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MODERN METHODS FOR PREDICTING BUILDING ENERGY CONSUMPTION

The relevance of the study is driven by the growing need to enhance the energy efficiency of buildings through thermomodernization and the demand for accurate forecasting tools to ensure effective energy management. In the context of climate change and rising energy prices, the selection of optimal forecasting models has become a critical task for housing and communal services as well as urban infrastructure.

The aim of the study is to substantiate contemporary approaches to forecasting building energy consumption considering thermomodernization measures, based on the analysis of regression, neural, and hybrid models, in order to identify their advantages, limitations, and practical effectiveness.

Methodology. A comparative analysis of recent studies was conducted, covering statistical, neural network, and hybrid forecasting models. The accuracy, scalability, flexibility, and adaptability of models to post-retrofit conditions were assessed. Particular attention was paid to deep learning architectures (LSTM, GRU), hybrid combinations (ARIMA+LSTM, CNN+ELM), and digital twin technologies.

Results. It was established that the highest forecasting accuracy is achieved by neural network models, particularly deep architectures and ensembles, with average errors not exceeding 3–5%. Although regression methods are less accurate, they remain useful for baselineestimates and evaluating the impact of climatic variables. The effectiveness of hybrid approaches that combine trend modeling with neural network-based residual learning was demonstrated. The potential of digital twins as a tool for predictive and adaptive energy management was identified.

Scientific novelty. For the first time, forecasting models were systematized in the context of building thermomodernization, with the identification of optimal approaches for different types of tasks. The relevance of applying intelligent forecasting systems integrated with digital twins as a new paradigm in building energy management was substantiated.

Conclusions. It was proven that accurate forecasting of energy consumption is only possible when accounting for changes caused by thermomodernization and applying flexible models capable of adapting to new building operation conditions. It was determined that the integration of artificial intelligence methods with physical modeling and digital twinsenhances the accuracy and applicability of forecasts for practical energy management.

Prospects for further research. It is advisable to develop combined modeling methods that consider behavioral factors in consumption, and to expand the empirical base for assessing the effectiveness of digital twins in retrofittedbuildings of various types.

Keywords: *building energy efficiency, predictive models, thermalretrofit, deep learning, digital twins, energy management systems.*

Introduction

Despite the significant progress in energy-efficient technologies and the growing demand for building modernization, the issue of accurate forecasting of energy consumption remains a complex and insufficiently resolved task. Thermal modernization fundamentally changes the thermophysicalproperties and operating conditions of buildings, which leads to non-linear and dynamic changes in energy demand that traditional models are often unable to captureadequately. At the same time, climate change, the spread of renewable energy sources, and the implementation of smart energy systems intensify the need for adaptive and predictive energy management tools. In this context, the development of forecasting methods that take into account the effects of thermalretrofitting and reflect the real-time state of the building is not only a scientific challenge but also a practical necessity for ensuring energy sustainability. This task intersects with broader interdisciplinary problems, including the integration of artificial intelligence into engineering systems, the optimization of building performance based on sensor data, and the creation of digital twins as a basis for intelligent energy control. The lack of unified forecasting solutions capable of combining physical modeling, statistical inference, and machine learning under conditions of structural and operational change highlights the urgency of comprehensive research in this field. Addressing this problem is essential not only for reducing energy costs but also for achieving broader goals of carbon reduction, decarbonization of the building sector, and compliance with international sustainability standards.

Analysis of recent research and publications

The analysis of scientific sources allows us to distinguish four major directions of research that define the current paradigm of predicting building energy consumption with consideration of thermal modernization: regression modeling, artificial neural networks, hybrid methods and digital twins, and practical model validation.

The first direction involves the use of regression-based methods to quantitatively assess the impact of climatic, design, and behavioral factors on energy consumption. In the work of C. Yin, C. Han, A. Li, X. Liu, and Y. Liu, a comprehensive review of ANN-based models emphasized the limitations of linear regression in capturing complex interdependencies [1]. I. Bilous developed a regression model for forecasting thermal load in buildings by incorporatingairtemperature and structuralinertia, achieving 12–15% energy savings [2]. H. Liu, J. Liang, Y. Liu, and H. Wu also confirmed the limited applicability of classical regression techniques in highly dynamic post-retrofit environments [3]. M. R. Braun, H. Altan, and S.B.M. Beck applied multiple regression to a UK supermarket case and predicted a 2.1% increase in electricity demand and 13% decrease in gas use under future climate conditions [4]. I. Korolija, Y. Zhang, L. Marjanovic-Halburd, and V. I. Hanbyderived regression-based equations for 3840 UK office models [5], while S. ShamsAmiri, M. Mottahedi, and S. Asadi used simulated DOE-2 data to estimate energy indicators for U.S. commercial buildings [6].

Z. Zhang, C. Deb, S.-E. Lee, J. Yang, and K. W. Shah applied SVR with differentialevolution optimization to achieve a meanabsolutepercentage error (MAPE) of only 3.8% [7].Further studies in this direction should focus on enhancing regression models by incorporatingretrofit-sensitive variables and nonlinear interactions.

The second direction centers on the application of artificial neural networks (ANNs) to capturenonlineardependencies between multiple input variables and energy use. S. R. Mohandes, X. Zhang, and A. Mahdiyarreviewed over 90 studies, highlighting the shift from traditional MLPs to deep and recurrent neural networks [8]. K. Sun, Z. Dou, B. Zhang, and H. Zou proposed a CNN-ELM hybrid with FOA optimization that significantly improved both accuracy and speed [9]. B. Carrera, S. Peyrard, and K. Kim developed a stacking ensemble model for Songdo smart city combining CatBoost, ANN, and XGBoost, which achieved $R^2 = 0.9789$ and MAE ≈ 2% [10]. In a subsequent study, B. Carrera and K. Kim implemented an encoder–decoder LSTM architecture for urban energy forecasting [11]. A. A. Pierre,S.A. Akim, A.K. Semenyo, and B. Babiga demonstrated that an ARIMA–LSTM hybrid yielded the lowest RMSE (7.35) when compared to standalone models [12]. D. So, J. Oh, I. Jeon, J. Moon, M. Lee, and S. Rho created the BiGTA-Net model integrating GRU, TCN, and attention, outperformingconventional methods with MAPE = 5.37% [13]. M. Anan, K. Kanaan, D. Benhaddou, and N. Nasser further improved prediction accuracy by including occupancy data in the LSTM architecture, reducing error to 2% [14].Future research should prioritize transfer learning, explainability of ANN models, and strategies to overcome data scarcity in retrofittedbuildings.

The third direction involves hybrid and ensemble approaches that leverage the strengths of statistical and AI models. R. Evans and J. Gao pioneered deep learning applications for real-time cooling optimization in Google data centers, cutting energy use by 40% [15]. B. Arsecularatne, N. Rodrigo, and R. Changoutlined the growing role of digital twins in online forecasting and adaptive control [16]. S.S. MdRamli, M.N. Ibrahim, A. Mohamad, K. Daud, A.M.S. Omar, and N.D. Ahmad confirmed that ANN models generallyoutperform SVM and regression-based methods in various building contexts [17]. C. Lu, T. Hong, and L. Yang identified several challenges in ANN deployment, such as hyperparametertuning, model interpretability, and insufficient training data [18].

Y. Nam, Y. Hwangbo, and J. Yoo developed an LSTM–Prophet hybrid that improved short-term forecasting accuracy over standalone LSTM [19].Further work should investigate the integration of hybrid models into cloud-based control platforms and their robustness under changing operational conditions.

The fourth direction focuses on real-world validation of forecasting methods in various building types. C. Fan, F. Xiao, C. Madsen, K. Wang, and S. J. Zuo compared ML models for offices, retail, and healthcare facilities, identifying MLP and Random Forest as optimal for different use cases [20]. T. Ahmad, H. Chen, M. A. Butt, B. A. Bawazir, and S. Sreeraj emphasized the advantages of hybrid approaches after analyzing over 50 studies published between 2010 and 2020 [21]. V. I. Deshko proposed the use of nonlinear multivariate regression to evaluate external and internal factors influencing building energy behavior, contributing to a broader modeling foundation [22].Future investigations should aim at expanding case studies across climaticzones and integrating forecasting modules into municipal energy management systems.

Despite the growing academic and political attention to the Arctic, several critical aspects of the problem remain insufficiently explored. There is still a lack of comprehensive understanding of the geopolitical attractiveness of the region in the context of global strategic transformation. The resource and economic priorities of leading Arctic states are often examined in isolation, without comparative assessment of their competing models. China'sArctic strategy, despite its increasing relevance, remains under-analyzed, particularly regarding informal instruments of geo-economic presence. Legal uncertainty, the absence of universal regulatory mechanisms, and the potential impact of Arctic competition on the global balance of power also remain unresolved challenges in international discourse.

This study aims to address these gaps by offering a systematic analysis of both Arctic and non-Arctic state strategies, comparing economic models of regional development, and identifying sources of institutional instability. By applying an interdisciplinary approach that integrates geopolitical, economic, and legal dimensions, the research will deepen understanding of the mechanisms driving Arctic competition and contribute to a more coherent view of the region's role in shaping the evolving architecture of international relations.

Research aim - to substantiate contemporary approaches to forecasting building energy consumption considering thermomodernization measures, based on the analysis of regression, neural, and hybrid models, in order to identify their advantages, limitations, and practical effectiveness.

Research objectives:

1.To systematize the principal methods for predicting building energy consumption using regression analysis, artificial neural networks, and hybrid models.

2.To analyze how thermomodernization factors are incorporated into these predictive models.

3.To determine future directions for improving forecasting approaches in terms of accuracy, adaptability, and integration with energy efficiency management systems.

3.1. Regression models

Statistical regression models have long been employed in predicting building energy consumption due to their transparency, computational efficiency, and suitability for baselineassessments. Multiple linear regression (MLR) remains a foundational approach that enables the estimation of energy use based on independent variables such as outdoortemperature, building envelopeproperties, and operational schedules. For example, in the analysis of a UK supermarket, MLR was applied to identify climate sensitivity in consumption trends, revealing the relationship between risingtemperatures and changes in electricity and gas usage [4]. Similarly, for officebuildings, simulation-based regression models have been developed to predict annualheating and cooling demands as a function of design and usage parameters [5]. Another notable study in the U.S. context utilized regression techniques on DOE-2 simulation data to generate performance indicators across commercial building types, accounting for 17 architectural and operational factors [6].

Beyond MLR, autoregressive models such as ARIMA are frequently adopted for short-term energy forecasting due to their ability to model seasonal and trend components. Nevertheless, these models often face limitations when nonlinear dynamics are dominant or post-retrofit conditions significantly alter consumption patterns. To mitigate this, extensions like ARIMAX incorporate exogenous weather variables, while hybridization with machine learning techniques is increasingly pursued (as explored in Section 3.3).

Support vector regression (SVR) and decisiontreeensemblesrepresent advanced statistical learning methods that expand upon classical regression. SVR, particularly when optimized using metaheuristic algorithms such as differentialevolution, has demonstrated improved accuracy in forecasting high-resolution load profiles [7]. Meanwhile, regression trees and random forests offer flexible alternatives capable of capturing complex interactions between features. These methods are often further enhanced in ensemble architectures, providing a bridge between interpretable models and machine learning performance.Overall, while regression-based models may underperform in highly dynamic or non-linear contexts, they remain valuable for their interpretability, adaptability to limited datasets, and role in initial scenario analysis, especially in early-stage assessments of thermomodernization impacts.

3.2 Methods of artificial neural networks

The use of ANNsfor modeling building energy consumption has been intensively studied since the 1990s and is currently recognized as one of the most effective approaches [1]. The advantage of neural networks is the ability to take into account nonlinearrelationships between many factors (weather conditions, usageschedule, building characteristics, etc.) and energy consumption. Classical multilayerperceptrons (MLPs) have been widely used as a "black box" for predicting the daily or hourly load of a building. However, the choice of the optimal architecture and the tuning of MLP scales was traditionallydonemanually, which could limit the accuracy. Modern research is focused on improving the training algorithms and structure of MLPs. For example, in 2019, Lu et al. analyzed 12 different neural network architectures, pointing out open problems in their application - the need for a large amount of training data, optimization of hyperparameters, and interpretation of results [18]. DimitriGuillot et al. (2021) reviewed the features and limitations of neural networks in the context of architectural design, which confirmed the interdisciplinary nature of this topic [1]. According to reviews [8], [17], there is a transition from traditional learning algorithms (gradientdescent, methods of direct error propagation) to the use of modern types of networks - radial basis networks, recurrent networks, etc. to improve convergence and accuracy. In particular, recurrent neural networks of longshort-term memory (LSTM) are currently showing the best results in predicting time series of consumption. In a study [14], an LSTM model trained on one-minute data from an office building, taking into account the presence of people, outperformed traditional ARIMA and SVR, achieving a significantly lower error (conditional error rate of 2.05 versus significantly higher values for other models) [14]. Thus, the LSTM is able to take into account the time dynamics of thermal processes and changes in operatingmodes after the implementation of energy-saving measures. Another area is convolutional neural networks (CNNs), which are typically used to process spatial data or detect local patterns in a series. In energy forecasting tasks, CNNs are used to automatically extract features from load time series, especially in combination with recurrent networks or simplified neurons. For example, in [9], a hybrid is proposed where the CNN acts as a feature extractor and the output is passed to a simple neural classifier such as ELM. This approach improved the accuracy and speed of calculation compared to the standard CNN, since the Extreme Learning Machine (ELM) instantlydetermines the weights of the output layer without a longgradient training procedure [9]. In , attention mechanisms and other improvements to the network architecture are gaining more and more attention. Their integration allows the network to emphasize significant features of the input data. For example, in 2023, the BiGTA-Net model was proposed, which combines a bidirectional GRU, a temporal convolutional network, and an attention mechanism; this hybrid network achieved a MAPE of 5.37% and 36.9% higher accuracy than traditional deep networks when predicting the daily power load for the training corpus [13]. Thus, modern neural network methods (especially recurrent and deep ensembles) provide high accuracy in predicting building energy consumption. In the future, the role of ensemble and hybrid neural networks is expected to increase, as well as the consideration of physical constraints to improve the reliability of models [3].

3.3 Hybrid methods and digital twins

No single model can fully capture the complex dynamics of building energy consumption, which has prompted researchers to combine different modeling approaches. Hybrid models integrate statistical methods (e.g., ARIMA) with neural networks (e.g., LSTM) to improve accuracy by modeling both trend/seasonality and nonlinear residuals. The ARIMA+ANN hybrid consistently outperforms standalone models; for example, Pierre et al. [12] showed that ARIMA-LSTM reduced RMSE to 7.35 compared to 49.9 for ARIMA and ~18 for LSTM alone.

Another effective strategy is combining machine learning algorithms. Nam et al. [19] proposed an LSTM-Prophet hybrid that improved short-term electricity demand forecasts compared to conventional LSTM. Synergistic combinations of CNNs with simpler classifiers such as ELM have also proven effective: in the CNN-ELM model by Sun et al. [9], the convolutional output fed into an ELM trained via the FOA algorithm, resulting in improved accuracy and computational speed.

Ensemble methods (e.g., bagging, boosting, stacking) currently demonstrate the best performance by leveraging the diversity of individual models. Carrera et al. [10] developed a stacked ensemble combining an artificial neural network, CatBoost, GradientBoosting, and an XGBoost meta-regressor, achieving $R^2 = 0.9789$ in predicting total energy use in the Songdo smart city—outperforming any individual model.

The digital twin concept, increasingly adopted in recent years, provides a dynamic virtual model of a building that is continuously updated with real-time sensor data [16]. In energy forecasting, digital twins enable the integration of physical (white-box) and data-driven (black-box) models, forming a gray-box framework. This allows real-time monitoring, adaptive forecasting, and scenario testing (e.g., for thermal retrofit effects). According to Arsecularatne et al. [16], digital twins enhance building sustainability by optimizing HVAC control, monitoring indoor climate, and considering occupant behavior. Although still emerging, practical examples already exist where digital twins support heat load prediction and renovation planning. Thus, hybrid approaches—both algorithmic (e.g., ARIMA+LSTM, CNN-ELM) and structural (digital twins)—represent a promising direction for post-retrofit building energy management.

3.4. The project in Songdo (stacking model)

As an illustrative example of the modern approach, let's consider the project in Songdo (South Korea), a smart city built with full monitoring systems. Given the availability of a large array of energy consumption data for urban facilities (the so-calledmicrocities within Songdo), researchers set out to make a short-term forecast of total energy consumption for a 3-month horizon[10]. Carrera et . proposed a multi-level forecasting model consisting of several stages. First, basic forecasts are built using various machine learning algorithms (in particular, CatBoost gradientboosting, multilayer neural network, etc.) Next, they are combined by stacking: a meta-regression model is formed, which is trained on the outputs of the base models, predicting the final consumption value. The meta-regressor used is XGBoost (gradientboosting of solutions with weights that optimally combine the contribution of each base model. The resulting ensemble model demonstrated extremely high accuracy: the coefficient of determination $R^2=0.9789$, the rootmeansquare error (RMSE) was reduced to ~2%, which significantly exceeds the accuracy of each individual model. In fact, the forecast error at the city block level was only ~2-3% of actual consumption, which is an excellent indicator for such a longhorizon (90 days). Songdo's experience confirms the effectiveness of meta-ensembles for energy management tasks of entire groups of buildings. Interestingly, the baseline models included both classical algorithms (treeensembles) and ANNs; this emphasizes that the best results are achieved by combining heterogeneous approaches. Currently, the stacking approach, successfully tested in Songdo, can be transferred to the level of individual buildings (for example, creating an ensemble of building heat supply forecasts from different models - regression, LSTM, etc. - with subsequent meta-aggregation). Such a meta-model approach allows compensating for the shortcomings of individual methods and obtaining consistently high forecast accuracy.

3.5. Forecasting software tools

Implementation of forecasting models is possible with the use of various software tools. Energy modeling packages such as EnergyPlus, DOE-2/eQUEST, TRNSYS, etc. are widely used for deterministic modeling of building energy consumption. They allow for detailed simulations of thermal processes in a building before and after thermal modernization. In particular, in [6], the DOE-2 (eQUEST) program was used to generate a training sample (results of numericalexperiments), on the basis of which regression models of energy consumption were built. , in the dissertation[2], the thermalmodes of a building were modeled in the EnergyPlus environment, and the results were used for approximation by multivariate regression. The obtained simulation data can also be used to train or validate neural network models - this approach is the basis of digital twins. An indirect method of evaluation is the use of Building Energy Modeling (BEM) at the design stage: integration with BIM systems allows to predict savings from thermal modernization even before reconstruction[22].

To build actual predictive algorithms (regressions or neural networks), the most popular tools are universal programming languages and scientific computing libraries. In particular, Python with the scikit-learn, StatsModels (regression analysis, ARIMA), TensorFlow, and PyTorch (neural networks) libraries provides a full cycle - from data processing to model training and forecasting. R is also used for statistical forecasting of time series and building models based on machine learning methods. Among the engineering packages, MATLAB with System Identification, Deep Learning, etc. toolboxes is often used, mainly in academic research. Commercial building management systems (BMS/BEMS) increasingly include load forecasting modules. According to [13], modern building energy management systems (BEMS) in smart cities actively use the Internet of Things to collect big data and perform short-term forecasts of electricity consumption, which allows for better load balancing and prevention of peakoverloads. In general, the availability of flexible programming tools greatly simplifies the implementation of the methods discussed in practice. For example, machine learning models for real-time building monitoring can now be deployed in the Google Cloud or Azure cloud platform [17]. At the same time, there is still a need for specialized software products focused specifically on energy consumption forecasting: such solutions could integrate into existing BEMS and automate the process of data collection, model training, and issuing forecasts to the operator.

3.6. Practical application cases

The methods for forecasting energy consumption in buildings discussed above are already being used in real projects. Here are some illustrative examples. Office buildings: in the context of dynamic officeschedules and microclimate effects, ANN methods demonstrate high efficiency. A study for an office center in Houston (USA) showed that taking into account employee presence data significantly improves the accuracy of electricity consumption forecasts; the built LSTM model was able to predict the daily load curve with an error of only ~2% [14]. This opens up opportunities for the introduction of proactive HVAC control systems in offices, such as pre-cooling the premises before employees arrive according to the forecast, which increases comfort and reduces peakloads. Shopping centers and supermarkets: they are characterized by significant internal heatgain and dependence on the outside temperature. Study [4] assessed the impact of climate change on supermarket energy consumption based on regression analysis of operational data: it was confirmed that after insulation (reduction of heat loss), electricity consumption may increase slightly due to a greater need for cooling, while gas consumption for heating is significantly reduced [4]. Such forecasts help retail managers plan the modernization of HVAC systems and evaluate the economic effect. Data centers: Google, in collaboration with DeepMind, successfully used a deep neural network to optimize the cooling of its data centers back 2016. With the help of an ensemble of several deep neural networks trained on large amounts of historical sensor data (temperatures, fanspeeds, etc.), it was possible to predict the PUE (power usage efficiency ratio) in real time and recommend optimalcooling system settings [15]. The implementation of this system made it possible to reduce energy consumption for airconditioning by up to 40%, which is equivalent to 15% savings in total data center energy costs. This case study clearly demonstrates the potential of ANNs and reinforcement learning in energy efficiency tasks: although the data center is not a "building" in the classical sense, the principles are the same - model-based microclimate forecasting and optimization. Examples in Ukraine: in our country, predictive methods for energy consumption in buildings are still being implemented locally, mainly as part of scientific experiments or pilot projects of energy service companies. In particular, in the above-mentioned thesis by Bilous (NTUU "KPI", 2018), a heating control system with a predictive module was developed on the basis of the university building - the model takes into account the temperature of the outside air and the thermalinertia of the building and predicts the required level of heat consumption, which made it possible to save up to 12-15% of thermal energy without losingcomfort[2]. Some Ukrainian cities (e.g., Vinnytsia, Lviv) are experimenting with installing monitoring systems in residential high-rise buildings and hospitals as part of their energy efficiency programs; the data collected can serve as a basis for implementing predictive algorithms, in particular in heat points. Thus, the experience of using these methods in real-world conditions - from office centers to industrial facilities and municipal buildings - is being gained, which confirms their practical value.

3.7. Comparative analysis of methods

The diversity of approaches to forecasting building energy consumption calls for a comparative evaluation of their effectiveness. Table 1 summarizes selected studies that represent different classes of models, including artificial neural networks (ANN), hybrid models, digital twins, and machine learning ensembles. Unlike classical regression techniques discussed in section 3.1, these approaches emphasize learning from complex nonlinearpatterns and integrating real-time or multivariate data inputs.

Table 1 - Comparative characteristics of building energy consumption forecasting methods (selected sources)

Source	**Method(s) / Model**	**Forecast Object / Data**	**Key Results / Accuracy**
Pierre et al., 2023 [12]	Hybrid ARIMA + LSTM	National gridpeakloads (Benin)	RMSE reduced to 7.35 vs 49.90 (ARIMA); hybrid outperformsstandalone
So et al., 2023 [13]	BiGTA-Net (Bi-GRU + TCN + Attention)	University building, dailyelectricity	MAPE 5.37%; ~37% more accurate than CNN/LSTM
Anan et al., 2024 [14]	Occupant-aware LSTM	Office building, 1-min intervals	MAE ~2%; outperformed ARIMA; occupancy data improved precision
Carrera et al., 2021 [10]	Ensemble (ANN + CatBoost + XGBoost)	Smart city (Songdo), 3-month energy forecast	R^2 = 0.9789; MAE ~2%; validated meta-regression ensemble
Arsecularatne et al., 2024 [16]	Digital twins + AI	Commercial buildings	Real-time optimization; documented savings up to 20%
Nam et al., 2020 [19]	Hybrid LSTM + Prophet	Microgrid, hourly data (Korea)	MAE reduced by ~5–7% vs pure LSTM
Liu et al., 2023 [3]	Review of 116 data-driven studies	Zone/building/microgrid levels	30–80% savings confirmed with hybrid + hyperparameter optimization
Fan et al., 2019 [20]	ML comparison (RF, SVM, MLP)	5 building types, quarterly data	RF best for offices, MLP for retail/hospitals; average error 5–8%
Mohandes et al., 2019 [8]	Review: ANN in energy analysis	Various building types	ANNs reached 95–99% accuracy with deep networks (GRNN, RNN)
Ramli et al., 2023 [17]	ANN vs ML models review	Mixed-typebuildings (2010–2022)	DNNsoutperform regression and fuzzy models in most cases
Lu et al., 2019 [18]	Theoretical analysis of ANN issues	-	Highlighted key gaps: data scarcity, hyperparametertuning
Yin et al., 2024 [1]	Review: 116 ANN studies	Various building life cycle stages	Best practices: ensemble learning, data preprocessing, optimization

Note: abbreviations in the table: ANN - artificial neural network; MLP - multilayerperceptron; RBF - radial basis function; SVR - support vector regression; ELM - extreme learning; FOA - FruitFly Optimization Algorithm; GRU - gatedrecurrentunit; TCN - temporal convolutional network; RF - Random Forest; DT - digital ; EUI - specific energy consumption. Errors are based on primary sources: MAPE - meanabsoluterelative error, RMSE - rootmeansquare , R^2 - coefficient of determination, MAE - meanabsolute error.

Deep learning models such as LSTM, Bi-GRU, and hybrid ensembles typically demonstrate the highest accuracy. For example, the BiGTA-Net architecture achieved a meanabsolutepercentage error (MAPE) of 5.37%, significantly outperformingconventional CNN and LSTM approaches. Similarly, hybrid ARIMA-LSTM models have shown 2–3 times lower rootmeansquare error (RMSE) than their standalonecounterparts. Digital twin technology is gainingtraction due to its ability to simulate and optimize consumption in real time, with documented savings of 10–20%. Although still under development, digital twins are expected to play a critical role in intelligent energy management.

The evidence suggests that hybrid and ensemble methods (positions 1–5 in the table) consistentlyoutperform single-model approaches and are best suited for post-retrofit forecasting tasks or urbanscale smart energy systems. However, the suitability of any given method remains dependent on data availability, interpretability requirements, and implementation costs. Ultimately, the prevailing trend is toward integrated AI-driven forecasting frameworks that combine high accuracy with operational adaptability.

The table 1 presents a condensed comparison of methods based on the reviewed literature. Traditional regression models ([2], [4], [5], [6], [7]) remain effective for preliminaryestimations and energy audits, particularly when interpretability and limited data are prioritized. However, their accuracy significantly decreases in highly dynamic or nonlinear contexts, such as post-retrofitbuildings.

Artificial neural networks and deep learning architectures ([8], [10], [11], [13], [15], [17]) consistently demonstrate superior accuracy, especially when trained on granular time-series data and enriched with external variables (e.g., weather, occupancy). These models are especially suitable for modern buildings with complex HVAC systems and smart metering infrastructure.

Hybrid and ensemble models ([12], [14], [16]) outperform both individual statistical and neural models by combining their strengths. They are particularly recommended for forecasting under uncertainty, such as changing occupancypatterns or evolving energy profiles after thermal modernization.

Finally, review and meta-analytical studies ([1], [3], [18], [20], [21]) confirm a shift toward hybridization, model stacking, and the integration of digital twins. These trends indicate the growing importance of adaptive, scalable, and self-learning systems for intelligent building energy management.

Conclusions. This review has established that deep learning methods, particularly artificial neural networks such as LSTM, GRU, and their ensembles, currently provide the highest accuracy in forecasting building energy consumption. These models significantly outperform traditional regression techniques in dynamic and post-retrofit contexts, with typical forecast errors reduced to 2–5%. Nevertheless, regression-based models retain value for baseline diagnostics, energy audits, and scenarios requiring interpretability or limited input data.

A key limitation identified in the literature is the challenge of model generalization due to variability in building types, occupancypatterns, and climate zones. Inadequate training data, insufficient integration of physical knowledge into black-box models, and the lack of standardized evaluation frameworksremainpersistentobstacles. Furthermore, many models are still calibrated for stable operational conditions and perform poorly when building characteristics change after thermal modernization.

The study highlights the particular promise of hybrid and ensemble approaches—such as ARIMA+LSTM, CNN-ELM, and stackingregressors—which effectively combine trend detection and nonlinearresidual learning. These architectures demonstrated superior accuracy and adaptability across comparative benchmarks. Of special interest are digital twins, which enable real-time energy optimization based on synchronized virtual-physical models. Their integration into building energy management systems represents a strategic direction for increasing operational efficiency.

Future research should focus on the development of transferable hybrid models that can accommodatestructural, behavioral, and climatic changes in energy profiles. Special attention should be given to domain-informed model training, scalable deployment frameworks, and the use of synthetic or augmented data to mitigate dataset limitations. Expanding the application of digital twin technologies in post-retrofit building stock, particularly in emerging economies such as Ukraine, is a priority area for both academic investigation and policy support.

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СУЧАСНІ МЕТОДИ ПРОГНОЗУВАННЯ ЕНЕРГОСПОЖИВАННЯ БУДІВЕЛЬ

Актуальність дослідження зумовлено зростаючою потребою підвищення енергоефективності будівель шляхом термомодернізації, а також необхідністю у точних інструментах прогнозування, що дозволяють здійснювати ефективне управління енергоспоживанням. В умовах змін клімату та зростання вартості енергоресурсів вибір оптимальних моделей прогнозування набуває стратегічного значення для житлово-комунального господарства та об'єктів міської інфраструктури.

Метою дослідження є обґрунтування сучасних підходів до прогнозування енергоспоживання будівель з урахуванням заходів термомодернізації на основі аналізу регресійних, нейронних і гібридних моделей з метою виявлення їхніх переваг, обмежень та практичної ефективності.

Методологія. Проведено порівняльний аналіз результатів актуальних досліджень, що застосовують статистичні, нейромережеві та комбіновані моделі прогнозування. Оцінено точність, масштабованість, гнучкість моделей, а також їх здатність адаптуватися до змін після термомодернізації. Особливу увагу приділено архітектурам глибокого навчання (LSTM, GRU), гібридним комбінаціям (ARIMA+LSTM, CNN+ELM) та технології цифрових двійників.

Результати. Установлено, що найвищу точність прогнозування забезпечують нейромережеві моделі, зокрема глибокі архітектури та ансамблі. Виявлено, що середня абсолютна похибка у таких підходів не перевищує 3–5%. Регресійні методи, попри нижчу точність, залишаються актуальними для базової оцінки впливу кліматичних факторів. Доведено ефективність гібридних підходів, що комбінують трендову компонену зі здатністю нейронних мереж описувати залишкову нелінійність. Виявлено перспективність цифрових двійників як інструменту прогнозно-керованої енергетики.

Висновки. Доведено, що ефективне прогнозування енергоспоживання можливе лише за умови врахування змін, зумовлених термомодернізацією, та застосування гнучких моделей, здатних адаптуватися до нових умов експлуатації будівель. Визначено, що інтеграція методів штучного інтелекту з фізичними моделями та цифровими двійниками підвищує точність і корисність прогнозів для практичного енергоменеджменту.

Перспективи подальших досліджень. Доцільним є розвиток методів комбінованого моделювання з урахуванням поведінкових чинників споживання, а також розширення емпіричної бази для оцінювання ефективності цифрових двійників у контексті модернізованих будівель різного призначення.

Ключові слова: *енергоефективність будівель, прогнозні моделі, термомодернізація, глибоке навчання, цифрові двійники, системи управління енергоспоживанням.*

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