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Towards Nearly Zero-Energy Buildings (NZEB) Based on Edge Artificial Intelligence (EAI)

Mpelogianni V.G.[a,*], Groumpos P.[a], Tsipianitis D.[a], Papagiannaki A.[a], Gionas J., Koutroumpinas S.[b]

[a]*Electrical and Computer Engineering Department, University of Patras, Patras, Greece*
[b]*Meazon S.A., Greece*

v.mpelogianni@ece.upatras.gr

Abstract

Buildings account for a significant share of global energy consumption, necessitating innovative approaches for energy conservation and efficiency. Energy retrofitting faces two key challenges: the **pre-bound effect**, where actual consumption is lower than predicted, and the **rebound effect**, where post-retrofit usage increases due to behavioral changes. This paper proposes an **Edge Artificial Intelligence (EAI)-driven** approach to improve energy efficiency by integrating **sensor networks, data mining, and intelligent modeling**. The **Fuzzy Experts** program is extended to develop a smart platform that assesses building deficiencies and provides tailored solutions to enhance energy performance, supporting the transition to **Nearly Zero-Energy Buildings (NZEBs)**.

1. Main text

Buildings consume a significant percentage of the world's energy resources. The rapid depletion of energy resources has imparted researchers to focus on energy conservation and wastage. The next generation of intelligent buildings is becoming a trend to cope with the needs of energy and environmental ease in buildings. This advances the intelligent control of building to fulfill the occupants' need. Intelligent system control for sustainable buildings is dynamic and highly complex. The significance of improving energy efficiency in the building sector is well documented. There are two mechanisms to achieve this, as outlined in a report to the European Commission on 'Towards nearly zero-energy buildings' [1]. The first is the propagation of nearly zero energy buildings as per the European Energy Performance of Buildings Directive (EPBD) [2]. The second is the principle of cost optimality that will guide the energy performance requirements of new and existing buildings undergoing retrofitting. Although there are challenges in propagating energy retrofits in the residential sector, many studies present the long-term associated benefits [3].

There are, however, two major challenges in energy retrofitting in the residential sector.

A) The first is the pre-bound effect, which means that buildings consume less energy than the calculated rating [4]. Although there are numerous factors for this difference, a well-

known factor is the lack of accurate assessment of energy performance of buildings in their pre-retrofit stage.

B) The second challenge is the rebound effect that leads to higher operational energy by occupants after the building has been retrofitted [15–17].

Galvin [5], examined that this phenomenon can be extended as into the 'energy savings deficit' and the 'energy performance gap' [5]. The energy saving deficit is the shortfall in savings as a proportion of the expected savings, whereas, the energy performance gap is the excess consumption as a fraction of the design consumption. Aydin et al. [6], assessed 560,000 dwellings in the Netherlands to study this effect and found a rebound effect of 26.7% among homeowners, and 41.3% among tenants [6]. A solution to this is a systematic propagation of awareness related to energy efficient living. A promising way to address both pre- and rebound is to use energy models that are calibrated using measured data. Various studies in the literature have reported on this improvement through measurement of relevant building variables like U-values [7]. Monitoring of electrical energy consumption and indoor conditions also helps in validating the dynamic building energy models [8]. A surge in monitoring building variables has led to development and deployment of sensor networks. Such time series data is often used for modelling and forecasting [9]. Measured data has enormous benefits in treating each building individually since a generic solution for buildings is rather difficult [10]. Recent research focuses on reducing the development cost of sensors along with determining the number of sensors and placement locations. There is also substantial literature on anomaly detection, real-time activity recognition, and non-intrusive load monitoring [11–14]. However, most of these require installation of a high-resolution sensor network. A more easily available data set is the total electrical energy consumed in residences. This is also supported by the wide propagation of smart meters for electricity consumption [15]. Such data can be effectively analyzed for daily and segmented load profiles using data mining techniques [16]. In residences where electricity is the only source of energy, monitoring of electrical consumption can reveal interesting insights on the usage of major energy systems. The availability of large data sets has paved way to numerous data mining methods for building energy consumption analysis [17-25].

This paper sets the basis of extending the Fuzzy Experts program. The objective is to design and implement a tool which combines the insights gained from compiling the energy profiles of different buildings and create a platform that taking into consideration the deficiencies of the buildings will provide solutions that will help to further increase their energy efficiency.

The overall of the paper will include and cover scientifically the following topics:

2. Overview of methods

3. Basics of Edge Artificial Intelligence (EAI)

4. Nearly Zero-Energy Buildings (NZEB) Definitions and Mathematical Methods

5. Problem Formulation and Edge Artificial Intelligence System

6. Developed Algorithms

7. Real Case Applications and Obtained Simulation Results

8. Conclusions and Future Research

Acknowledgements

Acknowledgements and Reference heading should be left justified, bold, with the first letter capitalized but have no numbers. Text below continues as normal.

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