



Smart Optimization of Energy Management in Properties

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Abstract

Energy Management (EM) involves the strategic monitoring, control, and optimization of energy usage in buildings to reduce costs, enhance efficiency, and minimize environmental impact. Traditional EM systems often rely on manual interventions or basic automation, which struggle to adapt to dynamic changes in energy demand. The integration of Artificial Intelligence (AI), particularly Long Short-Term Memory (LSTM) networks, in smart optimization offers a transformative solution. LSTM, a type of recurrent neural network, excels in processing and predicting time-series data, making it ideal for EM in properties. By leveraging AI-driven LSTM models, energy consumption patterns can be predicted with high accuracy, enabling systems to make real-time adjustments based on factors such as occupancy, weather, and energy demand fluctuations. AI-powered smart optimization algorithms continuously monitor various energy systems, including HVAC, lighting, and electrical appliances, optimizing their operation to reduce energy waste and operational costs. Additionally, this approach facilitates the integration of renewable energy sources and energy storage, enhancing sustainability. Ultimately, AI-based LSTM optimization in EM leads to improved efficiency, cost savings, and a reduced environmental footprint, offering an advanced strategy for modern property management.

Keywords: Artificial intelligence, long short- term memory, energy efficiency, energy management.

Introduction

In comparison to the 2020 base scenario forecasts for both initial and terminal usage of energy, 39% and 36% energy reductions are the ambitious performance targets established by the EU's Energy Efficiency Directive. The EU's energy efficiency goals are significantly aided by Small and Medium-Sized Enterprises (SMEs). The Energy Efficiency Directive, in particular, now requires EU Member States to develop suitable policies and plans for SMEs that promote energy evaluations and the implementation of related activities that might efficiently increase their energy usage. Urbanisation and information technology advancements have accelerated energy demand, strained energy supplies, and contributed to environmental issues in today's society. Energy use is a major aspect that affects both the operational costs of businesses and the sustainability of the environment, particularly in the construction and property management industries. The conventional property management approach is based on manual labour and experience judgement, which makes it impossible to satisfy the demands of modern cities' green sustainable development and unproductive in terms of energy distribution, fault avoidance, and efficiency assessment [1]. The idea of "smart city construction" has gained popularity in recent years, and it has become widely accepted that high-tech methods may be used to optimise EM and accomplish efficient resource planning and utilisation. Thus, in order to maximise EM and discover a novel approach to enhancing energy efficiency and advancing environmental sustainability, this study focusses on the use of AI in managing real estate. In addition to having significant theoretical value, this research offers a fresh viewpoint and methodology for multidisciplinary studies in the fields of energy and property management. It also has broad implications for encouraging the wise conversion of the property management sector and attaining a mutually beneficial economic and environmental advantages on a practical level [2]. Increased energy efficiency is a crucial tactic for mitigating the consequences of climate change and is also necessary for individual enterprises to survive and grow in profitability. A considerable improvement in the utilisation of energy would be easy to accomplish with the help of energy services. The building sector is arguably the most prominent example, as energy-related policies may be similar for multiple buildings in a particular area, indicating lower transaction costs for energy service agreements. In particular, SMEs have paid much less focus on energy services than the industrial sectors. The energy consumption of SMEs might be reduced by 30% through the implementation of affordable energy saving solutions. According to estimates, implementing strategies like using EM software may save more energy than Korea and Japan combined within the course of a year. From a financial standpoint, SMEs themselves may benefit

from increased energy efficiency. The organisation becomes more resilient, inventive, and competitive when expenses are reduced and resources are allocated to more lucrative and efficient endeavours. As per the International Energy Agency (IEA), "energy efficiency can yield numerous additional growth advantages, such as enhancing production and product quality." SMEs that practise energy efficiency can also lessen their need on power imports, the need to invest in more power production, and their environmental effects, including local air pollution and greenhouse gas emissions. There would undoubtedly be a wide range of diverse initiatives, applications, and techniques to improve their energy efficiency given the sheer range of SMEs operating worldwide and the correspondingly infinite diversity of manufacturing procedures involved. Interconnecting devices is made possible by the widespread use of Internet of Things (IoT) technology, and the real-time gathering of sensor data gives the system a rich foundation for decision-making. This makes intelligent control of air conditioning, lighting, and other platforms a reality and successfully lowers wasteful energy use. Furthermore, the AI-based fault identification and assessment function is steadily getting better. This reduces energy loss and maintenance costs by detecting abnormalities in equipment early [3].

Literature Review

Cavicchi et al., have stated that plans, procedures, and activities pertaining to the creation, use, distribution, and conservation of energy inside a company are all included in EM. By maximising and minimising energy consumption, energy expenses, and resource conservation—all without restricting the user's access to the amounts of energy they need—EM in SMEs aims to protect the climate. It has a tight connection to logistics, production management, environmental management, and other corporate activities. According to Cooremansa and Schönenbergerb, EM may play a significant role in encouraging the necessary financial outlays for SMEs to adopt energy-saving measures. A number of additional studies address various facets of EM used in SMEs [4,5]. According to Gbadega and Sun, energy-saving incentive mechanisms that include behavioural science concepts can successfully encourage renters to modify their energy-use patterns and meet energy conservation goals. Currently, property EM solutions are becoming more varied, concentrating on user behaviour advising in addition to hardware and system optimisation [6]. Cao and Grzywinski., have suggested that cloud-based EM systems have started to gain popularity. One such platform is the one proposed, which can implement policies, conduct data analysis, and manage remotely, increasing control's adaptability and effectiveness [7,8]. Southernwood et al., have stated that SMEs are known to place little emphasis on energy efficiency, and EM systems are rarely used. Small investments are made in SMEs to increase energy efficiency. This is mostly due to the lack of awareness of the various potential benefits that could be realised and the restricted availability of pertinent financial and temporal resources. Additionally, SMEs lack the necessary and specialised technical expertise to monitor, assess, and enhance their energy efficiency results, and their owners, executives, or decision-makers prioritise other investments over those that might enhance the organization's the energy productivity accomplishments. Adopting energy saving methods may not be economical, especially during the COVID-19 pandemic time when many SMEs were fighting for survival [9]. Mancini et al, have provided a solution to the question of how Big Data software and machine learning might be integrated to produce an intelligent system for managing energy efficiency in the public sector, which is a key element of smart city concepts [10]. Sadeeq et al., have investigated EM in IoT systems. This essay reviews the research and analyses policy regarding EM system providers and affiliate system end users [11]. Silva et al. created an IoT and Web of Things-integrated smart home design to improve the network's efficiency of a proposed smart city design [12]. Shafik et al., have examined the issues and solutions related to smart cities in a paper named Object-Based EM. This paper provides a thorough examination of how to effectively handle object-based Internet in smart cities. The IoT has been shown to increase energy consumption in this study, and the summary study shows the most recent eight EM strategies that have been offered across several belts, including smart homes, buildings, and grids [13]. Jiang et al. have also researched cloud computing and the development of computer networks for smart cities based on the IoT. This study illustrates how this network may exchange, share, and combine data among different sensing subsystems and IoT-based, while considering energy savings and movable loads into account, in order to solve the problem of previous data enclaves and satisfy the real needs of smart cities. In order to provide an IoT-based system for managing energy and easily accessible distribution networks, this study employs a complex integer linear programming problem [14].

AI application technique for energy management in properties

Detailed explanations of the primary models and application situations utilised in this work are provided below. When working with time series data, a specific type of Recurrent Neural Network (RNN) called the LSTM is used. In this work, the LSTM model was used to predict future energy consumption. By using historical data on energy usage, models are able to recognise patterns and trends in data. This enables them to generate accurate load curve projections, which are crucial for predicting energy use. A model-based control methodology called

Model Predictive Control (MPC) is used in this work to improve the control strategy. Based on anticipated energy supply and demand, MPC employ predictive algorithms to identify the best control sequences that reduce energy usage while preserving steady system performance. EM systems benefit greatly from Reinforcement Learning (RL), a machine learning technique that lets agents interact in unfamiliar contexts to discover the best course of action. The equipment's running state can be dynamically changed by RL to maximise energy savings in response to shifting costs of energy and user demands. The best energy allocation method is found using Particle Swarm Optimisation (PSO), a heuristic search algorithm. Reducing waste, increasing energy efficiency, and optimising energy distribution all depend on precise energy consumption forecasting in the domain of property EM. When working with series data that exhibits long-term reliance, conventional time series predictive algorithms like Autoregressive Integral Moving Average (ARIMA) may not be as effective. The LSTM, a special RNN, on the other hand, is a well-liked option for energy consumption prediction since it successfully resolves the long-term dependence issue with its own memory unit mechanism. Nevertheless, when dealing with complex nonlinear connections, noisy disruptions, and data with high dimensions, the basic LSTM framework still has space for improvement. This section proposes an improved LSTM-based consumption of energy prediction network that incorporates a feature selection, multi-step predicted method, and attention mechanism to improve prediction accuracy and model dependability [15].

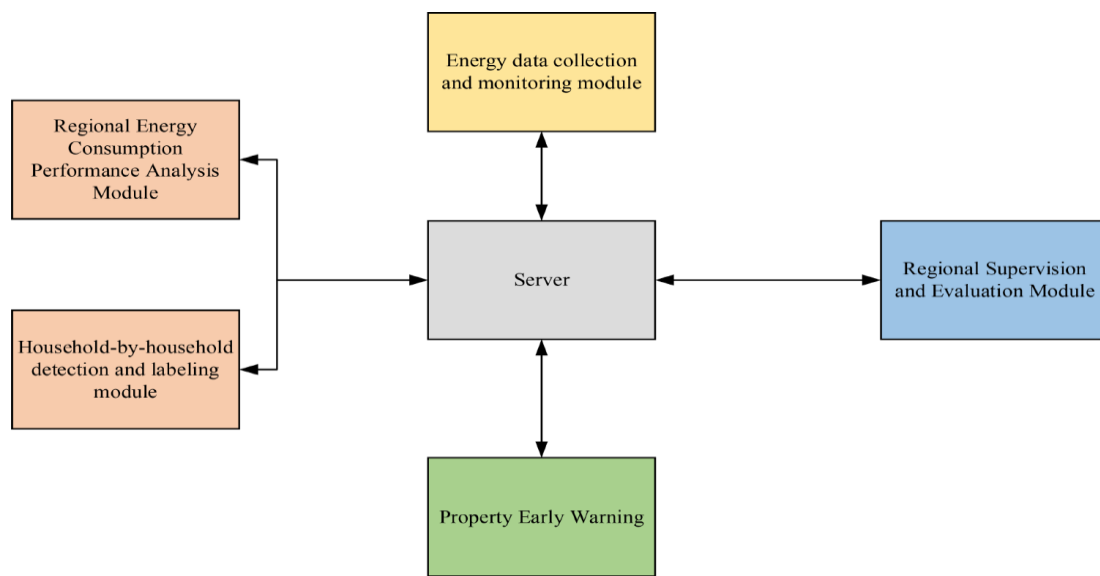


Figure 1. Integrated energy smart management platform

To derive the formula for the attention weight calculation in the context of LSTM hidden states (h_t) and inputs (x_t), we typically start with the attention mechanism, which assigns weights to various inputs or hidden states to focus on relevant parts.

The general attention weight formula involves the following steps:

The score function e_t evaluates the relevance of the hidden state h_t with respect to a query vector q . Common score functions include:

$$= q^T h_t$$

Dot product: $e_t = q^T h_t$

Additive: $e_t = v_a^T \tanh(W_a[q; h_t])$, where v_a and W_a are learnable parameters.

General: $e_t = q^T W_a h_t$, where W_a is a learnable weight matrix.

The attention weight α_t for each time step t is computed by normalizing the scores using a softmax function:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^T \exp(e_k)} \tag{1}$$

Where T is the total number of time steps.

Score Function Calculation: Let the score function be $e_t = q^T h_t$, where:

- q : Query vector (could be another hidden state or a representation of x_t).
- h_t : LSTM hidden state at time t .

Softmax Normalization: Compute the softmax over all scores e_t to ensure that the attention weights sum to 1:

$$\alpha_t = \frac{\exp(q^T h_t)}{\sum_{k=1}^T \exp(q^T h_k)} \tag{2}$$

Interpretation:

- α_t determines the importance of the hidden state h_t at time t .
- The weights α_t are used to compute a context vector, often as a weighted sum of h_t .

Multi-step prediction provides anticipated values at numerous future time points, which can provide more accurate data for EM than standard single-step forecasting techniques, which merely predict energy usage at the next time point. By employing a multi-step prediction technique that makes use of both past and present data to forecast future sequences, the enhanced LSTM model increases prediction practicality and consistency [16,17]. Preprocessing and appropriate feature selection prior to model input are essential for enhancing prediction performance. First, features that are directly linked to energy consumption, such as past energy usage, weather, holiday information, etc., are filtered out using Principal Component Analysis (PCA). The second step involves standardising or normalising the data in order to remove dimensional effects and guarantee the consistency of model training.

Eq. (3) displays the formula for principal component analysis that was applied.

$$X' = U \Sigma V^T \tag{3}$$

where, X' is the data that has lower dimensionality, U is the left singular matrix, Σ is the diagonal matrix, contains eigenvalues, and V^T is the right singular matrix.

During model training, optimisation procedures like gradient descent as well as back propagation are used to modify the model variables. The loss function is either mean square error (MSE) or Root Mean Square Error (RMSE). Regularisation words or strategies like Dropout and the early stop method can be used to prevent overfitting. Formula (4) defines the loss function

$$\text{Loss} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \tag{4}$$

As a result of the aforementioned enhancements, in addition to enhancing the model's ability to acquire significant data, the attention method in the LSTM framework also enhances prediction accuracy.

Optimisation control approach for equipment energy consumption

The goal of equipment efficiency optimisation control techniques is to reduce energy consumption while preserving or increasing equipment efficiency by dynamically modifying equipment operating parameters using advanced algorithms. Employing efficient control techniques for high-energy-consuming equipment, including air conditioners, lights, lifts, etc., is crucial for property EM. In order to optimise production measures for a future period, MPC, a closed-loop control method, uses an evolving model of the plant to forecast future states. It then modifies present control inputs accordingly. MPC's fundamental concept is to constantly optimise the control approach on a rolling basis, and Eq. (5) can be used to explain its control rule.

$$u^*(k) = \arg \min_{u(k), \dots, u(k+N-1)} \sum_{i=k}^{k+N-1} J(i|k) + \lambda J_{terminal}(k+N|k) \tag{5}$$

where, $u^{(k)}$ is the ideal input for control at time k , N is the predicted horizon, $J(i|k)$ is based on the current condition vs future time and represents the instantaneous cost function. i , $\lambda J_{terminal}(k+N|k)$ is the endpoint cost, which takes into consideration weights, λ , and the system state at the conclusion of the prediction.

Three distinct control strategies—MLC, RL, and PSO—are depicted in Figure 2. Online learning processes are necessary for these techniques to adapt. Parameter optimisation is the focus of PSO, dynamic strategy learning is the focus of RL, and quick precision control is the objective of MPC. A layer of "self-tuning and optimisation" may also be added, which might combine all of the previously mentioned tactics to create a more complete automated control system.

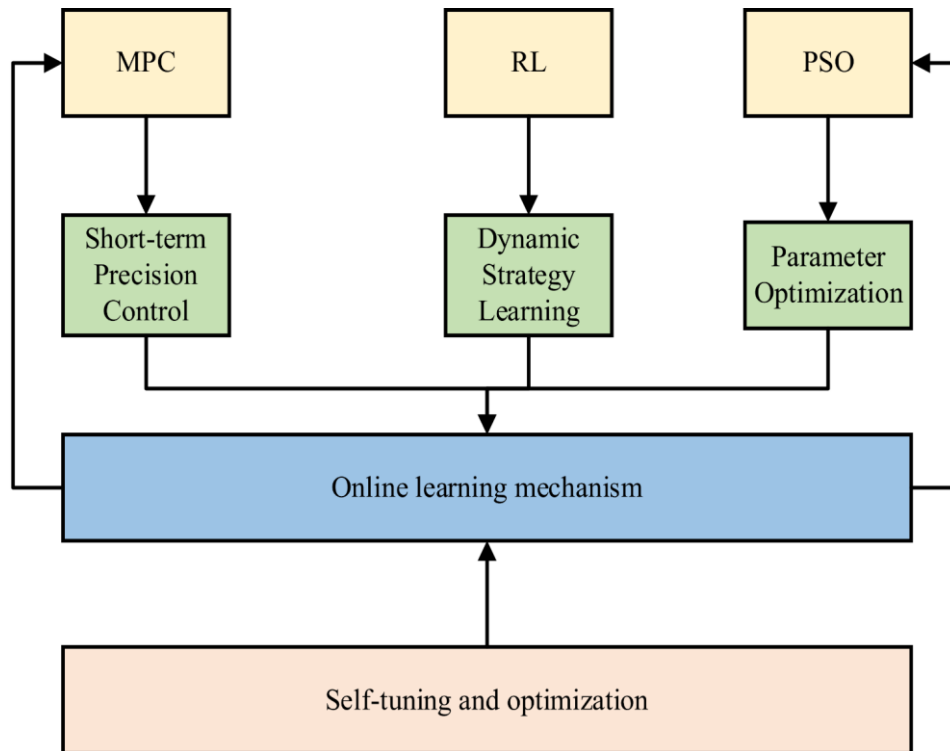


Figure 2. Structure of Fusion model

Result and Discussion

Examples of energy usage records for natural gas, water and electricity use across five randomly chosen dates and time periods are shown in Table 1. The energy consumption numbers in kWh, m³, and m³ are displayed in the table together with the date and time interval. Energy-saving plans can be developed with the help of this data, which is beneficial to analyse patterns of usage of energy over the day and detect fluctuations in consumption.

Table 1. Energy consumption Records

| date | time | Electricity consumption (kWh) | Water consumption (m ³) | Natural gas consumption (m ³) |
|------------|-------------|-------------------------------|-------------------------------------|---|
| 2023-03-15 | 14:00–15:00 | 320 | 12 | 22 |
| 2023-05-20 | 09:00–10:00 | 380 | 15 | 18 |
| 2023-07-10 | 21:00–22:00 | 260 | 9 | 15 |
| 2023-09-25 | 01:00–02:00 | 180 | 7 | 12 |
| 2023-11-30 | 18:00–19:00 | 450 | 18 | 25 |

The impact of the change is assessed from the viewpoint of end users in Table 6. The high degree of approval suggests that the modification techniques are not only technically sound but also recognised by users, which is crucial for the continued advancement and implementation of energy efficiency and emissions reduction strategies. An important soft indication for assessing the success of an endeavour is user approval for initiatives that reduce emissions and save energy, as well as for lighting and comfort. Table 2 presents the results of a user feedback survey and shows the percentage of respondents who were satisfied with the lighting, the restored environment, and their understanding of emission-reduction and energy-saving techniques. According to the study results, consumers are quite satisfied, with 88% of respondents believing the illumination to be both acceptable and aesthetically pleasant, and 92% finding the atmosphere inside to be more comfortable.

Table 2. Results of used satisfaction survey

| survey items | very satisfied | satisfaction | general | not satisfied | very dissatisfied |
|--|----------------|--------------|---------|---------------|-------------------|
| environmental comfort | 520 | 360 | 80 | 30 | 10 |
| lighting effect | 480 | 400 | 90 | 20 | 10 |
| Awareness of Energy Conservation and Emission Reduction Measures | 300 | 450 | 150 | 70 | 30 |

The financial advantages of energy saving initiatives are summarised in Table 3. The reduction in service and electricity expenses can be used to compute the overall economic gain. According to the table, energy-saving initiatives resulted in an overall economic advantage of 1.25 million yuan, such as 1.2 million yuan saved on power and 50,000 yuan spent on maintenance expenses.

Table 3. Overview of economic benefits

| Project | Amount (Ten Thousand Yuan) |
|--------------------------|----------------------------|
| Savings on Electricity | 120 |
| Maintenance Cost Savings | 5 |
| Total Economic Benefit | 125 |

Conclusion

The anticipated energy-saving objective is successfully met by this study, and user satisfaction evaluations confirm the system's efficacy. Subsequent investigations will concentrate on investigating elaborate AI technologies in order to enhance the system's prediction precision and flexibility. Furthermore, in order to increase the system's universality and range of applications, we intend to expand it to include additional building attribute types, such as different geographic regions and building uses. These investigations will ensure that research remains relevant and contributes to sustainable development by bringing new ideas to the field of energy conservation in buildings.

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