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DEEP LEARNING APPROACHES FOR BUILDING ENERGY CONSUMPTION PREDICTION

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Abstract: Building energy consumption prediction has emerged as a critical component in the global effort to achieve energy efficiency and sustainability in the built environment. This systematic review comprehensively analyzes the application of deep learning approaches in building energy consumption prediction, synthesizing findings from recent research published between 2018 and 2024. Our methodology involved a systematic search across major scientific databases, including IEEE Xplore, Science Direct, and Web of Science, yielding 127 relevant studies that met our inclusion criteria. The review reveals significant advancements in prediction accuracy through various deep learning architectures, with particular success in hybrid models combining multiple neural network types. Key findings indicate that transformer-based models and attention mechanisms show superior performance for long-term predictions, while LSTM networks excel in capturing short-term consumption patterns. However, challenges persist in data quality, model interpretability, and real-world deployment. This review provides valuable insights for researchers and practitioners, highlighting promising research directions in transfer learning, explainable AI, and integration with building management systems.
Keywords: Building management systems; Green building; Built environment; Deep learning

1 INTRODUCTION

The built environment accounts for approximately 40% of global energy consumption and 36% of greenhouse gas emissions [1]. Accurate prediction of building energy consumption has become increasingly crucial for energy efficiency, cost reduction, and environmental sustainability. Traditional prediction methods, primarily based on statistical and physics-based models, have shown limitations in capturing the complex, non-linear relationships between various factors affecting building energy consumption [2].

The evolution from conventional approaches to deep learning methods represents a paradigm shift in building energy prediction [3]. Deep learning's ability to automatically extract features and learn complex patterns from large datasets has demonstrated superior performance compared to traditional methods. This advancement has been particularly significant in handling the multifaceted nature of building energy consumption, which is influenced by numerous factors including weather conditions, occupancy patterns, building characteristics, and operational schedules.

The field currently faces several significant challenges in building energy prediction. The heterogeneous nature of building data creates complexity in integrating multiple data sources effectively [4]. Real-time prediction capabilities are increasingly necessary to support dynamic energy management systems, yet achieving this while maintaining accuracy remains challenging. Organizations must carefully balance model complexity with computational efficiency to ensure practical implementation. Furthermore, developing models that maintain robust predictions across diverse building types and operational conditions presents ongoing difficulties for researchers and practitioners [5].

This systematic review addresses four primary research questions that guide our analysis. First, we examine how different deep learning architectures compare in terms of prediction accuracy, computational efficiency, and practical applicability for building energy consumption prediction. Second, we investigate the critical factors affecting the performance of deep learning models in energy prediction, including their variation across different building types and prediction horizons. Third, we assess the effectiveness of current deep learning approaches in addressing challenges related to data quality, model interpretability, and real-world implementation. Finally, we explore emerging trends and promising directions in deep learning applications for building energy prediction.

2 METHODOLOGY

2.1 Search Strategy

Our systematic review employed a comprehensive search strategy across multiple scientific databases to ensure thorough coverage of relevant literature. The primary databases consulted included IEEE Xplore, Science Direct, Web of Science, Scopus, and Google Scholar. To capture relevant research, we developed a structured search string combining key terms related to deep learning and building energy prediction. The core search terms included variations of "deep learning," "neural networks," "building energy," "consumption prediction," and "forecasting," combined using appropriate Boolean operators.

The initial search focused on peer-reviewed articles published between January 2018 and January 2024, ensuring coverage of recent developments in the field. We established specific inclusion criteria to maintain the review's focus and quality. Selected papers needed to present original research specifically applying deep learning methods to building energy consumption prediction. We included only English-language publications in peer-reviewed journals and conference proceedings. Studies focusing solely on traditional machine learning methods or those addressing energy prediction without a building-specific context were excluded from the analysis.

2.2 Quality Assessment

The quality assessment process followed a rigorous multi-stage screening approach to ensure the inclusion of high-quality, relevant research. The initial screening examined titles and abstracts against our predefined criteria, followed by a detailed full-text review of promising articles. Each paper was evaluated using a comprehensive quality assessment framework considering multiple dimensions of research quality.

Our assessment criteria examined the clarity of research objectives, methodological rigor, data quality and preprocessing procedures, experimental design, and the validity of results and conclusions. Papers were required to provide sufficient detail about their deep learning architectures, training procedures, and evaluation metrics. We particularly valued studies that included comparative analyses with baseline methods and clear discussions of limitations and practical implications.

The screening process was conducted independently by multiple researchers to minimize bias, with disagreements resolved through consensus discussions. This approach resulted in the final selection of 127 papers that met all quality criteria and formed the core dataset for our analysis.

2.3 Classification Framework

To systematically analyze the selected literature, we developed a comprehensive classification framework addressing multiple aspects of deep learning approaches in building energy prediction. The framework consists of several key dimensions for analysis: architectural approaches, input features and data characteristics, prediction horizons, and implementation considerations.

In the architectural dimension, we classified studies based on their primary deep learning approaches, including feedforward neural networks, recurrent neural networks, convolutional neural networks, and advanced architectures such as transformers and hybrid models. Each architecture was further analyzed based on its specific variations and modifications for energy prediction tasks.

The performance evaluation framework incorporated both quantitative and qualitative metrics. Quantitative assessment included standard metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Qualitative assessment examined factors such as model complexity, computational requirements, and practical implementation considerations.

Our analysis methodology combined statistical synthesis of performance metrics with narrative analysis of methodological approaches and implementation strategies. We particularly focused on identifying patterns in the relationship between architectural choices, input features, and prediction accuracy across different building types and prediction horizons. This comprehensive approach enabled us to draw meaningful conclusions about the effectiveness of different deep learning approaches and their practical applicability.

The classification framework also incorporated contextual factors such as building type, geographical location, and data availability, allowing us to analyze how these factors influence model selection and performance. This systematic categorization facilitated the identification of trends, gaps, and promising directions in the field of building energy prediction using deep learning approaches.

3 DEEP LEARNING ARCHITECTURES FOR ENERGY PREDICTION

3.1 Feedforward Neural Networks

Feedforward Neural Networks (FNNs) serve as the foundational architecture in building energy prediction, offering a straightforward yet effective approach to modeling energy consumption patterns [6]. The basic architecture typically consists of an input layer processing building-related features, multiple hidden layers for pattern recognition, and an output layer producing energy consumption predictions. Our analysis reveals that modern implementations have evolved significantly from basic multilayer perceptrons to incorporate sophisticated variations.

Recent studies have demonstrated particular success with deep feedforward networks employing residual connections [7]. These connections help mitigate the vanishing gradient problem common in deeper architectures while enabling the model to capture both linear and non-linear relationships in energy consumption patterns. Several researchers have implemented

adaptive activation functions, moving beyond traditional ReLU activations to capture more complex patterns in energy usage data.
Performance analysis of FNN implementations shows strong results for medium-term predictions, particularly in scenarios with stable occupancy patterns and regular usage cycles [8]. The architecture demonstrates robust performance in processing structured input features such as weather data, occupancy schedules, and historical consumption patterns. However, their effectiveness diminishes when dealing with long-term dependencies or complex temporal patterns in energy consumption data.

3.2 Recurrent Neural Networks

Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variants, have emerged as powerful architectures for capturing temporal dependencies in energy consumption patterns [9]. LSTM networks excel in modeling both short-term and long-term temporal relationships, making them particularly suitable for predicting energy consumption patterns that exhibit strong seasonal or cyclical components.
The analysis of LSTM implementations reveals several innovative approaches to handling building energy prediction [10]. Bidirectional LSTM architectures have shown superior performance in capturing both past and future dependencies in energy consumption patterns. These models demonstrate particular strength in handling variable-length sequences and adapting to changing consumption patterns over time. GRU networks, while less commonly implemented than LSTMs, show comparable performance with reduced computational complexity, making them attractive for real-time applications.
Temporal modeling capabilities of these architectures extend beyond simple sequence prediction [11]. Advanced implementations incorporate attention mechanisms to weight the importance of different time steps, improving prediction accuracy during irregular events or unusual consumption patterns. Our review indicates that RNN-based models consistently outperform traditional time series approaches, particularly in scenarios requiring adaptation to dynamic building usage patterns.

3.3 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have found novel applications in building energy prediction, particularly in scenarios involving spatial-temporal data or multiple input streams [12]. While traditionally associated with image processing, CNNs have demonstrated remarkable effectiveness in extracting hierarchical features from energy consumption data and related parameters.
The application of CNNs in energy prediction often involves innovative adaptations of the architecture to handle time series data [13]. One-dimensional CNN variants process temporal sequences of energy consumption, while two-dimensional implementations handle multiple parallel input streams, such as weather data alongside consumption patterns. Hybrid approaches combining CNNs with other architectures have shown particular promise, with CNN layers serving as feature extractors before temporal processing stages.
Recent implementations have explored dilated convolutions to expand the receptive field of the models without increasing computational complexity [14]. This approach has proven especially effective in capturing long-range dependencies while maintaining computational efficiency. The spatial feature extraction capabilities of CNNs have also been leveraged in processing building sensor network data, where spatial relationships between different zones or systems influence energy consumption patterns.

3.4 Advanced Architectures

The evolution of deep learning has introduced several advanced architectures that address specific challenges in building energy prediction [15]. Transformer-based models have emerged as particularly powerful tools for handling long-sequence predictions and complex dependencies. These models leverage self-attention mechanisms to capture relationships across different timescales and input features, often outperforming traditional recurrent architectures in long-term prediction scenarios.
Graph Neural Networks (GNNs) represent another significant advancement, particularly suitable for modeling building energy systems as interconnected networks [16]. These architectures excel in capturing the relationships between different building zones, systems, and components, providing insights into how energy consumption patterns propagate through building systems. The ability to model non-sequential relationships makes GNNs particularly valuable for complex building environments with multiple interconnected zones and systems.
Attention mechanisms have become increasingly prevalent across different architectural approaches [17]. Beyond their use in transformer models, attention layers have been successfully integrated into CNN and RNN architectures to improve feature selection and temporal dependency modeling. These mechanisms help models focus on relevant features and time periods, improving prediction accuracy during unusual events or changing consumption patterns.

Deep reinforcement learning approaches have begun to emerge in recent literature, particularly in scenarios combining prediction with control optimization [18]. These implementations show promise in developing predictive models that can adapt to changing conditions while optimizing energy consumption patterns. While still in early stages, reinforcement learning approaches offer potential for creating more adaptive and autonomous building energy management systems.

4 INPUT FEATURES AND DATA PROCESSING

4.1 Feature Categories

The effectiveness of deep learning models in building energy prediction heavily depends on the selection and quality of input features [19]. Weather data represents one of the most significant feature categories, encompassing temperature, humidity, solar radiation, wind speed, and atmospheric pressure. Our analysis reveals that temperature and solar radiation consistently demonstrate the strongest correlations with energy consumption patterns across different building types and geographical locations.

Building characteristics form another crucial feature category, including both static and dynamic properties. Static features encompass physical attributes such as building age, floor area, insulation properties, and construction materials. Dynamic characteristics include HVAC system configurations, operational schedules, and equipment efficiency metrics. The integration of these features enables models to account for building-specific factors that influence energy consumption patterns [20].

Occupancy patterns have emerged as increasingly important predictors of energy consumption, particularly in commercial and institutional buildings. Advanced studies incorporate both scheduled occupancy data and real-time occupancy measurements from sensor networks. The relationship between occupancy and energy consumption exhibits complex non-linear patterns, making it particularly suitable for deep learning approaches that can capture these intricate relationships [21].

4.2 Data Preprocessing Techniques

The preprocessing of input features represents a critical step in developing effective prediction models. Missing data handling emerges as a common challenge, particularly in real-world implementations. Sophisticated approaches combine multiple techniques, including linear interpolation for short gaps, pattern-based filling for longer periods, and advanced imputation methods leveraging correlations between different features. The choice of missing data handling technique significantly impacts model performance, with more sophisticated methods generally yielding better results.

Time series preprocessing requires special attention in energy prediction applications [22]. Decomposition techniques separate consumption patterns into trend, seasonal, and residual components, enabling models to capture different aspects of consumption behavior. Advanced implementations incorporate domain-specific preprocessing steps, such as day-type encoding and holiday effect handling, to account for systematic variations in consumption patterns.

Feature selection methods have evolved beyond traditional statistical approaches to incorporate domain knowledge and automated selection techniques. Wrapper methods using neural network-based feature importance estimation have shown promising results, though at the cost of increased computational complexity [23]. Filter methods based on mutual information and correlation analysis provide efficient alternatives for large-scale implementations.

4.3 Data Quality and Availability

Data quality considerations present significant challenges in practical implementations of deep learning models for energy prediction [24]. Common data quality issues include sensor malfunction, communication errors, and systematic biases in measurement systems. Successful implementations incorporate robust data validation procedures, including automated anomaly detection and correction mechanisms.

The availability of comprehensive datasets remains a limiting factor in many applications. While several public datasets exist for building energy consumption, they often lack the full range of relevant features needed for optimal prediction performance [25]. Data collection methodologies have evolved to address these limitations, with modern building management systems increasingly incorporating comprehensive sensor networks and data logging capabilities. Edge computing implementations enable preprocessing and validation of data closer to the source, improving data quality and reducing communication overhead. The integration of different data sources presents technical challenges, particularly in terms of temporal alignment and feature consistency [26].

5 APPLICATIONS AND CASE STUDIES

5.1 Building Types

Residential buildings present unique challenges and opportunities for energy prediction applications [27]. Single-family homes demonstrate highly individualistic consumption patterns influenced by occupant behavior and lifestyle factors.

Commercial buildings represent a more complex application domain characterized by regular operational patterns overlaid with significant variability. Office buildings, in particular, have served as prominent test cases for advanced deep learning implementations. Large-scale commercial implementations demonstrate the value of hybrid architectures that combine multiple prediction horizons, with short-term models handling daily variations while longer-term models address seasonal planning requirements [28].

Industrial facilities pose distinct challenges due to their high energy intensity and complex operational patterns. Deep learning implementations in industrial settings often incorporate process-specific features alongside traditional building characteristics [29]. These applications demonstrate particular success in facilities with multiple energy carriers and complex interaction patterns between different systems. The integration of deep learning models with industrial control systems has shown potential for significant energy savings, typically ranging from 10-15% of total consumption [30].

Smart buildings represent the cutting edge of deep learning applications in energy prediction [31]. These implementations leverage comprehensive sensor networks and advanced building management systems to provide real-time predictions and optimization recommendations. The integration of multiple subsystems, including HVAC, lighting, and occupant comfort controls, creates rich datasets that enable more sophisticated prediction approaches. Smart building implementations demonstrate the potential for continuous learning and adaptation, with models improving their accuracy over time through automated refinement processes.

5.2 Prediction Horizons

Short-term prediction implementations focus on horizons ranging from hours to days, primarily supporting operational optimization and demand response applications. These implementations typically achieve the highest prediction accuracy, with mean absolute percentage errors below 5% for day-ahead predictions in well-instrumented buildings [32]. The success of short-term predictions relies heavily on the quality of recent historical data and the accuracy of weather forecasts.

Medium-term prediction applications address planning horizons from weeks to months, supporting maintenance scheduling and resource allocation decisions. These implementations must balance the incorporation of seasonal patterns with adaptation to changing usage patterns. Successful medium-term implementations demonstrate the importance of feature selection and data preprocessing, with models achieving typical prediction errors in the 8-15% range [33].

Long-term prediction represents the most challenging temporal horizon, extending from months to years to support strategic planning and investment decisions. These implementations must account for factors such as building degradation, climate change impacts, and evolving usage patterns. While prediction accuracy typically decreases with longer horizons, successful implementations achieve usable results by focusing on trend analysis and scenario planning rather than precise consumption predictions [34].

5.3 Real-world Implementation

Success stories from real-world implementations demonstrate the practical value of deep learning approaches in building energy prediction. A notable implementation in a large university campus achieved 25% energy savings through the integration of deep learning predictions with building control systems [35]. Another successful case involved a commercial office complex where predictive models enabled optimal demand response participation, resulting in substantial cost savings while maintaining occupant comfort.

Implementation challenges encountered in real-world applications reveal important considerations for practical deployment. Data quality issues often emerge as the primary challenge, particularly in retrofitted buildings with incomplete or inconsistent historical data. The integration of deep learning models with existing building management systems presents technical challenges, especially in terms of real-time data flow and control system interfaces.

Integration with building management systems requires careful consideration of both technical and operational factors. Successful implementations typically employ a staged approach, beginning with parallel operation for validation before transitioning to active control integration. The development of standardized interfaces and communication protocols has emerged as a crucial factor in facilitating widespread adoption. Real-world implementations demonstrate the importance of user interface design and visualization tools in enabling effective interaction between building operators and predictive models.

6 FUTURE RESEARCH DIRECTIONS AND CONCLUSION

The systematic review of deep learning approaches in building energy consumption prediction reveals both significant progress and important challenges that warrant further investigation. Our analysis identifies several promising directions for future research that could substantially advance the field.

Transfer learning emerges as a particularly promising avenue for future research, addressing the persistent challenge of limited training data in many building applications. Initial studies demonstrate the potential for pre-trained models to adapt effectively to new buildings with minimal additional training data. Further research is needed to develop standardized transfer learning frameworks that can accommodate different building types and operational patterns. The development of pre-trained models that capture fundamental patterns in building energy consumption could significantly reduce the implementation barriers for new applications.

Explainable AI represents another crucial research direction, particularly important for gaining stakeholder trust and enabling effective human oversight. Current deep learning models often function as black boxes, making it difficult for building operators to understand and verify their predictions. Future research should focus on developing interpretable architectures and explanation mechanisms that provide insights into the factors driving predictions. This includes the development of visualization techniques that can effectively communicate model reasoning to non-technical stakeholders.

The integration of physics-based knowledge with deep learning approaches presents opportunities for improving model robustness and generalization. Hybrid approaches that combine data-driven learning with domain-specific constraints show promise in reducing the data requirements for accurate predictions. Future research should explore architectures that can effectively incorporate building physics principles while maintaining the flexibility to learn from operational data.

Edge computing and distributed learning architectures represent emerging areas with significant potential impact. As building systems become increasingly decentralized, research is needed to develop efficient architectures that can operate effectively on edge devices while maintaining prediction accuracy. This includes investigating techniques for model compression, distributed training, and efficient inference on resource-constrained devices.

The impact of climate change on building energy consumption patterns presents a significant challenge for current prediction approaches. Future research should address the development of adaptive models that can account for changing climate patterns and extreme weather events. This includes investigating techniques for incorporating climate projection data and developing models that can maintain accuracy under evolving environmental conditions.

The successful implementation of deep learning approaches depends on careful consideration of multiple factors, including data quality, architectural choice, and implementation constraints. Our analysis reveals the importance of matching model complexity to application requirements and available resources. The development of standardized evaluation frameworks and benchmark datasets would facilitate more meaningful comparisons between different approaches and accelerate progress in the field.

The future of building energy prediction lies in the development of more adaptive, interpretable, and efficient deep learning approaches. Success will require continued collaboration between researchers in deep learning, building science, and practical implementation domains. As buildings continue to evolve toward greater intelligence and automation, the role of accurate and reliable energy prediction becomes increasingly crucial for achieving sustainability goals and operational efficiency.

This review contributes to the field by providing a comprehensive analysis of current approaches, identifying key challenges, and highlighting promising research directions. The findings suggest that while deep learning has demonstrated significant potential in building energy prediction, realizing this potential requires addressing several key challenges. Future developments in the field should focus on improving model robustness, reducing implementation barriers, and enhancing the practical applicability of deep learning approaches in real-world building operations.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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