; and the model is finally calibrated and updated using observed building responses.

This iterative view is essential for operational twins because boundary conditions, equipment behavior, and control knowledge change over time. A digital twin for zero-energy operation therefore needs to evolve with newly sensed conditions, newly interpreted events, and updated knowledge rules, particularly when the objective is to support IEQ control and future decision-making rather than only display data [6,9,15,16].

$$T(k+1)=V(A(M(C(Ds, Dd, K)), T(k))) \quad (1)$$

where T(k) is the digital twin state after iteration k; Ds denotes static building data; Dd denotes dynamic monitoring data; K denotes domain knowledge; C is the collection and fusion process; M is model development; A is simulation and analysis; and V is verification and iterative updating.

The collection stage is broader than sensor acquisition alone. It includes the retrieval of as-designed and as-built BIM information, the acquisition of monitored operational data, and the formalization of domain knowledge from standards, manuals, and practitioner experience. In many building projects, these resources are produced by different actors using incompatible schemas and timescales. Treating them as a unified collection problem forces the modeling process to define identifiers, metadata, temporal conventions, and quality requirements at an early stage. This is important because integration failures in operational twins often originate from neglected data governance rather than from deficiencies in analytics.

The modeling stage translates the collected resources into reusable structures. Geometric and physical data are assembled into spatially explicit objects; monitored variables are converted into time-stamped operational states; and rule knowledge is transformed into structured entities and relations. The simulation-analysis stage then uses these structures to generate interpretable outputs, such as monthly energy patterns, IEQ status recognition, rule checking, and scenario-based operational assessment. Importantly, simulation is not treated here as a detached design exercise. Instead, it becomes one analytical module of the digital twin, complementing real-time sensing by providing physically informed context, expected behavior ranges, and exploratory what-if capability.

Verification closes the loop by comparing modeled states, simulated tendencies, and rule outcomes with observed building conditions. In an operational twin, verification may involve checking sensor plausibility, aligning simulated energy behavior with measured patterns, reviewing whether rules generate sensible actions, and updating ontology links when physical or organizational changes occur. Therefore, the iteration updates not only numerical parameters but also semantic definitions and operational logic. This broader understanding of verification is essential for knowledge-enhanced twins, because a system may be numerically correct yet still operationally weak if its concepts, object mappings, or rule sets are outdated.

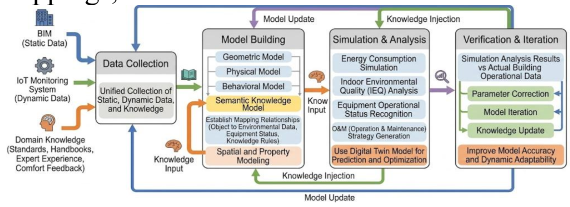

Figure 2. Closed-loop Construction Process of the Knowledge-Enhanced Digital Twin

2.3. Multi-source Data Acquisition and Fusion

The data basis of the proposed twin is divided into three categories: static data, dynamic data, and domain knowledge. Static data describe building geometry, construction layers, equipment attributes, and spatial topology. These data are primarily obtained from BIM and provide the stable object structure required for mapping and simulation [1,7,25]. Dynamic data are generated during operation and include IEQ variables, equipment states, energy use, and renewable energy outputs. These time-stamped data streams are collected through IoT devices and are necessary for real-time synchronization and feedback [8,17-24]. Domain knowledge includes comfort criteria, building standards, equipment manuals, operator experience, and control logic. This knowledge is required to interpret monitored states and define meaningful responses [10-12,15].

Fusion is implemented at three complementary levels. First, object mapping links each room, envelope component, and equipment element in BIM to sensor points, database tags, and knowledge graph nodes through unique identifiers. Second, temporal synchronization uses time stamps to connect changing operating states to the relevant model objects and historical records. Third, semantic association links monitored variables with threshold rules, functional roles, and response logic, thereby allowing a numerical value such as room temperature to be interpreted simultaneously as an IEQ indicator, a comfort assessment variable, and a control trigger [11,12,32].

Static data in the proposed framework are not limited to visually descriptive BIM attributes. For operation-oriented modeling, static information must be curated according to its downstream analytical value. This includes geometric descriptors of spaces and envelope components; material and thermal properties that influence heat transfer and storage; equipment metadata such as rated power, service zone, and installation location; and topological relations such as adjacency, containment, connection, and system membership. In practical terms, this means that the BIM model needs to be developed beyond presentation-grade detail. Attributes that appear secondary during design, such as naming consistency, room identifiers, or system-zone correspondence, become fundamental when the model is expected to support operational mapping and semantic reasoning [1,5,6].

Dynamic data are treated as event-bearing time series rather than as isolated measurements. Each data point is associated with a timestamp, a source device, a mapped spatial or system object, and an interpretable parameter type. This representation allows the twin to answer questions such as where a deviation occurred, what variable it concerns, and whether it is persistent or transient. For IEQ-related operation, temperature, relative humidity, illuminance, CO_2 concentration, and noise levels are particularly valuable because they collectively reflect thermal, visual, acoustic, and air-quality dimensions of indoor conditions [17-24]. However, their usefulness depends heavily on sensor placement, sampling strategy, communication reliability, and data cleaning procedures. A knowledge-enhanced twin must therefore treat data quality as part of the operational model rather than as a purely preprocessing issue.

Domain knowledge constitutes the third data category and is the least standardized in typical building digitalization workflows. In this study, domain knowledge covers explicit normative knowledge and contextual operational knowledge. Normative knowledge includes thresholds, comfort ranges, and equipment-related constraints derived from standards and technical documentation. Contextual operational knowledge includes practitioner heuristics, building-specific control preferences, and interpretations of how multiple parameters should be evaluated jointly in a given use case. For example, a temperature threshold may be straightforward in isolation, but practical operation often requires contextual interpretation, such as whether the room is occupied, whether daylight is sufficient, or whether renewable generation is currently available. Structuring such knowledge improves the twin's ability to move beyond passive display toward active interpretation.

To align these heterogeneous data categories, the fusion strategy relies on three governance mechanisms in addition to the previously mentioned object mapping, time synchronization, and semantic association. The first mechanism is identifier management. A persistent identifier is assigned to each relevant room, component, equipment item, sensor point, and knowledge node so that cross-system references remain stable even when source files evolve. The second mechanism is metadata harmonization. Parameter names, units, update frequencies, and coordinate references are normalized to avoid semantic drift during data exchange. The third mechanism is quality annotation. Missing values, abnormal readings, model uncertainty, and rule provenance can be tagged so that analytics and operators understand the reliability of the information being used.

This fusion strategy also clarifies the relationship between BIM, database records, and knowledge graphs, as illustrated in Figure 3. BIM provides the core spatial and object scaffold; the time-series database provides operational evidence of how states evolve; and the knowledge graph provides the semantic and rule context through which those states are interpreted. None of the three can fully replace the others. A BIM-only solution lacks temporal awareness, a time-series-only solution lacks object meaning, and a knowledge-only solution lacks empirical grounding. The knowledge-enhanced digital twin emerges precisely from their coordinated use. This coordinated view is critical for zero-energy building operation because it allows energy behavior, indoor environment, and control logic to be examined as coupled aspects of one evolving system rather than as disconnected information streams.

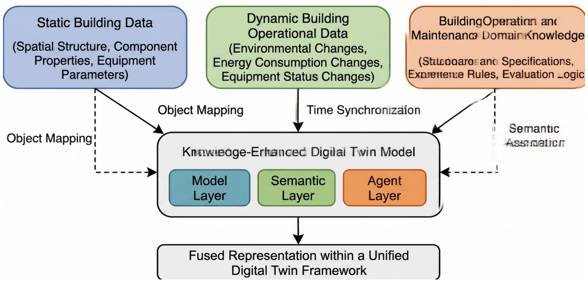

Figure 3. Static Data-Dynamic Data-Knowledge Fusion Mechanism of the Proposed Digital Twin

2.4 Composite Model Development

The knowledge-enhanced digital twin is structured as a composite model with four interrelated sub-models: a geometric model, a physical model, a behavioral model, and a semantic knowledge model. The geometric model provides the three-dimensional description of spaces, envelope components, and systems. The physical model enriches these objects with material, thermal, and equipment attributes that are needed for performance analysis. The behavioral model introduces temporal evolution by describing energy use, IEQ changes, sensor streams, and equipment operation patterns. The semantic knowledge model organizes concepts such as space, sensor, state, threshold, rule, and control action into a formal representation that connects data and operational meaning [8,10-12,15].

This composite arrangement reflects the view that the twin of a building in operation is not only a geometric mirror but also a performance-, behavior-, and knowledge-aware representation. The semantic model is particularly important because it transforms isolated data points into interpretable operational states. For example, a measured temperature value becomes meaningful when linked to a specific room, an indoor thermal condition class, a comfort range, and a control response such as cooling activation [17,20,25].

The four sub-models are intentionally arranged as a progression from representation to interpretation. The geometric model answers where building objects are and how they are spatially related. The physical model answers what those objects are made of and which performance-relevant properties they embody. The behavioral model answers how the building and its systems change over time under operation. The semantic knowledge model answers how those changing states should be understood within an operational decision context. By separating these questions, the framework avoids overloading any single model component while still preserving integrative reasoning capability.

A useful way to conceptualize the composite model is as a chain of transformations from object to state, state to event, and event to action. A room, device, or envelope element first exists as an identifiable object in the geometric and physical models. Sensor readings and simulation outputs then instantiate states related to that object, such as room temperature, window solar exposure, or equipment runtime. Semantic rules subsequently determine whether particular state combinations qualify as events, such as overheating, insufficient illuminance, or humidity deficiency. Finally, operational logic links events to candidate actions, including visualization alerts, equipment switching, or decision-support recommendations. This object-state-event-action chain is particularly important for explainability, because it makes automated outputs traceable to explicit model elements and rule definitions.

The semantic knowledge model also provides a bridge between generic and building-specific knowledge. Generic concepts such as room, sensor, device, comfort parameter, and threshold can be reused across projects, while building-specific instances such as a particular office zone, lighting circuit, or monitored sensor node are instantiated within the case. This layered ontology strategy supports reuse without sacrificing contextual accuracy. It also makes future extension more feasible: additional concepts related to fault diagnosis, occupancy prediction, renewable energy dispatch, or demand response can be introduced without redesigning the entire twin structure. In this sense, the semantic layer is not an optional enrichment, but the mechanism that enables modular growth of the operational twin over time.

3. Case study and Implementation

3.1 Case Building and Digital Twin Scope

The proposed method was demonstrated using a zero-carbon house located at Beijing University of Technology. The case was selected because it combines a compact building envelope, renewable energy utilization, and a controllable operation environment suitable for integrating BIM, sensing, simulation, and rule-based control. The digital twin scope in this study covers the building envelope, key indoor spaces, core environmental variables, selected equipment, and a human-comfort-oriented operation scenario.

The implementation integrates four technical components: (1) a Revit-based BIM model for the geometric and physical representation of the building; (2) a Grasshopper-based simulation workflow employing Ladybug and Honeybee for energy-related analysis; (3) an IoT sensing and database pipeline using sensor modules, microcontrollers, Wi-Fi transmission, and InfluxDB for real-time data storage; and (4) a Unity-based interactive environment for visualization, dashboarding, and operation logic execution.

The choice of a zero-carbon house as the demonstrator is methodologically meaningful. Small demonstrator buildings provide a manageable scale for tracing the complete modeling chain from object definition to control response, which is often difficult to document in larger building portfolios where multiple legacy systems, organizations, and exceptions are involved. At the same time, such buildings still embody the essential challenges of zero-energy operation: interaction between envelope performance and internal loads, dependence on renewable generation, sensitivity to occupant comfort, and the need to interpret multi-source operational evidence. The case therefore functions as an experimental microcosm for the proposed methodology rather than merely as a simplified visualization exercise.

In defining the scope of the twin, the study prioritized functions that are highly relevant to operation and likely to benefit from semantic enhancement. These functions included envelope-aware energy representation, room-level IEQ monitoring, rule-based comfort assessment, equipment-state visualization, and controlled linkage between monitoring and response. The scope intentionally excludes more ambitious modules such as predictive control optimization or portfolio-level benchmarking, because the primary aim at this stage is to demonstrate how a knowledge-enhanced twin can be assembled as a reliable operational substrate. Establishing such a substrate is a necessary precursor to more advanced intelligent services.

From a systems-integration perspective, the case also illustrates the need for careful boundary definition. Not every available data source or analytical function needs to be embedded directly into the twin at once. Instead, the implementation delineates a core operational loop: building objects and properties are defined in BIM, energy tendencies are explored in simulation, real-time states are captured through sensing, and rule knowledge is evaluated within the application environment. This staged integration reduces implementation complexity while preserving extensibility. It also mirrors realistic practice, in which digital twin capability often evolves incrementally rather than being deployed as a fully mature platform from the outset.

3.2 Geometric and Physical Model

A high-fidelity BIM model of the zero-carbon house was established in Revit based on the design drawings and construction-stage adjustments, as illustrated in Figure 4. The model integrates architectural, structural, and MEP information and preserves the topology required for mapping spaces, envelope components, and equipment objects. In the operation phase, this BIM model functions not only as a visualization medium but also as the anchor model to which sensor data, semantic labels, and control logic are attached.

To support performance-oriented operation analysis, the building envelope and opening elements were enriched with physical attributes such as thickness, thermal conductivity, density, specific heat capacity, and optical properties where applicable. These data were subsequently used in the energy model to represent the thermal behavior of roof, wall, floor, window, and door assemblies.

Embedding physical properties into the BIM model serves more than documentation purposes. In operation-oriented digital twins, the thermophysical properties of envelope assemblies influence how operators interpret indoor conditions and energy behavior. For example, when an indoor space exhibits overheating or excessive cooling demand, the twin should allow the analyst to relate this condition not only to equipment operation or weather but also to the thermal resistance, thermal mass, and solar transmittance characteristics of the relevant building elements. By preserving these attributes in the model, as illustrated in Figure 5. the digital twin gains the ability to connect sensed phenomena with likely physical causes, thereby supporting more informed diagnosis and strategy discussion.

Another important aspect is topological readability. Building operation is rarely performed at the level of isolated components; instead, it concerns relationships among spaces, systems, and service zones. The geometric-physical model therefore provides the backbone for mapping monitored variables to rooms, linking devices to the spaces they condition, and associating envelope elements with exposed zones. This topological clarity improves both visualization and reasoning. In practical use, it allows an operator to move from a high-level alert to the relevant room, then to the implicated device or envelope component, and finally to the applicable rule set, all within one coherent model environment.

3.3 Behavioral Model: Energy Simulation and Real-Time Sensing

The behavioral model was developed from two complementary sources. First, a simulation workflow was built in Grasshopper using Ladybug and Honeybee to represent monthly energy behavior under the modeled envelope, occupancy schedule, equipment schedule, and on-site solar generation assumptions. Second, a real-time sensing workflow was deployed to capture indoor environmental conditions and equipment-related states during operation.

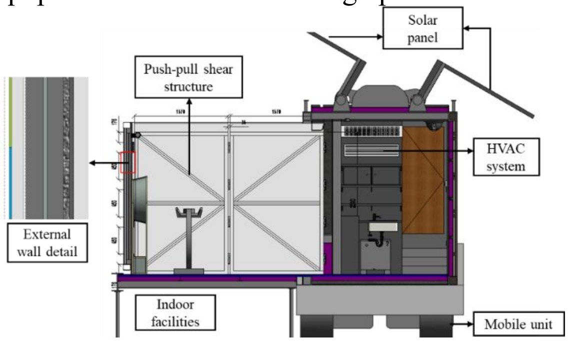

Figure 4. Topological Representation of the Zero-carbon House Envelope and BIM Object Relationships.

Table 2. Main physical Properties of Envelope and Opening Elements used in the Case Model.

Component	Layer/ material	Thk. (mm)	k (W/m·K)	Density (kg/m³)	Cp (J/kg·K)	Notes
Roof	Galv. steel sheet	2	45	7850	450	Outer
Roof	Polyurethane	75	0.0028	40	1300	Insulation
Roof	Air layer	125	26	1.225	1005	Cavity
Roof	Gypsum board	10	0.26	1100	900	Finish
External wall	Galv. steel sheet	2	45	7850	450	Outer
External wall	Air layer	125	26	1.225	1005	Cavity
External wall	Polyurethane	75	0.0028	40	1300	Insulation
External wall	Fiber-cement board	18	0.7	1000	1100	Substrate
External wall	Aluminum panel	9	2	2500	1000	Interior finish
Internal wall	Steel plate / PU / steel plate	10/ 75/ 10	50/ 0.0028/ 50	7850/ 40/ 7850	480/ 1300/ 480	Sandwich wall
Floor	Steel + C30 concrete + PU + composite board + wood	2/ 63/ 75/ 20/ 8	50/ 1.6/ 0.0028/ 0.27/ 0.1	7850/ 2400/ 40/ 1750/ 500	480/ 900/ 1300/ 850/ 2000	Layered floor
Insulated door	Composite panel	50	0.5	700	900	Opaque
Electrolytic glass window	Glazing	50	0.9	-	-	Trans.0.07; refl.0.5
Glass door	Glazing	50	0.85	-	-	Trans.0.05; refl.1.5

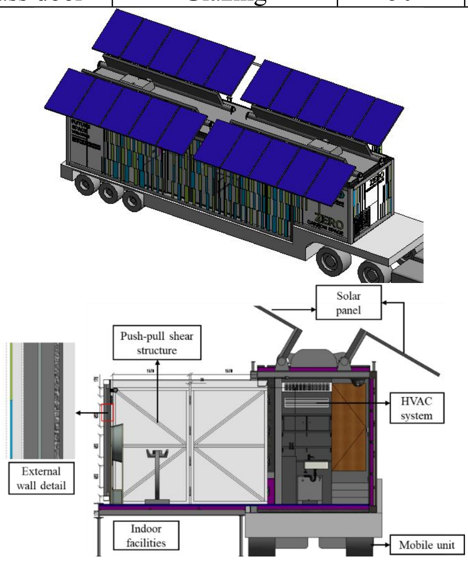

Figure 5. Geometric-Physical Model and Section of the Zero-Carbon House.

The sensing system included environmental sensors, a microcontroller, and wireless data transmission modules, as illustrated in Figure 6. Temperature, relative humidity, illuminance, CO2 concentration, and sound intensity were sampled and transmitted via Wi-Fi to an InfluxDB time-series database. The resulting data pipeline formed a complete chain from environment sensing and local preprocessing to network transmission, time-stamped storage, and platform retrieval. Sensor positioning was arranged with reference to room layout, distances to openings, and measurement height so that the collected data could be mapped to the relevant spatial entities.

The behavioral model combines simulation-based and sensing-based representations because each addresses a different temporal function in operation. Simulation provides a structured view of expected energy tendencies across seasons and operating scenarios, which is useful for understanding baseline behavior, interpreting anomalies, and assessing the implications of control strategies before implementation. Sensing, by contrast, captures the actual short-term state of the building and is indispensable for responsive operation. Their combination allows the twin to connect long-cycle performance interpretation with real-time evidence, thereby reducing the separation that often exists between design-oriented performance analysis and day-to-day operation management.

Sensor deployment was organized with explicit consideration of spatial representativeness. In a compact building, small changes in placement relative to windows, doors, occupied zones, or equipment outlets can substantially affect measured values. Therefore, the arrangement of the three sensor nodes was defined not merely for convenience, but to capture spatially differentiated indoor conditions while preserving practical installation feasibility. This is important for knowledge-enhanced operation because rule interpretation is only meaningful when the data can be associated with a credible spatial context. An overheated reading near direct solar gain, for instance, may imply a different operational response from a persistently elevated temperature in a core occupied zone [18,19].

The data pipeline also required attention to frequency and continuity. High-frequency sensing increases temporal granularity, but it can also generate communication noise, storage burdens, and misleading short-lived fluctuations if not properly filtered. In the present implementation, the use of InfluxDB as a time-series repository supports efficient storage, querying, and retrieval of timestamped operational records. More importantly, the database enables historical review and trend comparison, which are critical for iterative twin refinement. A knowledge-enhanced twin is not only interested in the latest value; it also needs to know whether a condition is exceptional, recurrent, or slowly evolving, because this temporal interpretation affects whether the system should display information, trigger an alert, or recommend operational intervention.

The coupling between sensing and the virtual environment further demonstrates why behavioral modeling cannot be reduced to raw telemetry. Once values are attached to virtual rooms and devices, they can be interpreted in relation to the building model, simulation tendencies, and operational rules. For example, real-time temperature values can be compared with comfort thresholds, recent temporal history, and seasonally expected conditions. Similarly, illuminance values can be understood in relation to daylight availability and room function, while humidity values can be evaluated in relation to user comfort and system response logic. This contextualization is what transforms monitoring into operational cognition.

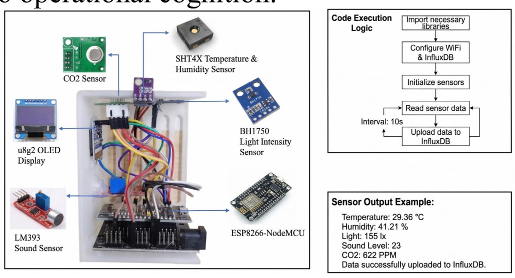

Figure 6. IoT sensing Module, Data Acquisition Logic, and Time-Series Database Workflow

3.4 Semantic Knowledge Model and Operation Rules

The semantic model was designed to formalize the meaning of building spaces, devices, environmental parameters, operational states, thresholds, and response rules. Concepts such as Room, Sensor, Device, Environmental Variable, Comfort Threshold, and Control Action were linked through object-property relations so that a sensed value could be interpreted in context. In practical terms, the semantic model associates a sensor reading not only with a database record, but also with a spatial entity, an IEQ category, and an operational implication.

For the comfort-oriented control demonstration in this study, knowledge rules were derived from the indoor air quality standard GB/T 18883-2022 and the building lighting design standard GB/T 50034-2024, together with project-specific operational practice for summer cooling setpoints [35,36]. Table 3 summarizes the threshold logic implemented in the case system.

The semantic model in the case study was deliberately constructed around interpretable operational classes instead of an overly broad ontology. Core entities included Room, EnvelopeElement, Device, Sensor, EnvironmentalParameter, ComfortThreshold, State, and ControlRule. These entities were linked through relations such as locatedIn, monitors, affects, hasThreshold, exceeds, and triggers, the sensor layout is illustrated in Figure 7. This structure is sufficient to support room-level reasoning while remaining compact enough for practical implementation. The intention was not to build a universal ontology in one step, but to demonstrate how a focused operational ontology can enrich a digital twin with enough semantic structure to support explanation and rule execution.

A key benefit of this approach is that thresholds become first-class knowledge objects rather than hard-coded constants buried in scripts. Once represented semantically, a threshold can carry information about provenance, applicability, season, parameter type, or associated device logic. This allows the system to distinguish, for example, between a comfort threshold used for supervisory alerts and a stricter control threshold used for device switching. It also facilitates future extension toward personalized or context-adaptive comfort models. In a larger deployment, threshold objects could be differentiated by room type, occupancy pattern, or user group without rebuilding the entire operational workflow.

The present case uses a human-in-the-loop control paradigm. Rules are formalized in machine-readable form, but the overall intent remains defined by the operator. This arrangement is appropriate for an early-stage knowledge-enhanced twin because it balances automation with transparency and accountability. In building operation, especially in experimental or educational buildings, full autonomy is often neither necessary nor desirable at the initial deployment stage. Instead, it is more valuable to create a reliable semantic foundation that can later support escalating levels of automation, from advisory functions to supervised control and eventually to optimization-based autonomous response when sufficient trust, data quality, and safety validation have been established.

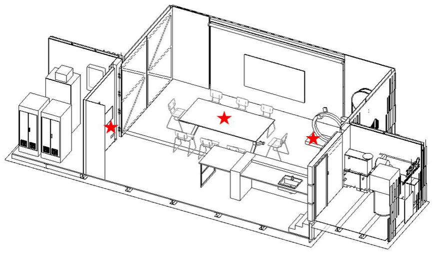

Figure 7. Sensor Layout in the Zero-Carbon House and Mapping of Sensing Points to Spatial Entities

Table 3. IEQ control Thresholds and Rule Logic Applied in the Case Demonstration.

Parameter	Comfort/control range	Controlled device	Rule logic
Temperature	26-28 °C	Air conditioner	Activate cooling when room temperature exceeds 28 °C
Relative humidity	40%-80%	Humidifier	Activate humidification when RH falls below 40%
Illuminance	≥300 lx	Lighting system	Activate lighting when indoor illuminance drops below 300 lx

4. Results and Discussion

4.1 Integrated Twin Implementation

The case implementation demonstrates that the proposed framework can integrate BIM geometry, time-series sensing, simulation outputs, and rule-based knowledge into a unified operational environment. The Revit model was exported as FBX and imported into Unity for visualization; energy-simulation outputs were transferred in JSON format; and environmental data were retrieved from InfluxDB through the API interface. This enabled real-time charting and state visualization in a single interface while preserving links between sensor streams and the corresponding building objects.

Compared with conventional visualization-only twins, the integrated system improved the interpretability of operational data because object identities, environmental semantics, and response logic were explicitly linked. As emphasized in recent digital twin studies, the practical value of an operational twin depends on its ability to support decision-making rather than simply to display real-time values [8,9,15,25,26]. The present implementation contributes to that direction by treating semantic relations and rule logic as core parts of the model.

From an operator's viewpoint, the integration provides three practical advantages. First, it reduces the cognitive burden of switching among disconnected software environments, because geometry, monitoring, and rule interpretation are presented through a single logical interface. Second, it improves data explainability: when a value is abnormal, the system can identify not only the number but also the room, the parameter category, the applicable threshold, and the linked response logic. Third, it supports traceable action preparation. Even if the operator does not accept a suggested response, the system still makes the basis of that suggestion explicit. Such traceability is essential for building trust in digital-twin-assisted operation.

The implementation also illustrates that integration quality should not be judged solely by whether data can be displayed in real time. In an operational setting, a successful twin must maintain consistent semantics across modules. A room in the BIM model, a sensor tag in the database, a chart in the interface, and a rule node in the semantic layer should all refer to the same operational entity without ambiguity. Achieving this consistency often requires more effort than the visible front-end integration, yet it is precisely this hidden consistency that determines whether the twin can evolve into a dependable operational system rather than remaining a sophisticated visualization prototype.

4.2 Representation of Monthly Energy Behavior

The energy simulation results indicate clear seasonal variation in the case building. Plug and equipment loads remain comparatively stable throughout the year, while heating demand increases markedly during winter and cooling demand rises during summer. Lighting demand is relatively low and shows limited seasonal variation. This pattern is consistent with the climatic characteristics of Beijing and suggests that the model can capture the broad operational profile needed for zero-energy building analysis, as illustrated in Figure 8.

Although the present study does not report a full calibration exercise with long-term metered energy data, the integration of the energy model into the digital twin offers an operational benefit: simulation outputs can be interpreted alongside sensed environmental states and renewable energy contributions. This creates a foundation for future scenario testing, predictive control, and energy-comfort co-optimization under real operating conditions [13,14,16,27-29].

The monthly pattern is operationally useful for another reason: it establishes a context for interpreting short-term events. Without such context, operators may overreact to transient conditions or fail to recognize slow seasonal drifts. When heating loads are known to dominate in winter and cooling loads in summer, deviations from those expected seasonal tendencies can be examined more meaningfully. For example, unusually high summer electricity consumption can be reviewed together with cooling runtime, indoor comfort readings, and solar generation conditions, rather than being treated as an isolated metering anomaly. The behavioral model therefore helps bridge the gap between strategic energy understanding and day-to-day building operation.

For zero-energy buildings, this contextual role is particularly valuable because renewable generation and demand are tightly coupled in time. A twin that represents only real-time device states cannot fully support energy-aware operation if it lacks an understanding of broader seasonal and monthly tendencies. Conversely, a simulation model without live operational data cannot reveal whether actual use patterns diverge from expectations. By combining both, the proposed system provides a basis for future functions such as energy-flexible scheduling, renewable-aware comfort control, and performance drift detection, even though those advanced functions were not yet implemented in the present case.

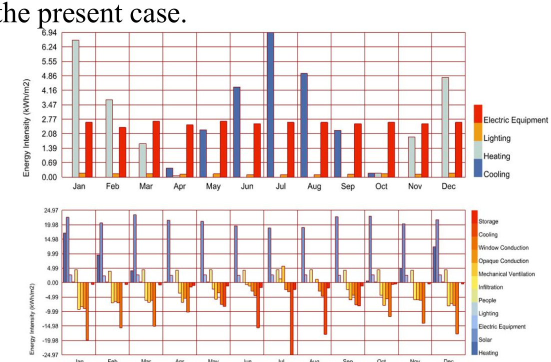

Figure 8. Monthly Distribution of Building Energy Consumption from the Case Energy Model.

4.3 IEQ Monitoring and Comfort-oriented Control Demonstration

The sensing layer allowed continuous monitoring of indoor environmental parameters and the mapping of these parameters to room-level virtual objects. Within the Unity environment, sensor values and equipment states could be visualized in near real time, and threshold-based rules were evaluated continuously. When temperature exceeded the cooling threshold, the air-conditioning device was triggered; when relative humidity fell below the lower limit, the humidifier was activated;

and when illuminance dropped below the office reference value, the lighting system was switched on.

This control demonstration should be understood as assisted automation rather than full autonomous optimization. The operator still defines the threshold rules and supervisory intent, while the digital twin provides the data structure, semantic interpretation, and execution channel for response. Even in this rule-based form, the case shows the practical significance of knowledge enhancement: sensor values are translated into actionable events through explicit operational semantics. The case therefore bridges a gap between monitoring and control that has been highlighted in prior literature on building digital twins and semantic FM systems [5,8,15,31,32].

Even in this supervised form, the control demonstration reveals an important methodological benefit of knowledge-enhanced twins: operational decisions become inspectable. Instead of embedding opaque logic within a control script, the system makes visible which parameter was evaluated, which threshold was referenced, and which action became eligible as a result. This visibility is valuable for debugging, commissioning, and operator learning. It also helps prevent overconfidence in automation, because users can see whether an action is based on a single threshold crossing, a persistent condition, or a combination of states.

The demonstration further highlights the possibility of multi-criteria expansion. Thermal comfort, humidity control, illuminance sufficiency, acoustic comfort, and indoor air quality need not remain independent dashboards. Once represented within a semantic rule structure, they can be coordinated into richer control logic, as illustrated in Figure 9. For example, lighting activation can be conditioned on both illuminance deficiency and occupancy, while cooling strategies can be reviewed together with humidity and renewable power availability. The current case therefore serves as a foundational implementation from which more sophisticated IEQ-energy coordination mechanisms can be developed.

4.4 Contributions, Limitations, and Implications

The study contributes to the Journal of Building Engineering literature in three ways. First, it provides an operationally oriented modeling pathway that combines BIM, IoT, energy simulation, and ontology-based knowledge in a single zero-energy building framework. Second, it clarifies how static data, dynamic data, and domain knowledge can be fused through object mapping, temporal synchronization, and semantic association. Third, it demonstrates a feasible route for extending digital twins from descriptive monitoring to knowledge-supported operation assistance.

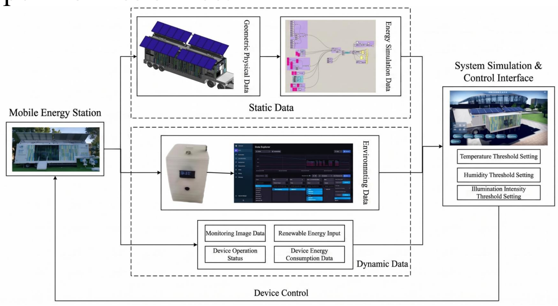

Figure 9. Digital Twin Interface for Real-Time IEQ Visualization and Comfort-Oriented Equipment Control.

Several limitations should be acknowledged. The case study is based on a single small-scale building, which limits generalizability to larger or more complex facility portfolios. The comfort-control demonstration is threshold-based and does not yet include predictive optimization, occupant feedback loops, or multi-objective control. In addition, the study demonstrates semantic integration conceptually and procedurally, but a more formal ontology evaluation and benchmarked interoperability test are still needed. These limitations point to important future research directions, including multi-agent reasoning, data-driven prediction, fault diagnosis, occupant-centric adaptation, and carbon-energy-comfort co-optimization in larger operational twins [15,16,24-26,33,34].

Despite these limitations, the study offers several implications for future Journal of Building Engineering research on digital twins. First, it reinforces the argument that operational twins should be studied as socio-technical information systems rather than as isolated visualization engines. Their effectiveness depends on how well they encode domain meaning, workflow logic, and accountability in addition to sensing and modeling capacity. Second, it suggests that semantic enrichment is most valuable when it is tied to concrete operational use cases. A knowledge graph or ontology becomes practically relevant only when it improves traceability, rule management, or reasoning about building states. Third, it shows that small demonstrator buildings remain valuable research platforms because they allow full-stack integration to be observed and reported with a level of clarity that is difficult to achieve in highly fragmented real-estate portfolios.

The study also has implications for deployment strategy. In many facilities, digital twin adoption is hindered by the expectation that a twin must deliver complete autonomy from the beginning. The present work suggests a more realistic pathway: start with semantic consistency and operational transparency, then progressively add analytics and automation as data quality, organizational readiness, and validation maturity improve. In this pathway, the semantic layer functions as a durable backbone that survives changes in sensors, interfaces, and analytical algorithms. This is especially relevant in building operation, where hardware replacement, control retrofits, and workflow changes are common over the life cycle of the asset [25,26,30,33].

Scalability remains an important challenge. When moving from a single demonstrator building to a campus or building portfolio, the number of spaces, devices, streams, and rules increases dramatically. Direct one-off integration becomes difficult to maintain, and semantic governance becomes more important. Future research should therefore investigate reusable ontology modules, automated mapping routines, and template-based rule libraries that can reduce the manual effort of scaling knowledge-enhanced twins. At the same time, large-scale deployment will require attention to cybersecurity, edge-cloud data architecture, user permission management, and long-term model maintenance, all of which influence the practical sustainability of operational digital twins [6,7,9,30,33].

Another avenue for extension concerns the relationship between knowledge-enhanced twins and advanced intelligence. Recent literature has begun to explore ontology-enabled agents, anomaly detection, and data-driven knowledge discovery for built assets [15,31,34]. The present study suggests that such intelligence will be most reliable when it is grounded in explicit object semantics and validated operational context. Purely data-driven algorithms may detect patterns, but without semantic anchoring they can be difficult to explain or operationalize. Conversely, purely rule-based systems may be transparent but insufficiently adaptive. A promising future direction is therefore the hybridization of semantic rules with machine learning, whereby learned models identify patterns or forecast states, while the semantic layer constrains interpretation, links outputs to building entities, and ensures that resulting actions remain understandable to operators.

Finally, the present work underscores that zero-energy operation should be studied as an integrated performance problem. Energy balance, IEQ, occupant response, and equipment operation are interdependent, and digital twins can support decarbonization only if they reflect that interdependence. A knowledge-enhanced twin offers one pathway toward such integration because it can connect sensed states with formalized rules and decision context. The value of the approach is therefore not limited to the specific case building. Rather, it lies in the transferable modeling logic through which high-performance buildings can be represented as evolving systems of objects, states, meanings, and responses.

5. Conclusions

This study proposed a knowledge-enhanced digital twin modeling method for zero-energy building operations and demonstrated it using a zero-carbon house case. The method integrates a seven-layer architecture, a closed-loop construction process, a multi-source data fusion mechanism, and a composite model composed of geometric, physical, behavioral, and semantic knowledge sub-models.

The case implementation shows that the proposed approach can organize building objects, operational states, and rule knowledge within a unified digital twin environment. By combining Revit-based BIM, Grasshopper/Ladybug/Honeybee simulation, IoT sensing with InfluxDB, and Unity-based interaction, the model supports real-time IEQ visualization and rule-based comfort-oriented control. The semantic layer is the key differentiator from conventional BIM-IoT integration because it connects observed values to building objects, evaluation criteria, and operational responses.

Overall, the study demonstrates a practical transition from data-centric digital twins toward knowledge-enhanced operational twins for zero-energy buildings. Future work should focus on expanding the framework to multi-building scenarios, integrating predictive and optimization algorithms, formalizing ontology evaluation, and quantifying operational improvements through long-term field validation. In methodological terms, the central message of this paper is that digital twins for zero-energy building operation should be conceived as knowledge-organizing systems as much as data-organizing systems. The proposed framework does not attempt to replace detailed simulation tools, control platforms, or databases; instead, it coordinates them through a semantically explicit operational model. This coordination is what enables the twin to support not only visualization and monitoring, but also interpretation, traceability, and progressively richer decision support. As the building sector moves toward low-carbon and net-zero operation, such semantically grounded twins may provide an important bridge between fragmented digital assets and truly intelligent operational workflows.

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CRediT authorship contribution statement
Author Name 1: Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft. Author Name 2: Supervision, Validation, Writing - review and editing, Project administration. Please replace this placeholder statement with the actual contributor roles before submission.

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
The data that support the findings of this study are available from the corresponding author upon reasonable request. Project-specific operational records and configuration files are not publicly released in this draft version. If a repository DOI is available, replace this statement accordingly before submission.

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