AI- driven optimization of energy consumption in smart residential complexes

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Abstract. This article examines the application of artificial intelligence technologies for optimizing energy consumption in smart residential complexes. The study analyzes contemporary approaches to implementing machine learning algorithms, neural networks, and predictive analytics for managing energy resources in multi-apartment buildings. The research demonstrates that AI-driven systems can reduce energy consumption by 25-40% compared to traditional management methods. The article presents a comprehensive analysis of architectures for intelligent energy management systems, including integration with Internet of Things sensors, smart meters, and building automation systems. Particular attention is given to machine learning methods for forecasting energy demand, optimizing heating, ventilation, and air conditioning systems, and managing renewable energy sources. The study examines challenges associated with implementing AI solutions, including data privacy, system integration complexity, and the need for substantial initial investments. The results show that deep learning algorithms demonstrate the highest efficiency in predicting consumption patterns, while reinforcement learning methods are most effective for real-time optimization. The article also discusses the economic feasibility of implementing such systems, demonstrating payback periods of 3-5 years depending on building size and climatic conditions. Recommendations are provided for developers, building managers, and policymakers regarding the implementation of AI-based energy management systems in residential complexes.

Keywords: artificial intelligence, energy optimization, smart buildings, machine learning, residential complexes, energy management systems, predictive analytics, neural networks.

INTRODUCTION

The global energy crisis and increasing environmental concerns have made energy efficiency in residential buildings a critical priority for sustainable urban development. Residential buildings account for approximately 30-40% of total energy consumption in developed countries, with significant potential for optimization through intelligent management systems (International Energy Agency, 2023). Traditional energy management approaches rely on predetermined schedules and manual adjustments, which fail to account for dynamic occupancy patterns, weather variations, and individual user preferences.

The emergence of artificial intelligence technologies, combined with the proliferation of Internet of Things (IoT) devices and smart sensors, has created unprecedented opportunities for optimizing energy consumption in residential complexes. AI-driven systems can analyze vast amounts of data from multiple sources, identify complex patterns, and make real-time decisions to minimize energy waste while maintaining occupant comfort (Zhang et al., 2022). These technologies enable predictive maintenance, demand forecasting, and automated control of heating, ventilation, air conditioning (HVAC), lighting, and other building systems.

Smart residential complexes equipped with AI-based energy management systems represent the convergence of several technological domains: machine learning algorithms, IoT infrastructure, cloud computing, and building automation systems. Recent studies indicate that implementing such integrated solutions can reduce energy consumption by 25-40% while simultaneously improving occupant comfort and reducing operational costs (Marinakis et al., 2023). However, the successful deployment of these systems requires addressing multiple challenges, including data privacy concerns, integration complexity, high initial costs, and the need for continuous system adaptation.

The significance of this research lies in its comprehensive examination of AI technologies specifically tailored for residential energy optimization, as opposed to commercial or industrial applications. Residential buildings present unique challenges due to diverse occupancy patterns, varying user behaviors, and the need to balance energy efficiency with individual comfort preferences. Understanding how AI can effectively address these challenges is essential for achieving significant reductions in residential energy consumption and associated carbon emissions.

PURPOSE AND METHODS

The primary purpose of this research is to analyze the effectiveness of AI-driven technologies for optimizing energy consumption in smart residential complexes and to provide practical recommendations for their implementation. Specific objectives include: (1) examining various AI algorithms and architectures suitable for residential energy management; (2) evaluating the performance of different machine learning approaches in predicting energy demand and optimizing system operations; (3) analyzing the economic feasibility and environmental impact of AI-based energy management systems; and (4) identifying key challenges and barriers to widespread adoption.

The research methodology employed a mixed-methods approach combining literature review, case study analysis, and simulation modeling. A systematic literature review was conducted analyzing 127 peer-reviewed articles published between 2019 and 2024, focusing on AI applications in residential energy management. Selection criteria included empirical studies with quantifiable energy savings, implementation details of AI algorithms, and peer-reviewed publications in indexed journals. The review utilized databases including IEEE Xplore, ScienceDirect, Scopus, and Web of Science.

Case study analysis examined eight real-world implementations of AI-based energy management systems in residential complexes across Europe, North America, and Asia. These case studies were selected to represent diverse climatic conditions, building types, and occupancy patterns. Data collection involved reviewing technical documentation, analyzing performance metrics, and conducting structured interviews with system developers and building managers. Key performance indicators included energy savings percentage, payback period, system reliability, and occupant satisfaction scores.

Simulation modeling was performed using MATLAB and Python-based frameworks to evaluate different AI algorithms under controlled conditions. The simulation environment incorporated realistic building models based on EnergyPlus, occupancy patterns derived from time-use surveys, weather data from meteorological databases, and equipment efficiency specifications from manufacturer data. Multiple AI algorithms were tested, including artificial neural networks (ANNs), convolutional neural networks (CNNs), long short-term memory (LSTM) networks, reinforcement learning agents, and hybrid approaches. Algorithm performance was evaluated using metrics such as prediction accuracy (RMSE, MAE), energy savings potential, computational efficiency, and adaptability to changing conditions.

Comparative analysis was conducted to assess the relative effectiveness of different AI approaches for specific energy management tasks. This included benchmarking against traditional rule-based control systems and evaluating the impact of different data preprocessing techniques, feature selection methods, and hyperparameter configurations. Statistical significance testing was applied to ensure the reliability of findings.

RESULTS AND EXPLANATIONS

The analysis of AI-driven energy optimization systems revealed several key findings regarding algorithm performance, system architecture, and practical implementation outcomes. Deep learning algorithms, particularly LSTM networks, demonstrated superior performance in predicting short-term and medium-term energy demand, achieving mean absolute percentage errors (MAPE) of 3-7% compared to 12-18% for traditional statistical methods (Ahmad et al., 2024). This accuracy improvement directly translates to more effective energy management decisions and reduced waste.

Reinforcement learning approaches showed exceptional effectiveness in real-time HVAC optimization, achieving 28-35% energy savings in tested environments. Q-learning and Deep Q-Network (DQN) algorithms successfully learned optimal control policies by continuously interacting with building systems and adapting to changing conditions. A notable implementation in a 120-unit residential complex in Stockholm demonstrated annual energy cost reductions of €47,000 while maintaining thermal comfort within acceptable ranges (Eriksson & Lindholm, 2023). The system learned to pre-cool or pre-heat apartments during off-peak electricity hours, reducing peak demand charges and taking advantage of time-of-use tariffs.

Hybrid AI architectures combining multiple algorithms produced the most comprehensive energy optimization results. A representative architecture integrates LSTM networks for demand forecasting, CNN-based occupancy detection, and reinforcement learning for control optimization. This multi-layered approach addresses different aspects of energy management simultaneously: prediction, pattern recognition, and decision-making. Case studies implementing hybrid systems reported average energy savings of 32-41% across various building types and climates (Patel & Singh, 2023).

The integration of renewable energy sources with AI-based management systems emerged as particularly promising. Machine learning algorithms successfully predicted solar photovoltaic generation with 90-95% accuracy, enabling optimal battery charging strategies and minimizing grid dependency. In a pilot project involving 85 apartments in California, AI-coordinated solar-plus-storage systems achieved 68% energy self-sufficiency and reduced grid electricity consumption by 71% (Chen et al., 2024). The system learned to anticipate high-consumption periods and manage battery discharge accordingly, maximizing the utilization of locally generated renewable energy.

Occupancy prediction using AI demonstrated a significant impact on energy savings. Computer vision algorithms analyzing camera feeds (with privacy protection) and sensor fusion techniques combining motion, CO_2, and temperature sensors achieved 92-97% accuracy in determining room-level occupancy. This enabled dynamic adjustment of heating, cooling, and lighting based on actual usage rather than fixed schedules, resulting in 18-24% additional energy savings compared to schedule-based control (Liu et al., 2023).

The economic analysis revealed that implementation costs vary substantially based on building size, existing infrastructure, and system sophistication. Initial investment ranges from €80-150 per apartment for basic AI-enhanced control systems to €300-500 per apartment for comprehensive systems including extensive sensor networks and advanced analytics capabilities. However, energy cost savings typically result in payback periods of 3.2-5.8 years, with longer payback times in regions with lower electricity costs (Martinez & Rodriguez, 2024).

Challenges identified in real-world implementations include data quality issues, where 23-31% of installations experienced problems with sensor malfunction, communication failures, or data inconsistencies. System integration proved complex when retrofitting older buildings with legacy HVAC systems not designed for digital control. User acceptance emerged as a critical factor, with successful implementations involving occupant education programs and providing transparency regarding system operation and energy savings achieved.

Privacy concerns regarding data collection represent a significant barrier to adoption. Effective implementations addressed these concerns through anonymization techniques, edge computing for local data processing, and transparent data governance policies. In one study, 78% of initially hesitant residents accepted the system after receiving detailed explanations of data protection measures (Brown & Wilson, 2023).

The analysis of algorithm computational requirements revealed that while deep learning models require significant training resources, their inference computational needs are modest enough for deployment on standard building management hardware. Edge computing architectures, where AI processing occurs locally rather than in the cloud, demonstrated faster response times and enhanced reliability, though at higher hardware costs.

CONCLUSIONS AND RECOMMENDATIONS

The research conclusively demonstrates that AI-driven optimization systems can achieve substantial energy savings in residential complexes, with typical reductions of 25-40% compared to traditional management approaches. Deep learning algorithms, particularly LSTM networks, excel at demand prediction, while reinforcement learning proves most effective for real-time system control. Hybrid architectures combining multiple AI approaches deliver optimal results by addressing different aspects of energy management simultaneously.

Several key conclusions emerge from this analysis:

First, the economic feasibility of AI-based energy management systems is established, with payback periods of 3-6 years justifying the initial investment for most residential applications. The business case strengthens in regions with high energy costs, significant heating or cooling requirements, and availability of time-of-use electricity tariffs. Building managers and developers should prioritize implementations in larger complexes where economies of scale reduce per-unit costs.

Second, system integration represents the primary technical challenge, particularly in retrofit applications. Successful implementations require careful planning, phased deployment approaches, and collaboration between AI specialists, building automation experts, and facility managers. New construction projects should incorporate AI-ready infrastructure from the design phase, including comprehensive sensor networks, digital control interfaces, and adequate computing resources.

Third, occupant engagement and acceptance are critical success factors. Implementations must address privacy concerns through transparent data governance, provide occupants with visibility into energy savings, and allow individual preference settings within system optimization constraints. Educational programs explaining system benefits and operation significantly improve acceptance rates.

Fourth, data quality and system reliability require ongoing attention. Implementing redundant sensors, automated anomaly detection, and regular maintenance protocols ensures consistent performance. Machine learning models require periodic retraining to adapt to changing occupancy patterns, weather conditions, and equipment characteristics.

The following recommendations are proposed for stakeholders:

For developers and building managers: Conduct detailed feasibility studies evaluating building characteristics, energy costs, and occupancy patterns before system selection. Implement phased approaches beginning with high-impact areas such as HVAC and lighting.

Establish performance monitoring systems to track energy savings and system reliability. Invest in occupant education and engagement programs to maximize system acceptance and effectiveness.

For policymakers: Develop incentive programs supporting AI-based energy management system adoption, particularly in existing building stock where retrofitting challenges are greatest. Establish data privacy guidelines specifically addressing smart building applications. Support research and development of standardized communication protocols facilitating system integration. Consider incorporating AI-based energy management as a component of building energy codes and green building certification programs.

For researchers: Continue developing more efficient algorithms reducing computational requirements and training data needs. Investigate federated learning approaches enabling collaborative model development while preserving data privacy. Explore transfer learning techniques allowing models trained on one building to be adapted for others with minimal additional data. Develop more sophisticated occupant behavior models improving comfort prediction and personalization capabilities.

For technology vendors: Focus on developing user-friendly interfaces accessible to non-technical building managers. Create modular, scalable solutions allowing gradual system expansion as budgets permit. Ensure compatibility with diverse equipment manufacturers through open protocols and APIs. Provide comprehensive training and support services facilitating successful implementations.

The transition to AI-driven energy management in residential complexes represents a significant opportunity for advancing sustainability goals while providing tangible economic benefits. As AI technologies continue advancing and costs decline, these systems will become increasingly accessible and effective. The evidence presented demonstrates that the technology is mature enough for widespread adoption, with remaining barriers primarily relating to integration complexity, initial costs, and stakeholder education rather than fundamental technical limitations.

Future developments will likely emphasize greater personalization, more sophisticated prediction capabilities, and improved integration with broader smart city infrastructure. The convergence of AI-based building management with electric vehicle charging, distributed energy resources, and grid demand response programs will create even greater optimization opportunities and energy savings potential.

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АНОТАЦІЯ

У даній статті досліджується застосування технологій штучного інтелекту для оптимізації енергоспоживання в розумних житлових комплексах. Дослідження аналізує сучасні підходи до впровадження алгоритмів машинного навчання, нейронних мереж та прогнозної аналітики для управління енергоресурсами в багатоквартирних будинках. Дослідження демонструє, що системи на основі штучного інтелекту можуть знизити енергоспоживання на 25-40% порівняно з традиційними методами управління. Стаття представляє комплексний аналіз архітектур інтелектуальних систем управління енергоспоживанням, включаючи інтеграцію з датчиками Інтернету речей, розумними лічильниками та системами автоматизації будівель. Особлива увага приділяється методам машинного навчання для прогнозування енергетичного попиту, оптимізації систем опалення, вентиляції та кондиціювання повітря, а також управління відновлюваними джерелами енергії. Дослідження розглядає виклики, пов'язані з впровадженням рішень на основі штучного інтелекту, включаючи конфіденційність даних, складність інтеграції систем та потребу в значних початкових інвестиціях. Результати показують, що алгоритми глибокого навчання демонструють найвищу ефективність у прогнозуванні моделей споживання, тоді як методи навчання з підкріпленням є найбільш ефективними для оптимізації в режимі реального часу. Стаття також обговорює економічну доцільність впровадження таких систем, демонструючи періоди окупності 3-5 років залежно від розміру будівлі та кліматичних умов. Надано рекомендації для забудовників, керуючих будівлями та розробників політики щодо впровадження систем управління енергоспоживанням на основі штучного інтелекту в житлових комплексах.