

Research Article

AI-Driven Optimization of Smart Energy Systems Using Advanced Materials and IoT for Sustainable Environments in Emerging Economies

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Abstract

The transition toward sustainable energy systems requires the integration of advanced digital technologies, intelligent control strategies, and high-performance materials capable of improving energy efficiency while reducing environmental impacts. In this context, the convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and advanced energy materials offers significant opportunities for developing more adaptive, predictive, and sustainable energy systems. This study proposes an integrated framework combining AI, IoT, and advanced energy materials for the monitoring, prediction, optimization, and intelligent management of smart energy systems. The proposed architecture is structured into four complementary layers: intelligent sensing and IoT-based data acquisition, secure data transmission and data preprocessing, AI-based prediction and decision-making, and dynamic energy optimization. Linear Regression (LR), Random Forest (RF), and Long Short-Term Memory (LSTM) models are considered as representative approaches for energy-consumption prediction, enabling the analysis of relationships between energy demand and relevant environmental and operational variables. The methodology incorporates climatic conditions, indoor temperature and humidity, occupancy, energy demand, solar-related parameters, and material-related thermal characteristics. Advanced materials, including thermal energy storage and phase-change materials, are considered as functional components capable of improving thermal stability and reducing energy demand. Experimental and real-world evidence from international building-energy studies supports the feasibility of the IoT-AI and advanced-material components. In addition, the UCI Appliances Energy Prediction dataset provides an experimentally measured benchmark for investigating data-driven energy prediction using real building-energy and environmental measurements. The integrated framework further introduces multi-objective optimization to balance energy consumption, operating costs, carbon emissions, thermal performance, and system constraints. By establishing a continuous feedback loop between sensing, prediction, optimization, and control, the proposed approach provides a flexible basis for intelligent energy management. The framework is designed to be transferable to buildings and distributed energy systems in emerging economies, where energy efficiency, environmental sustainability, digitalization, and resource constraints represent major challenges. Overall, the study highlights the potential of integrating AI, IoT, and advanced materials as complementary technologies for developing resilient, efficient, and sustainable smart energy systems.

Keywords

Artificial Intelligence, Internet of Things, Smart Buildings, Energy Efficiency, Advanced Materials, Phase Change Materials, Random Forest, LSTM, Sustainable Energy, Emerging Economies

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1. Introduction

The global transition toward sustainable energy systems is driven by the need to reduce energy consumption, greenhouse-gas emissions, and fossil-fuel dependence while maintaining economic development and human comfort. Buildings are a major domain for energy-efficiency improvement because demand depends on climate, building characteristics, occupants, equipment and control strategies [4-7]. Conventional systems based on fixed schedules and predefined rules have limited adaptability to weather, occupancy, energy prices, renewable generation and equipment degradation [8, 9]. AI, ML and IoT enable continuous sensing, prediction and adaptive control [10-13]. Linear models provide transparent baselines, Random Forest captures nonlinear relationships, and LSTM represents temporal dependencies [14-18]. Advanced materials such as PCMs, high-performance insulation and glazing can increase thermal inertia and reduce peak loads [19-23]. The central hypothesis is that integrating intelligent sensing, AI prediction, dynamic optimization and advanced materials can provide greater energy-management flexibility than treating these technologies independently.

2. Literature Review

Machine-learning methods are increasingly used for building-energy prediction [14-18]. IoT provides the sensing infrastructure required for real-time monitoring and control [10-13]. Advanced materials provide a physical mechanism for modifying thermal response; experimental PCM studies demonstrate delayed thermal peaks and lower peak energy demand [2, 19-23].

3. Research Gap

AI prediction, IoT monitoring and advanced materials are often studied independently. The present work addresses this gap through a closed-loop framework in which advanced materials modify physical response, IoT measures system behaviour, AI predicts demand, and optimization determines control actions [10-23].

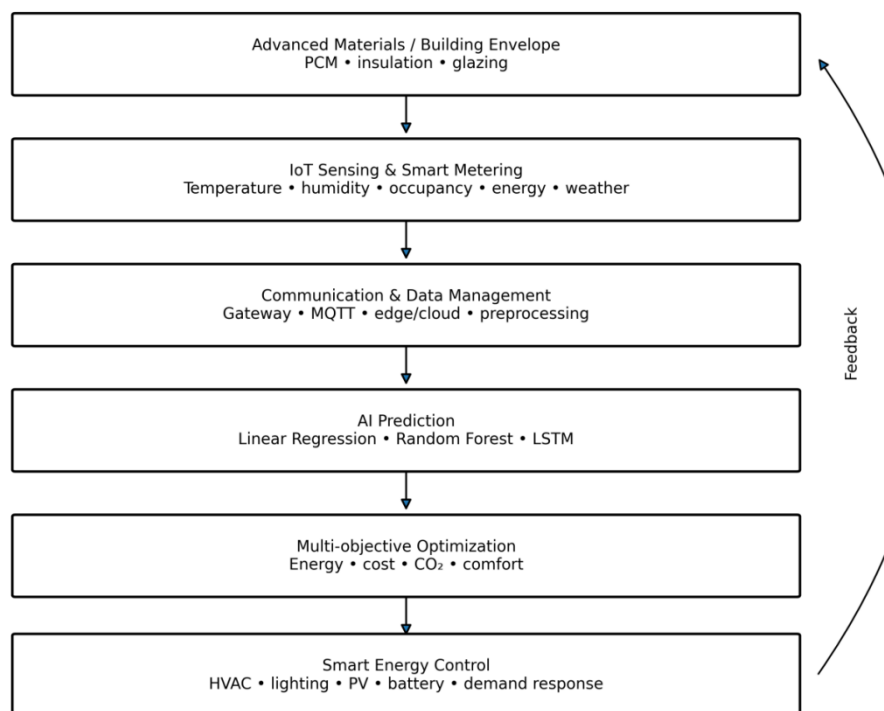


Figure 1. Proposed integrated AI-IoT-Advanced Materials architecture for smart energy optimization.

4. Proposed AI-IoT-Advanced Materials Architecture

The framework contains four functional layers: intelligent

sensing and the material interface; communication and data management; AI prediction and decision support; and dynamic optimization. Variables may include temperature, humidity, occupancy, solar radiation, energy consumption, HVAC status, photovoltaic production, battery state of charge and material-related thermal parameters.

$$\hat{y}_{t+h} = f(X_t) \quad (1)$$

where $\hat{y}_{t+h}$ is predicted energy consumption, h is the forecasting horizon, X_t is information available at time t , and f is the selected AI model.

5. Mathematical Formulation

The energy-consumption prediction can be expressed as a function of environmental, operational, temporal and material-related variables:

$$y = f(T_{out}, T_{in}, RH_{out}, RH_{in}, Occ, Solar, E_{t-1}, M, \tau) \quad (2)$$

For PCM-integrated construction, M may include latent heat, phase-change temperature, thermal conductivity, heat capacity and effective thermal resistance [2, 19-22].

6. Dataset and Experimental Framework

The UCI Appliances Energy Prediction dataset contains 19,735 observations and 28 features, sampled every 10 minutes over approximately 4.5 months in a low-energy building. Indoor temperature and humidity were monitored through a Zigbee wireless sensor network, while energy consumption was measured using energy meters.

Table 1. Characteristics of the experimental benchmark dataset.

Parameter	Description
Observations	19,735
Features	28
Sampling	10 min
Monitoring period	≈4.5 months
Indoor measurements	Temperature and humidity
Energy measurement	Electricity meters
Communication	Zigbee
Task	Energy-consumption regression

7. AI Model Comparison

The models are evaluated using MAE, RMSE and R^2 .

$$MAE = (1/n) \sum |y_i - \hat{y}_i| \quad (3)$$

$$RMSE = \sqrt{[(1/n) \sum (y_i - \hat{y}_i)^2]} \quad (4)$$

$$R^2 = 1 - [\sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2] \quad (5)$$

Lower MAE and RMSE indicate smaller prediction errors, while higher R^2 indicates that more variability is explained by the model.

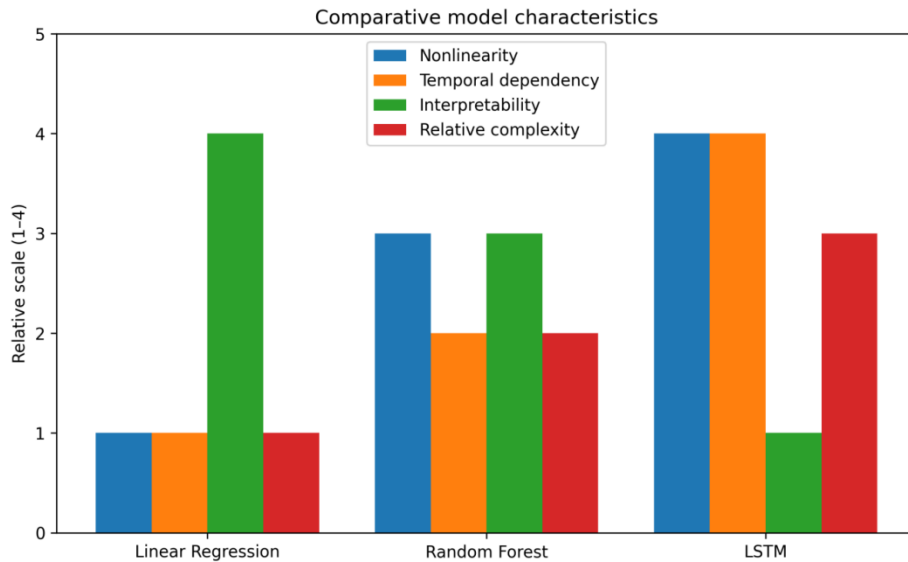


Figure 2. Comparative characteristics of Linear Regression, Random Forest and LSTM. Relative characteristics are conceptual, not measured prediction scores.

8. Cross-Validation and Generalization

For time-series energy data, chronological validation is

preferable to a random split because random mixing can cause information leakage between training and testing periods.

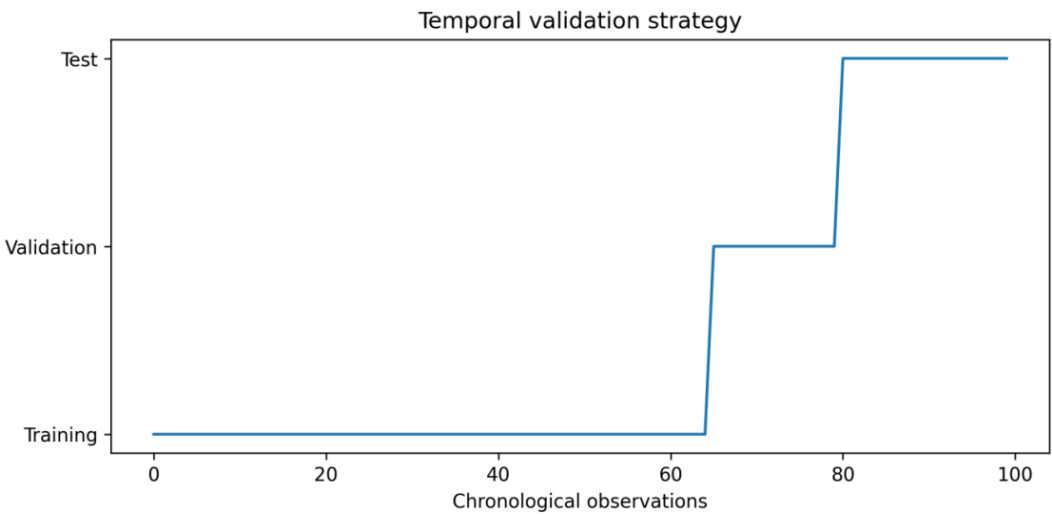


Figure 3. Temporal validation strategy for time-series energy prediction.

9. International Experimental Evidence

9.1. IoT and AI Building Case

Rojek et al. investigated an actual building-energy-management case integrating IoT and AI, including sensors, smart

meters, HVAC and lighting management, predictive analysis and intelligent control [1, 27]. The study reported approximately 20.9-33.8% energy savings across investigated configurations, including about 29.7% for HVAC and 23.4% for intelligent lighting [1]. These are reported literature results, not measurements generated by the present study.

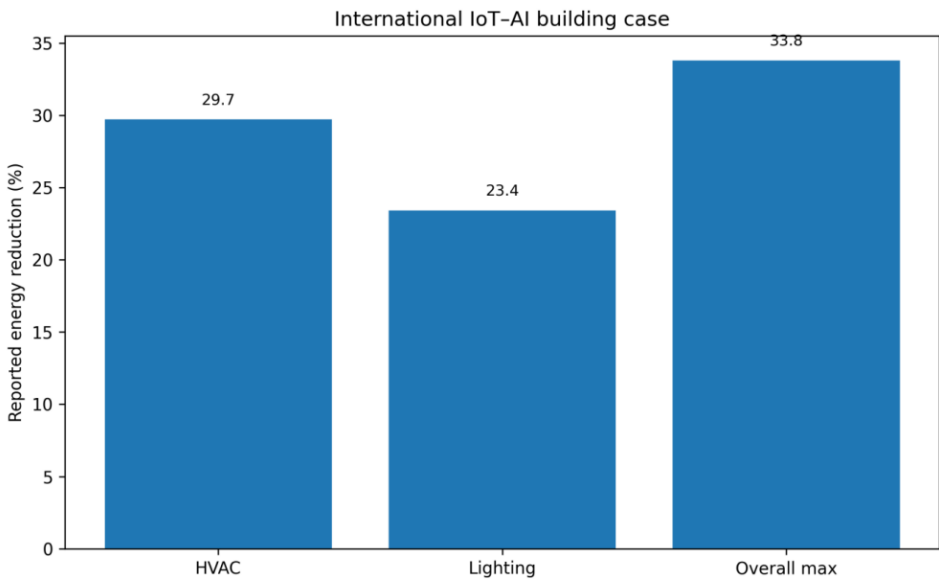


Figure 4. Reported energy-saving performance in the international IoT-AI building case [1].

9.2. Experimental Evidence for Advanced Materials

Zhang et al. experimentally investigated copper-foam/par-

affin composite PCM materials integrated into building models. The study reported approximately 1.5 h delay in the indoor-temperature peak, up to about 1.2 °C indoor-temperature reduction, and approximately 21% reduction in maximum indoor energy consumption [2].

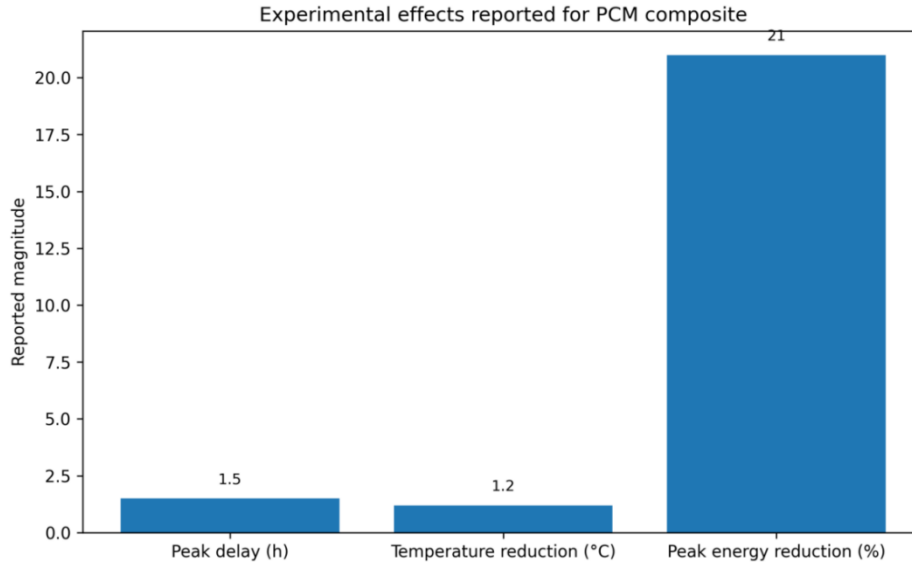


Figure 5. Experimental effects reported for a PCM composite building application [2].

10. Comparative Prediction Framework

Linear Regression provides a transparent baseline, Random Forest represents nonlinear interactions, and LSTM is designed for temporal dependencies [14, 17, 24-26, 35, 36]. Final rankings must be established from measured data using identical training, validation and testing procedures.

11. Measured versus Predicted Energy Consumption

A quantitative comparison between measured energy consumption and predictions obtained from LR, RF, and LSTM models requires independent model training and evaluation on an unseen test dataset. Since the present study focuses on the development of an integrated AI-IoT-advanced materials framework, no unverified model-specific prediction curves are reported. Such comparative experimental validation is therefore considered as a subsequent stage of the proposed research framework.

12. Energy Optimization

Prediction is only the first stage of intelligent energy management. The system can optimize HVAC operation, lighting, thermal storage, photovoltaic self-consumption, battery

charging and demand response. The multi-objective optimization [27-39] function is:

$$J = \alpha E + \beta C + \gamma \text{CO}_2 + \delta D \quad (6)$$

$$u^*(t) = \arg \min_{u(t)} J \quad (7)$$

where $u(t)$ represents controllable inputs, E is energy consumption, C is energy cost, CO_2 represents associated carbon emissions, D represents comfort deviation, and α , β , γ and δ are weighting factors.

The optimization is subject to:

$$T_{\min} \leq T_{\text{in}}(t) \leq T_{\max} \quad (8)$$

$$0 \leq P_{\text{HVAC}}(t) \leq P_{\text{HVAC}}^{\max} \quad (9)$$

$$0 \leq \text{SOC}(t) \leq \text{SOC}^{\max} \quad (10)$$

$$0 \leq P_{\text{PV}}(t) \leq P_{\text{PV}}^{\max} \quad (11)$$

13. Multi-Objective Sustainability Assessment

The framework simultaneously considers energy, economic, environmental and comfort objectives.

$$S = w_E S_E + w_C S_C + w_{\text{CO}_2} S_{\text{CO}_2} + w_D S_D \quad (12)$$

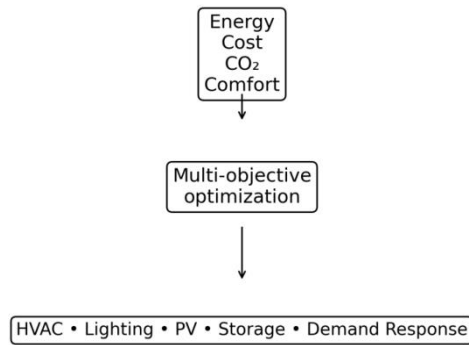


Figure 6. Multi-objective optimization framework linking energy, cost, CO₂ and comfort.

14. Carbon-Emission Reduction

Carbon reduction can be estimated from the difference between baseline and optimized energy consumption:

$$\Delta\text{CO}_2 = (E_{\text{baseline}} - E_{\text{optimized}}) \times \text{EF} \quad (13)$$

EF is the applicable electricity-emission factor; national or regional factors should be used for international comparisons.

15. Economic Assessment

Economic feasibility depends on sensors, communication, computing, installation, maintenance, energy savings, equipment lifetime and electricity prices.

$$\text{PBP} = C_{\text{investment}} / C_{\text{annual savings}} \quad (14)$$

An international AI-IoT building study reported an estimated ROI period of approximately 2.7 years in its investigated context [1], which should not be generalized to other markets.

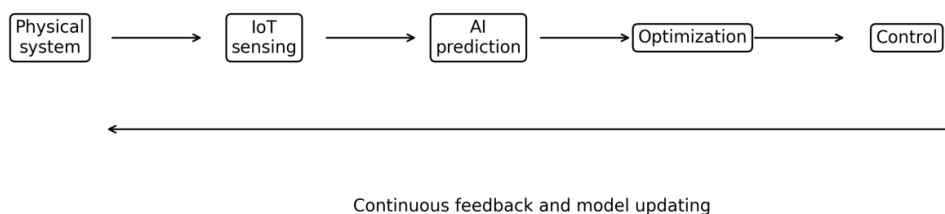


Figure 7. Integrated feedback loop between the physical energy system, IoT sensing, AI prediction, optimization and control.

The international evidence supports the individual components: the IoT-AI case demonstrates practical intelligent building-energy management [1], while experimental PCM research demonstrates that advanced materials can modify thermal behaviour and reduce peak demand [2]. The complete integrated architecture still requires synchronized experimental validation.

16. Application to Emerging Economies

Emerging economies face rapid urbanization, increasing electricity demand, limited infrastructure, high cooling loads, heterogeneous building quality and financing constraints. The architecture can be deployed progressively [29, 30, 37-39]: monitoring, prediction, optimization, advanced materials, and integration with PV, batteries, microgrids and demand response.

17. Relevance to Algeria and Other Mediterranean Contexts

The framework is relevant to Mediterranean and North African climates where cooling demand, solar availability, building quality and electricity demand favor combinations of passive thermal strategies, advanced materials, PV, IoT and AI. Algeria is considered as one potential application context rather than the sole validation environment [37, 38, 40].

18. ESG and Sustainable Development Implications

The framework supports environmental performance through lower energy use and emissions; social performance through comfort and resilience; and governance through continuous monitoring, traceable indicators and data-driven decision-making.

19. Discussion

AI provides predictive intelligence, IoT provides real-time information, advanced materials modify physical behaviour, and optimization converts predictions into operational decisions [27-34].

20. Limitations

AI models require representative datasets; LSTM requires careful hyperparameter selection [14, 17, 26]; IoT introduces cybersecurity and data-privacy challenges [10-13]; advanced

materials can increase initial costs and their performance depends on climate and configuration [19-23]. The UCI benchmark does not directly contain advanced-material parameters, so full integration requires additional experimental data.

21. Future Experimental Validation

Future work should combine a monitored building or test cell, IoT sensors, smart meters, advanced-material components, weather measurements, AI prediction, real-time optimization and automated control. The final comparison should include conventional control, AI-only control, AI + IoT, and AI + IoT + advanced materials.

22. Scientific Contribution

Unified AI-IoT-Advanced Materials architecture.

Comparative LR, RF and LSTM prediction framework.

Explicit incorporation of material-related thermal parameters.

Multi-objective optimization of energy, cost, carbon and comfort.

International experimental evidence supporting the component technologies.

Transferable methodology for emerging economies and diverse climates.

23. Conclusions

This study presented an integrated framework for AI-driven optimization of smart energy systems using advanced materials and IoT. The architecture combines sensing, data management, AI prediction and dynamic optimization. Linear Regression provides a transparent baseline, Random Forest captures nonlinear relationships, and LSTM represents temporal dependencies [14, 17, 24-26, 35, 36]. Advanced materials, particularly PCMs, provide a physical mechanism for improving thermal performance, with experimental evidence showing delayed thermal peaks and reduced peak energy consumption [2]. International building-energy research demonstrates substantial potential for AI and IoT in intelligent management [1]. The integration of AI, IoT and advanced materials creates a closed-loop system in which physical performance, sensing, prediction and optimization continuously interact.

Abbreviations

AI	Artificial Intelligence
IoT	Internet of Things
ML	Machine Learning
LR	Linear Regression
RF	Random Forest
LSTM	Long Short-Term Memory

PCM	Phase Change Material
HVAC	Heating, Ventilation and Air Conditioning
PV	Photovoltaic
SOC	State of Charge
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
R ²	Coefficient of Determination
RH	Relative Humidity
PBP	Payback Period
CO ₂	Carbon Dioxide
ESG	Environmental, Social and Governance

Supplementary Material

The supplementary material can be accessed at <https://doi.org/10.11648/j.ajmie.20261105.14>

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Author Contributions

Djilali Khaine: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing

Data Availability Statement

The UCI Appliances Energy Prediction dataset is publicly documented and suitable as an experimental benchmark for the predictive component [3].

Conflicts of Interest

The author declares no conflicts of interest related to this study.

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