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DIGITAL TWINS IN BUILDING ENERGY MANAGEMENT FOR ELECTRICITY CONSUMPTION FORECASTING AND ENERGY EFFICIENCY IMPROVEMENT

Abstract. *The article examines the application of digital twins as a tool for modernizing building energy management aimed at electricity consumption forecasting and improving energy efficiency. Based on a review of contemporary approaches, the study analyzes how the integration of BIM/semantic models, IoT data, and operational systems with machine learning methods enables the implementation of a closed-loop control framework. Methods for electricity consumption forecasting are systematized according to time horizons and their suitability for operational tasks. Typical scenarios for improving energy efficiency through the use of digital twins are presented. A methodological framework for the implementation of digital twins in buildings is proposed, taking into account measurement and verification, model drift, interoperability, and cybersecurity. The impact of digital twins on the quality of managerial decision-making is identified, particularly in enhancing energy consumption controllability and enabling a transition to proactive control of building engineering systems based on predictive models and scenario analysis, as well as in creating conditions for the development of more flexible and sustainable building energy systems. The practical implementation cycle of digital twins in building energy management is generalized. Key limitations of digital twin deployment in buildings are outlined. The dependence of digital twin effectiveness on data consistency and the correctness of energy management problem formulation is demonstrated.*

Keywords: digital twin, building, electricity consumption forecasting, energy efficiency, IoT, BMS/EMS, machine learning, optimization.

1. Introduction

Building energy consumption is shaped by the complex interaction of engineering systems, external conditions, and user behavior. The main consumers of electricity include HVAC systems, lighting, elevator equipment, and IT infrastructure, while weather conditions, operational schedules, and patterns of space usage determine temporal variability of energy demand. Under such conditions, the application of static control strategies proves insufficiently effective, as it does not account for process dynamics and limits the potential for energy savings without compromising comfort. In this context, digital technologies that enable the integration of data, models, and decision-making algorithms into a unified information environment are becoming increasingly relevant [1].

According to international energy agencies, buildings account for approximately 30–40 % of global final energy consumption and represent a significant source of greenhouse gas emissions. Therefore, improving building energy efficiency is one of the key directions in the development of sustainable energy systems. Modern approaches to building management increasingly rely on digital technologies such as the Internet of Things (IoT), energy management systems, big data analytics, and artificial intelligence [2]. One of the most promising tools for the digitalization of building operation in this context is digital twin (DT) technology, which involves the creation of a dynamic digital model of a physical asset synchronized with the real environment through data streams from sensors, meters, and building management systems. Such a model not only reflects the current state of the asset but also enables forecasting, scenario analysis, and optimization of system operation [3], integrating geometric, semantic, and physical models with analytical algorithms and decision-support tools, which distinguishes it from traditional BIM models or BMS/SCADA systems [5].

One of the key functions of a digital twin in energy management is electricity consumption forecasting, which enables advance planning of equipment operation, optimization of HVAC schedules, reduction of peak loads and energy costs, and implementation of demand response mechanisms. In addition, predictive models can be used for the integration of local renewable energy sources, optimization of energy storage operation, and early detection of anomalies in engineering systems. Contemporary studies employ various approaches to building energy consumption forecasting, including statistical methods, machine learning algorithms, and deep neural networks. Their integration with digital twins forms the basis for adaptive energy management, in which control decisions for building systems are made based on forecasts, data analysis, and optimization algorithms [4].

The aim of this study is to analyze current approaches to the application of digital twin technology for electricity consumption forecasting and improving building energy efficiency, as well as to develop methodological provisions for their implementation in the operation of building engineering systems.

To achieve this aim, the following main tasks are addressed: (1) systematization of the concept and architecture of a building digital twin; (2) analysis of electricity consumption forecasting methods and their suitability for different time horizons; (3) investigation of the potential of digital twins for improving energy efficiency; (4) development of methodological provisions for implementing a digital twin based on a closed-loop energy management approach.

2. Method and materials

The study is conducted as a review-based analysis of contemporary approaches to the application of digital twins in building energy management systems. The research methodology is based on the systematization of findings from scientific publications addressing digital twin architectures, energy consumption forecasting methods, and optimization algorithms for building engineering systems. The digital twin is considered as an integration platform for data acquisition, modeling, forecasting, and optimization of building operation modes. Within such a system, real-time operational data from engineering systems are continuously used to update the digital model, while the results of forecasting and optimization are applied to support control decisions, integrating models, data, and control algorithms into a unified information system [5, 6].

The analysis of the digital twin is carried out with consideration of its key functional components, which form a sequential logic of data processing and decision-making. The first component is the building representation, which includes the use of Building Information Modeling (BIM), semantic descriptions of engineering systems, and technical attributes of equipment. This enables the creation of a structured digital representation of the asset and the establishment of relationships between spaces, zones, and engineering systems. On this basis, operational data from multiple sources are integrated, including smart electricity meters, BMS/SCADA systems, IoT sensors, and external information services providing weather data or occupancy schedules. Their integration ensures a comprehensive view of building operation and forms the foundation for developing predictive models [7].

Subsequently, the digital twin incorporates electricity consumption forecasting models, including statistical methods, machine learning algorithms, deep learning models, and hybrid approaches that combine data-driven techniques with physical building models. The selection of a specific model type depends on data availability, forecasting horizons, and system complexity [8]. The forecasting results are then used by control and optimization algorithms to determine efficient operating modes of engineering systems. These include rule-based approaches, mathematical optimization methods, Model Predictive Control (MPC), and reinforcement learning, enabling adaptive building operation under changing conditions [9].

The final stage involves model verification and refinement procedures, including the evaluation of forecasting accuracy, analysis of the energy impact of control actions, and periodic model retraining in response to changes in building operation. In modern energy management systems, these processes are often implemented within the Measurement and Verification (M&V) framework, which allows for objective assessment of the effectiveness of energy efficiency measures [10].

3. Literature review

The concept of a building digital twin and its distinction from related approaches. A digital twin is defined as a dynamic digital representation of a physical object that reflects its structure, parameters, and current state, and maintains continuous synchronization with the real environment through data streams from sensors and information systems. In the context of buildings, such a model integrates various types of data and modeling approaches, forming a comprehensive digital environment for monitoring, forecasting, and optimizing the operation of engineering systems. Unlike traditional building information models, which are primarily used during the design and construction phases, a digital twin is mainly focused on the operational phase of the building lifecycle and involves continuous interaction with real-time operational data [11].

The main difference between a digital twin and building automation systems such as BMS or SCADA lies in the presence of an integrated digital model of the object and enhanced analytical capabilities. While such systems provide monitoring of equipment parameters and perform operational control functions, they typically do not support advanced forecasting or scenario-based simulation. In contrast, a digital twin combines geometric, physical, and behavioral models with data analysis and optimization algorithms, enabling a more comprehensive approach to building management. An effective digital twin should ensure the integration of different types of information, including geometric models of the building, characteristics of engineering systems, streams of operational data, and analytical algorithms. Such integration forms the foundation for next-generation energy management systems capable of adapting equipment operation modes to changing building conditions [7].

Levels and data of a building digital twin. A multi-level representation of a building allows it to be considered as an information system in which different types of models and data are integrated to reflect the structure, functioning, and operational characteristics of the object. At the basic level, a geometric representation of the building is formed, describing its spatial structure, the arrangement of rooms, floors, and functional zones, and typically based on BIM models or other digital architectural descriptions.

The semantic and physical descriptions of a building constitute key layers of the digital twin, complementing its geometric representation. The semantic layer includes information about equipment, engineering systems, and the relationships between them; such models enable linking system components to corresponding building zones and play an important role in data integration and interoperability between information systems [12]. The physical modeling layer, in turn, covers thermal, ventilation, and electrical processes within the building. Depending on the task, these models may be based on simplified energy approaches or detailed simulations that allow evaluation of thermal inertia, heat losses through the building envelope, and interactions between engineering systems. This structure is further complemented by the behavioral layer, which accounts for building usage patterns, occupancy schedules, and user behavior – factors that significantly influence energy consumption and improve the accuracy of predictive models [13].

The integration of operational data from various sources ensures the functioning of all these layers of the digital twin and forms the basis for its analytical capabilities. The main data sources include smart electricity meters, which generate detailed time series of consumption at both the building level and the level of individual systems or zones [14], as well as sensor data from engineering systems, including temperatures, airflow rates, equipment status, and operating parameters. Contextual data also play an important role, particularly weather conditions, calendar factors, and occupancy indicators, all of which directly affect thermal loads and operating modes. The coordinated use of these data sources enables the creation of a comprehensive digital representation of the building and supports the development of accurate energy consumption forecasting models [15].

The final layers of a digital twin are the control and economic levels. The control level encompasses automation system logic, optimization algorithms, and equipment control strategies, while the economic level is associated with tariff analysis, operational costs, and the evaluation of energy efficiency measures.

Considering the described components, a building digital twin can be appropriately viewed as a multi-layered information system in which functional levels are organized as a sequence of data processing stages. At the initial stage, data are collected from sensors, smart meters, and building automation systems. These data are then transmitted to the integration layer, where they undergo cleaning, synchronization, and preparation for further analysis.

The next stage involves the formation of the modeling layer, where physical and statistical models are combined with machine learning algorithms. On this basis, energy consumption forecasting and the analysis of possible building operation scenarios are performed. The obtained results are used to generate control decisions and optimize the operating modes of engineering systems.

The final element of the architecture consists of monitoring and diagnostic modules that enable the assessment of deviations between predicted and actual values, as well as user interaction interfaces, including analytical dashboards, visualization systems, and software APIs for integration with BMS or EMS [16].

Forecast horizons and their role in energy management systems. Electricity consumption forecasting enables the assessment of the future state of a building's energy system and supports the formation of optimal control decisions. In energy management systems, load forecasting is used for planning the operation modes of engineering systems, managing peak loads, optimizing equipment schedules, and integrating renewable energy sources [17].

Building electricity consumption forecasting is commonly classified according to the time horizon of the prediction. Short-term forecasts, covering intervals from several minutes to a few hours, are used for real-time control of engineering systems, particularly HVAC systems, as well as for detecting anomalies in equipment operation. Forecasts with horizons ranging from several hours to up to two days are applied to optimize equipment schedules, implement Demand Response mechanisms, and prepare for potential peak loads in the energy system [18].

Medium-term forecasts, covering periods from several days to weeks, are used for analyzing building operation modes and evaluating different scenarios of engineering system usage. In contrast, long-term forecasts, which may span months or entire seasons, are applied for energy planning, assessing the effectiveness of retrofitting measures, and forming energy consumption budgets [20].

Classes of electricity consumption forecasting methods. Models for forecasting building electricity consumption can be broadly classified into statistical methods, machine learning algorithms, and deep learning models. Each of these approaches has its own advantages and limitations, which determine its area of application.

Statistical methods are a traditional tool for time series forecasting of energy consumption. These include autoregressive integrated moving average (ARIMA) models. The main advantages of statistical models are their relative simplicity and interpretability; however, they have a limited ability to capture complex nonlinear relationships between system parameters [22].

Machine learning algorithms demonstrate better performance in energy consumption forecasting tasks when large volumes of data are available. Commonly used models include Random Forest, Gradient Boosting, XGBoost, and LightGBM, as well as Support Vector Regression. These algorithms perform well with tabular data and allow the incorporation of a wide range of factors, including weather parameters, time-related indicators, and building operation characteristics.

In recent years, deep learning models have become increasingly widespread due to their ability to effectively capture complex temporal dependencies. These include recurrent neural networks, particularly LSTM and GRU architectures, as well as convolutional neural networks and transformer-based models for time series analysis.

Such approaches demonstrate high forecasting accuracy in multi-step energy consumption prediction tasks, although they require large training datasets and significant computational resources [23].

A separate group consists of physical and hybrid models. Physical approaches are based on thermal or energy models of a building, taking into account the properties of the building envelope, thermal inertia, and characteristics of engineering systems. Hybrid models combine physical principles with machine learning algorithms, which makes it possible to improve forecasting accuracy while maintaining interpretability of the results [1].

The classes of electricity consumption forecasting methods, along with their characteristics and limitations, are summarized in Table 1.

Table 1. Classes of Electricity Consumption Forecasting Methods

Class of Methods	Typical Models	Advantages	Limitations
Statistical	ARIMA, SARIMA	Simplicity, interpretability	Limited ability to model nonlinear relationships
Machine Learning	Random Forest, XGBoost, SVR	High accuracy, ability to handle multiple features	Data requirements, lower interpretability
Deep Learning	LSTM, GRU, CNN, Transformer	Modeling complex temporal dependencies	High data and computational requirements
Physical	Building energy models	Interpretability, physical consistency	Complexity of calibration
Hybrid	Physical + Machine Learning	Balance between accuracy and interpretability	Implementation complexity

Input features for forecasting models. The accuracy of electricity consumption forecasting largely depends on the set of input parameters used for model training. Forecasting models typically rely on a combination of temporal, weather-related, and operational characteristics of the building.

The integration of temporal features, weather factors, and operational parameters enables the formation of multidimensional feature sets, which provide a more accurate representation of building energy behavior and improve the performance of predictive models. Temporal features include hour of the day, day of the week, seasonal indicators, and other calendar-related parameters that reflect cyclical patterns of building usage. Weather factors – such as outdoor air temperature, relative humidity, wind speed, and solar radiation – have a significant impact on energy consumption levels. To account for the thermal inertia of buildings, lagged values of these parameters are often incorporated into the models [17].

Occupancy indicators, such as building usage levels or user activity data obtained from access control systems or wireless networks, are also important inputs. Additional features may include operational parameters of engineering systems, such as temperature setpoints, equipment operating modes, or temperatures in specific building zones [23].

The main groups of input features used in electricity consumption forecasting models are summarized in Table 2.

Forecast accuracy evaluation metrics. The evaluation of forecasting model accuracy makes it possible to determine the suitability of a model for practical application in building control systems. In electricity consumption forecasting tasks, the most commonly used metrics are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which quantify the deviation between predicted and actual values in physical units [24].

Table 2. Types of Input Features for Electricity Consumption Forecasting Models

Feature Group	Examples	Characteristics
Temporal	Hour of the day, day of the week, seasonal indicators	Reflect periodicity and cyclic patterns of consumption; enable modeling of daily and seasonal trends
Weather	Temperature, humidity, wind, solar radiation	Determine building thermal load; have a nonlinear impact on energy consumption
Operational	Operating modes, temperature setpoints, system parameters	Directly related to the control of engineering systems; reflect current operating conditions
Behavioral	Occupancy, access data, Wi-Fi activity	Account for user influence; may be noisy and incomplete
Lagged	Previous values of parameters	Allow capturing building inertia and dependence on past states

To compare models across different data scales, relative metrics are used, particularly Mean Absolute Percentage Error (MAPE) and its symmetric modification (sMAPE). In the case of probabilistic forecasting models, specialized metrics such as pinball loss or Continuous Ranked Probability Score (CRPS) are applied, allowing the evaluation of the accuracy of predicted value distributions [25].

In energy management systems, particular attention is paid to the accuracy of peak load forecasting, as peak values often determine electricity costs. Therefore, many studies complement general metrics with additional indicators that assess the accuracy of peak load predictions.

4. Application of a digital twin for improving the energy efficiency of buildings

Unlike traditional automation systems, which operate based on fixed rules or static schedules, a digital twin – through the integration of operational data, forecasting models, and optimization algorithms – creates new opportunities for improving energy efficiency and enabling adaptive control of engineering systems based on energy consumption forecasts and real-time building conditions. The integration of forecasting models with digital twins allows for the optimization of building electrical systems, reduction of peak loads, integration of renewable energy sources and storage systems, as well as diagnostics and predictive maintenance. Owing to its ability to simulate different operational scenarios, a digital twin can be used not only for real-time control but also for evaluating the effectiveness of energy efficiency measures and engineering system upgrades [26, 4].

The main applications of digital twins in building energy efficiency are summarized in Table 3.

Table 3. Main Application Areas of Digital Twins

Application Area	Description	Typical Outcomes
HVAC Operation Optimization	Control of temperature setpoints and ventilation based on load forecasts, occupancy, and building thermal inertia	Reduction in HVAC energy consumption
Peak shaving and load shifting	Forecasting peak loads and smoothing them by adjusting equipment operation schedules	Reduction in peak demand and electricity costs
Demand Response	Adaptation of consumption to energy market signals or DR events	Increased building flexibility
Integration of Storage and Renewables	Optimization of PV systems and battery operation based on generation and load forecasts	Increased self-consumption and reduced energy purchases
Fault Detection and Diagnosis (FDD)	Comparison of predicted and actual system behavior	Early detection of faults and equipment degradation
Scenario Analysis for Retrofits	Evaluation of energy efficiency measures through simulation	Forecast of energy savings and assessment of payback period

One of the most common applications of a digital twin is the optimization of HVAC system operation. By using load forecasts and information about the building's thermal inertia, the system can implement strategies such as pre-cooling or pre-heating during periods of lower electricity prices. This approach reduces energy consumption while maintaining comfortable conditions for building occupants [2].

Since, in many tariff structures, a significant portion of electricity costs is associated with peak demand, peak load management is an important direction for improving energy efficiency. Through load forecasting capabilities, a digital twin enables the implementation of peak shaving and load shifting strategies, which involve adjusting equipment operation schedules and redistributing loads over time.

Digital twins are also widely used for integrating renewable energy sources and energy storage systems. The combination of solar generation forecasts with building load forecasts allows for the optimization of battery charging and discharging schedules, reducing electricity consumption from the grid during peak hours [5, 9].

In addition to energy optimization tasks, a digital twin can be used for fault detection and predictive maintenance of equipment. In such systems, an expected behavior of engineering systems is established, after which deviations between predicted and actual parameter values are analyzed. Significant deviations may indicate sensor faults, incorrect setpoints, or equipment degradation, enabling timely maintenance actions [6].

Another promising application is the use of digital twins for scenario-based analysis of retrofits. Through simulations in a digital environment, it is possible to evaluate the impact of various energy efficiency measures, such as HVAC system upgrades, lighting replacement, building envelope insulation, or the installation of renewable energy systems. This approach allows for the assessment of economic efficiency of investments prior to their actual implementation [1, 5].

5. Results

The implementation of a digital twin in building energy management systems is a continuous process that integrates operational data collection, modeling, forecasting, optimization of engineering system operation, and evaluation of control results. In modern research and practical applications, this approach is described as a closed-loop control process, where the results of analysis and forecasting are used to update models and improve control strategies [14].

The methodological framework for digital twin implementation proposed in this study is based on a sequence of interconnected stages that form a closed-loop energy management cycle for a building.

The initial stage involves defining energy management objectives and key performance indicators (KPIs). These may include specific energy consumption, peak demand, electricity costs, thermal comfort parameters, or greenhouse gas emissions [10]. At this stage, system constraints are also defined, such as acceptable indoor temperature ranges or equipment operating limits.

The next step is the inventory of available data and building information systems. In practice, this includes assessing the availability of smart meters, sub-metering systems, sensors of engineering systems, and building automation systems (BMS or SCADA). An important aspect is also the evaluation of historical data availability and the possibility of integrating external data sources, such as weather services or calendar data [14].

This is followed by data preparation and processing, which includes time series synchronization, handling of missing values, anomaly detection, and validation of sensor performance. Data quality is a critical factor for developing reliable forecasting models and ensuring the effective operation of the digital twin.

Based on the prepared data, a digital model of the building is developed, forming the core of the digital twin. At this stage, the building zoning structure is defined, engineering systems are described, and relationships between model elements and data flows are established. Basic physical constraints are also incorporated, such as thermal properties of the building envelope or maximum equipment capacity.

The next stage involves training and calibration of electricity consumption forecasting models. This includes defining the forecasting horizon, selecting input features, and training models using historical data. The resulting models are evaluated using standard forecasting accuracy metrics and then integrated into the digital twin.

After model development, the digital twin is integrated with building control systems such as BMS or EMS. At the initial stages, the digital twin may operate in an advisory mode, where it provides recommendations for optimal equipment operation while the final decision is made by a human operator. Subsequently, a transition to semi-automated or fully automated control is possible, provided that established safety constraints are satisfied.

The obtained forecasts are used to optimize the operation modes of engineering systems, in particular for determining optimal temperature setpoints, equipment schedules, or strategies for building participation in Demand Response programs. The implementation of such decisions makes it possible to reduce energy consumption and optimize electricity costs [7].

After the implementation of control actions, measurement and verification of the energy effect are carried out. At this stage, actual energy consumption values are compared with baseline values, taking into account external factors such as weather conditions or changes in building usage patterns. In addition to energy indicators, occupant comfort parameters are also monitored.

The final stage of the cycle involves model correction and continuous system learning. During building operation, changes may occur in space usage patterns, equipment upgrades, or seasonal operating conditions. Therefore, forecasting models and control algorithms should be periodically updated and retrained using new data [3, 4].

Based on these stages, a digital twin operation cycle is formed, in which data, models, and control decisions continuously interact. Such an approach enables adaptive energy management of buildings and provides a foundation for scaling digital twin technology to building portfolios or urban energy systems.

A generalized structural scheme of the closed-loop operation of a building energy management system is shown in Fig. 1.

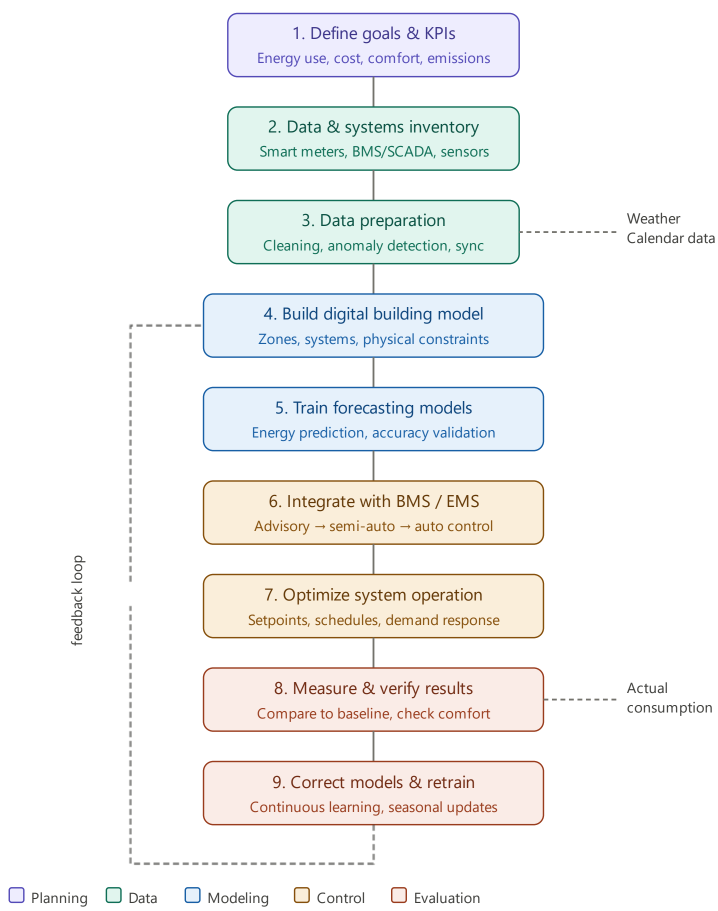

Figure 1. Closed-loop energy management cycle of a building

6. Conclusions

This paper examined the application of digital twin technology for electricity consumption forecasting and improving building energy efficiency. The analysis demonstrates that the integration of digital models, data acquisition systems, forecasting algorithms, and optimization methods creates new opportunities for efficient energy management in buildings. A digital twin acts as an integration platform that connects the physical infrastructure of a building with its digital model, enabling analysis of the current system state, forecasting of future loads, and generation of optimal control decisions. This enables the transition from traditional static control of engineering systems to adaptive management that accounts for changing operating conditions, weather factors, and occupant behavior.

The study systematized the main approaches to electricity consumption forecasting, including statistical methods, machine learning algorithms, deep neural networks, physics-based models, and hybrid approaches. It was shown that the choice of a specific method depends on data availability, system complexity, and the required forecasting horizon. Hybrid and physics-informed models are particularly promising, as they combine the interpretability of physical models with the accuracy of modern machine learning techniques.

The architecture of a digital twin for building energy management systems was also analyzed. A multi-layer structure was proposed, including data acquisition, integration and processing, modeling, forecasting, control optimization, as well as monitoring and diagnostics layers. Such an architecture ensures a complete operational cycle of the digital twin – from data collection to decision-making for optimal system operation.

The key result of this work is the development of a methodological framework for digital twin implementation, presented as a closed-loop cycle. This framework enables the systematization and standardization of the building energy management digitalization process by proposing nine clearly defined and interconnected stages – from KPI formulation to continuous model retraining. Its practical value lies in serving as a universal roadmap for engineers and energy managers, helping to minimize technical risks associated with integrating heterogeneous systems and ensuring transparency in decision-making throughout the building lifecycle.

Future work involves transitioning from theoretical analysis to practical validation of the proposed framework using a pilot building. This includes data inventory and preparation, development and calibration of hybrid forecasting models based on real operational data, and integration of these models into a decision-support system prototype to evaluate the actual effectiveness of optimization algorithms under dynamically changing external conditions.

The conducted analysis showed that the use of a digital twin can provide significant energy and economic benefits through the optimization of HVAC system operation, reduction of peak loads, implementation of demand response mechanisms, and integration of local renewable energy sources and storage systems. Additional advantages include early detection of equipment faults, predictive maintenance, and scenario-based analysis of energy efficiency upgrades.

At the same time, the implementation of digital twins is associated with a number of technical and organizational challenges. The main issues include data quality and availability, the complexity of integrating heterogeneous information systems, the need for model calibration for different types of buildings, as well as cybersecurity and data protection concerns. In addition, the economic effectiveness of implementation largely depends on the proper definition of energy management objectives and performance indicators.

It has been established that the use of a digital twin can provide significant energy benefits through HVAC system optimization, peak load reduction, and the implementation of Demand Response strategies.

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ЦИФРОВІ ДВІЙНИКИ В ЕНЕРГОМЕНЕДЖМЕНТІ БУДІВЕЛЬ ДЛЯ ПРОГНОЗУВАННЯ ЕЛЕКТРОСПОЖИВАННЯ ТА ПІДВИЩЕННЯ ЕНЕРГОЕФЕКТИВНОСТІ

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Анотація. *У статті розглянуто застосування цифрового двійника як інструмента модернізації енергоменеджменту будівель для прогнозування споживання електроенергії та підвищення енергоефективності. На основі огляду сучасних підходів проаналізовано, як інтеграція BIM/семантичних моделей, даних IoT та експлуатаційних систем із методами машинного навчання забезпечує реалізацію «замкненого циклу» керування. Систематизовано методи прогнозування електроспоживання за часовими горизонтами та придатністю до задач експлуатації. Наведено типові сценарії підвищення енергоефективності завдяки цифровому двійнику. Запропоновано концептуальну рамку впровадження цифрового двійника у будівлі з урахуванням вимірювання та верифікації, дрейфу моделей, інтероперабельності та кібербезпеки. Визначено вплив цифрового двійника на якість управлінських рішень у покращенні керованості енергоспоживання та переході до проактивного керування інженерними системами будівлі на основі прогнозних моделей і сценарного аналізу та створенні передумов для розвитку більш гнучких і сталих енергетичних систем будівель. Узагальнено практичний цикл впровадження цифрового двійника в енергоменеджменті будівель. Окреслено ключові обмеження впровадження цифрових двійників у будівлях. Показано залежність ефективності застосування цифрового двійника від узгодженості даних і коректності постановки задач енергоменеджменту.*

Ключові слова: цифровий двійник, будівля, прогноз електроспоживання, енергоефективність, IoT, BMS/EMS, машинне навчання, оптимізація.

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