Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 57-1 (2024) 143–148

Energy management set-up to exploit the flexibility potential of a multi-unit residential apartment building in a cold climate region ⋆

Shaival H. Nagarsheth * **Nilson Henao** * **Kodjo Agbossou** *
Michaël Fournier **

* *Laboratoire d'innovation et de recherche en énergie intelligent (LIREI), Institut de recherche sur l'hydrogène (IRH), Université du Québec à Trois-Rivières (UQTR), Québec G9A 5H7 Canada (e-mail: shaival.nagarsheth@uqtr.ca)*

** *Laboratoire des Technologies de l'Énergie (LTE), Centre de Recherche d'Hydro-Québec (CRHQ), Québec G9N 7N5 Canada*

Abstract:
Intelligent energy management and dispatch in a multi-unit residential apartment building is a non-trivial task owing to the thermal interactions and diverse requirements of thermal comfort during the peak hours of the winter season. To address such a challenge, in this work, a management entity is considered to manage the energy requirements of all the apartments in the building according to the price signal, minimizing the electricity cost for a 24-hour day ahead format. Accordingly, the management entity formulates an optimization problem considering the thermal model, energy utilization and weather. It is also equipped with fuzzy logic to smartly distribute the requirement for each unit based on the thermal interactions and thermal comfort levels. The proposed approach of centrally managing a multi-unit residential building is effectuated on a case study in Québec, Canada. Data-driven thermal modelling is carried out with actual weather data from Québec to perform the optimization. The results display the potential of the proposed approach to dispatch heating energy to each building unit with respect to time-of-use (TOU) price signal and shared objective.

Keywords: Building Energy Systems, Energy Management Systems, Optimization, Data-driven Thermal Modelling, Fuzzy Logic, Electric Baseboard Heaters.

1. INTRODUCTION

The global energy consumption situation is complex and constantly changing. In the 21st century, as nations work towards reducing their impact on the environment and transitioning to cleaner sources of energy, the energy transition has achieved the highest priority (Lee et al., 2021). Despite numerous global initiatives aimed at decarbonizing the energy sector, it continues to play a significant role in environmental pollution. In Canada, more than 80% of the country's greenhouse gas (GHG) emissions come from energy production and use, with the building sector alone contributing significantly to about 30% of total GHG emissions (IEA, 2022). Importantly, the residential sector is the largest electricity consumer in Québec (Hydro-Québec, 2022), with the building sector being a significant contributor to GHG emissions. Additionally, the construction and operation of buildings worldwide consume over a third of the world's energy (Sharmin et al., 2014). Therefore, it has become essential to focus on reducing energy consumption in the planning, construction, and use of buildings to mitigate environmental impacts. The building sector has substantial potential for energy and CO_2 emissions savings (Gökçe and Gökçe, 2013). Taking measures to optimize energy consumption in buildings is crucial for achieving sustainability goals and reducing environmental harm.

Moreover, in regions like Québec, Canada, where cold winters are prevalent, heating constitutes the largest portion of electricity consumption (Hydro-Québec, 2023b). This creates a challenge during winter peaks, which are periods of high demand when people simultaneously heat their homes and use energy-intensive appliances (Hydro-Québec, 2023a). The increasing demand for clean energy further exacerbates this challenge. Québec, being the largest electricity producer in Canada, generated 212.9 terawatt-hours of electricity in 2019, primarily through hydropower, which accounts for 94% of Quebéc's electricity generation (CER, 2023). However, reducing energy consumption during winter peaks is crucial to managing electricity costs and addressing environmental concerns. One of the promising ways to address such an issue is to enhance the grid performance by exploiting flexibility

⋆ This work was supported in part by the Laboratoire des technologies de l'energie (LTE) d'Hydro-Québec, the Natural Science and Engineering Research Council of Canada and the Fondation of UQTR.

10.1016/j.ifacol.2024.05.025

on the demand side via controllable loads resulting in reduced power losses, electricity cost, GHC, and grid load in winter peaks (Domínguez-Jiménez et al., 2023). Achieving this by maintaining thermal comfort in winter is an open challenge still prevailing (Fournier et al., 2016). This problem enhances and boils down to an effective management scheme particular to each multi-unit residential building (Foroozandeh et al., 2022).

In this regard, several researchers have come up with various schemes to manage and optimize the environment inside a building . For instance, Foroozandeh et al. (2022) proposed a contract-based power optimization scheme to manage a smart building centrally. Arcos-Vargas et al. (2018) suggested an energy management model for residential peaks via an energy storage option during peak hours. Drgoňa et al. (2020) provides a distinct viewpoint on building management systems. Various schemes have been explored for home energy management in a neighbourhood by considering each house as a thermal zone where the houses are considered detached without thermal interactions. Also, efforts have been put into making buildings grid-interactive in order to improve the efficiency of the grid and the building (Bay et al., 2022). A commercial building case study was explored where a simplified model was considered by lumping multiple zones into one, ignoring the thermal interaction possible between the zones and managing the energy resources of each.

Fuzzy Inference Systems (FIS) and optimization techniques have been widely utilized for controlling, managing and optimizing various energy sources in buildings, houses and grid levels (Dong et al., 2021; Arcos-Aviles et al., 2018). For instance, Ahn et al. (2017) developed FIS-based control strategies for heating energy supply with respect to the changes in user demands. A plethora of meta-heuristics optimization approaches in building energy management has been explored, namely PSO for a four-zone building (Wang et al., 2019), POSCO for office buildings (Yuan et al., 2023), comfort management by Bat algorithm (Fayaz and Kim, 2018). Particularly, meta-heuristics optimization approaches are better for non-convex types of the objective function and suffer from the inconsistent performance of finding local optima instead of global. Also, owing to the complexity of the multi-zone buildings attributed to multiple thermal interactions, many works consider limiting the zones or reducing them to one zone for the ease of simulations. Hosseini et al. (2022) explained the impact of zoning and power dispatch management for multiple zones in a residential house via difference of area technique. Zoning is an important aspect of consideration from the perspective of building flexibility potentials (Hosseini et al., 2022), which proves effective for dynamic thermal response against dynamic pricing. Nevertheless, it is evident that multi-unit residential building necessitates multi-zone modelling and an efficient power dispatch strategy to manage the energy consumption of the whole building centrally.

To overcome these problems, this paper focuses on suggesting a management framework for optimizing the energy utilization of every unit in an apartment building in response to the price signal. Specifically, the management entity is equipped with fuzzy logic to aid the power dispatch based on user-defined thermal comfort and thermal interactions among the zones. An optimization problem is framed, accounting for the thermal model and constraints of a multi-unit residential building, to optimize the energy consumption for a 24-hour day ahead format. This enables the flexibility analysis of the whole building, considering the influence of zoning on the thermal dynamic response and occupants' thermal preferences. Typically, the flexibility is analyzed in terms of energy usage by the electric baseboard heaters (EBHs) in response to winter demands. The proposed technique is effectuated in a multi-unit apartment building in Trois-Rivières, Québec, Canada. The building geometry with all the parameters is constructed in Building Energy Optimization Tool (BEopt) and utilized to generate consumption data in EnergyPlus, which is then utilized to model the dynamics and optimization tasks.

2. METHODOLOGY

In this framework, a manager is in charge of the energy consumption of each unit in the apartment building and maintaining their respective thermal preferences. Note the building is billed in bulk at the responsibility of the manager. Fig. 1 displays the overview of the building management scheme. The manager is responsible for learning a black-box thermal model from the data and performing offline optimization. Subsequently, fuzzy logic is constructed based on the thermal interactions and desired thermal comfort conditions to distribute the power consumption amongst the units as constraints to the optimization problem.

2.1 Buidling thermal dynamics

Let the indoor temperature for the building consisting of m units be represented as $X_{in} = \{x_i\}_{i=1}^{m}$, the energy consumption by the EBHs of m units be represented as $U_{ebh} = \{u_i\}_{i=1}^{m}$, outside temperature as X_{out} and solar radiation as S_r. Then, the following linear thermal model approximates the dynamics of an apartment building.

$$X_{in}^{k+1} = AX_{in}^{k} + BU_{ebh}^{k} + CW^{k}, \tag{1}$$

where A,B,C are the coefficient matrices of the thermal model, $A = \{a_{ij}\}_{1\leq i\leq m, 1\leq j\leq n}$, B is a diagonal matrix such that $B = \{b_{ij}\}$, $\forall i,j \in \{1,2,\cdots,m\}, i \neq j \Rightarrow b_{ij} = 0$ and $C = \{c_{ij}\}_{1\leq i\leq m, 1\leq j\leq 2}$, where m denotes the number of units in an apartment building. In (1), $W^k = \left(X_{out}^k \ S_r^k\right)^T$ represents the weather conditions, including outside temperature and solar radiations. Note that the simulation data from the EnergyPlus simulation of the designed apartment building geometry is utilized to calculate the parameters of the data-driven linear thermal model (Domínguez-Jiménez et al., 2023). The coefficient matrices are calculated using the ridge regression technique (Boyd and Vandenberghe, 2009).

2.2 Fuzzy Inference System

The purpose of FIS is to determine the values for energy constraints for the optimization problem depending on the desired temperature levels and thermal interactions. The fuzzy system forms a pipeline (Fig. 2) based on the fuzzy logic principles and the Mamdani inference method (Jang

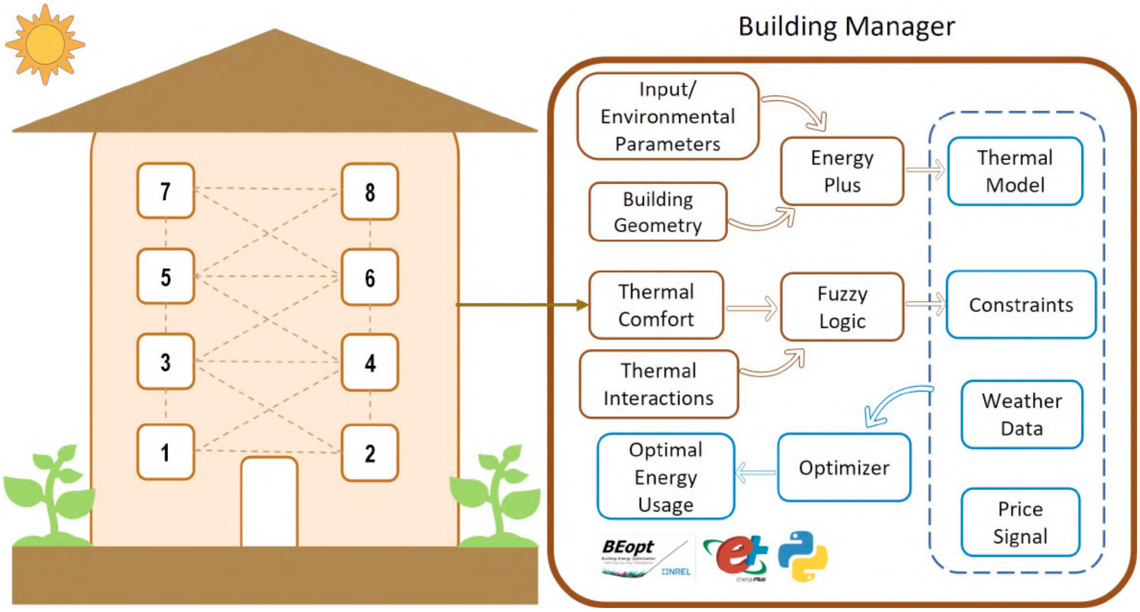

Fig. 1. Building Energy Management Scheme

et al., 2015). Intuitively, the first block creates the fuzzy set by taking crisp values as input and utilizing fuzzy membership functions (MFs). In this work, the three crisp inputs (desired temperature level and interactions) are fuzzified into three categories: low, moderate, and high. For the desired temperature levels, the trapezoidal membership curves are defined for fuzzification (Kontogiannis et al., 2021), i.e.

$$\mu_{trap}(x_c) = max\left(min\left(\frac{x_c - a}{b - a}, 1, \frac{x_c - d}{c - d}\right), 0\right), \quad (2)$$

where the parameters a, b, c, d (with $a < b \leq c < d$) determine the x_c coordinates of the four corners of the underlying trapezoidal membership function. In (2), x_c denotes the desired temperature level of each residential unit inside the apartment building for the next 24-hour window. Similarly, to fuzzify thermal interactions gaussian membership function is used, i.e.

$$\mu_{gauss}(x_{ti}) = e^{\left(x_{ti} - c/\sqrt{2}\sigma\right)^2}, \quad (3)$$

where c and σ denote MFs mean and variance. The next block is the decision-making unit that employs a set of fuzzy rules to map the input values to the desired output values (Jang et al., 2015). Effectively, the rules are the statements between antecedents (fuzzy region in the input) to result in a fuzzy set of the consequent (fuzzy region in the output); see Fig. 2. Consequently, an aggregator is established to yield an output MF $\mu_F(z)$, with F as the fuzzy set of a universe of discourse Z. Since rules constitute the basis for pattern identification, the number of rules should cover every possible outcome. The final block is the defuzzification unit utilizing the Mamdani approach to achieve crisp value by the centroid (centre of gravity) method (Jang et al., 2015), i.e.

$$z^* = \frac{\int_Z \mu_F(z) \cdot z dz}{\int_Z \mu_F(z) dz}.$$

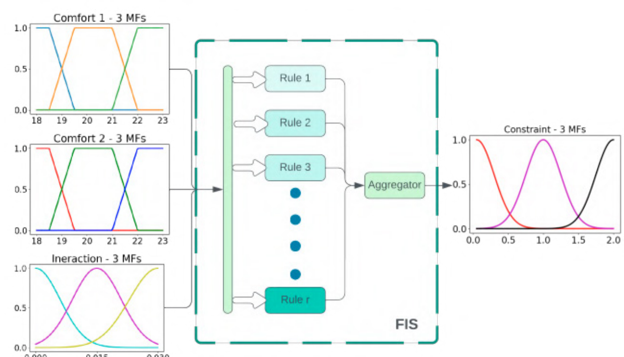

Fig. 2. Block diagram of a FIS

2.3 Optimization Problem

The main objective of the building manager is to minimize the electricity bill and maximize comfort (incurred discomfort) while respecting the constraints. The building manager acts as a centralized entity and poses the control rights to find the optimal solution and schedule the flexible loads accordingly. The optimization problem of the building manager is formulated to schedule the energy consumption of each unit in the building to reduce the total consumption of the building, which is given by

$$\begin{aligned}
\underset{u_i, \forall i \in m}{\text{minimize}} \quad & J = \sum_{1 \leq k \leq N} \sum_{1 \leq i \leq m} (d_i^k + g_i^k) && \text{(4a)}\\
\text{subject to} \quad & X_{in}^{k+1} = f(X_{in}^k, U_{ebh}^k, X_{out}^k, S_r^k), && \text{(4b)}\\
& 0 \leq u_i^k \leq u_i^{max}, \quad \forall i, k, && \text{(4c)}\\
& x_i^{min} \leq x_i^k \leq x_i^{max}, \quad \forall i, k. && \text{(4d)}
\end{aligned}$$

In (4a), d_i^k refers to a quadratic function depicting the inhabitant's discomfort as

$$d_i^k = \gamma_i^k (x_i^k - x_{i,sp}^k)^2, \quad \forall i \in m, \forall k \in N, \quad (5)$$

where x_i^k denotes the indoor temperature for i^{th} unit at k^{th} time step. $x_{i,sp}^k$ represents the desired comfort level (setpoint) of each unit, and γ_i^k is the preference value defining weight to the comfort level for each time step. Linear model (1) acts as linear constraint (4b), keeping the optimization problem convexified to achieve the global minimum. Furthermore, the term g_i^k in (4a) measures the cost of consumed energy by EBHs of each unit in the apartment building with total m units, i.e.

$$g_i^k = \varphi^k u_i^k, \quad \forall i \in m, \forall k \in N, \tag{6}$$

where φ^k is the price of energy per kWh and u_i^k is the energy usage by EBH of each unit. Note that the energy consumption u_i^k is inherently incorporated in the discomfort as well as energy cost function as a result of a specific consumption profile. Importantly, adopting dynamic rates (Domínguez-Jiménez et al., 2023) to consume the energy conservatively during peak periods in winter results in a prisoner's dilemma reflected as rebound peaks during the low pricing periods. Accordingly, (4a) can be recast as

$$\begin{aligned}
\underset{u_i, \forall i \in m}{\text{minimize}} \quad & J = \sum_{1 \le k \le N} \left(\sum_{1 \le i \le m} \left(d_i^k + g_i^k\right) \right) && \text{(7a)} \\
& + \psi^k max_i \{u_i\}_{i=1}^m \\
\text{subject to} \quad & |u_i - u_j| \le \beta_{ij}, \quad \forall i, j \in m, && \text{(7b)} \\
& \text{(4b)}, \text{(4c)}, \text{(4d)}. && \text{(7c)}
\end{aligned}$$

The constraint (7b) is the result of the fuzzy inference system in Section 2.2. Here, β_{ij} is deduced for each pair of units, which is the crisp value output from the FIS based on the desired comfort levels and thermal interactions. The modified optimization objective (7a) will mitigate the rebound peak to achieve flatter consumption profiles by penalizing the function to level the maximum heating power across all units. Besides, the coefficient ψ^k in (7a) adjusts the penalization to harmonize with (5) and (6).

3. CASE STUDY

To evaluate the efficacy of the proposed management and optimization scheme, we have adopted an actual apartment building situated in Trois-Rivières, Québec, Canada, as shown in Fig. 3(a). To generate the data for modelling purposes, a similar geometry is constructed in the BEopt software (Fig. 3(b)) (Christensen et al., 2005) by respecting all the characteristics of the apartment building, namely the total area, area per unit, window area, attic, insulation, slab, and orientation among others (see Table 1). The maximum power of the electric baseboard heaters for

Table 1. General properties of the modelled apartment building in BEopt

Building Specifications
Site location: Trois-Rivières
Weather data: Trois-Rivières weather conditions of 2022
Size: 2100sq ft (including corridor 300sq ft)
Number of units: 8 (900sq ft/unit)
Wall thermal resistance: Wood Stud, R23 (closed cell spray foam)

each unit is around 10kW. This study exercises a semi-synthetic dataset generated by EnergyPlus for the consumption profiles to build a data-driven building thermal model. Fig. 4 shows the indoor temperature predictions made by the building thermal model (1). For the brevity of presentations, the mean temperature plot is shown for

(a) Actual apartment building

(b) Building geometry in BEopt for EnergyPlus simulations

Fig. 3. Case study multi-unit apartment building in Trois-Rivières, Québec

eight units, indicating a deviation of $\pm 0.4(^\circ\text{C})$ from the actual trajectory during the transient. That makes it very useful for the optimization task without the intricacies of the white-box model, making predictive optimal control easier to realize (Drgoňa et al., 2020). Samples of 15 winter days were utilized to train the model at a sampling instance of 10 minutes.

The optimization schedules the consumption for the next 24 hours. The desired comfort levels of all the units in the building and their respective interactions are fed to the FIS for the relative constraint of the optimization. Fig. 5 depicts the working of FIS with respect to two inputs (desired temperature levels). Besides, Fig. 6 shows the crisp output result (moderate) of the FIS system for a set of inputs (high, moderate and low). Here, the aggregated output membership function is displayed as a result of the FIS with the defuzzified crisp output value. Note that the desired thermal comfort temperature range is allowed from $18(^\circ\text{C})$ to $23(^\circ\text{C})$, which is in accordance with the Canadian Center for Occupational Health and Safety, ASHRAE Standard-55-2004 (Henao et al., 2018). The crisp inputs for thermal interactions are attributed to $A = \{a_{ij}\}_{1 \le i \le m, 1 \le j \le n}$ achieved from the data-driven thermal model of the building.

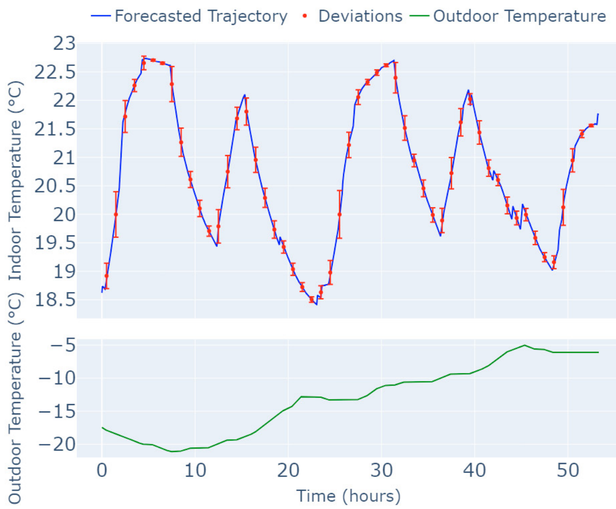

Fig. 4. Indoor temperature time-series prediction through trained model

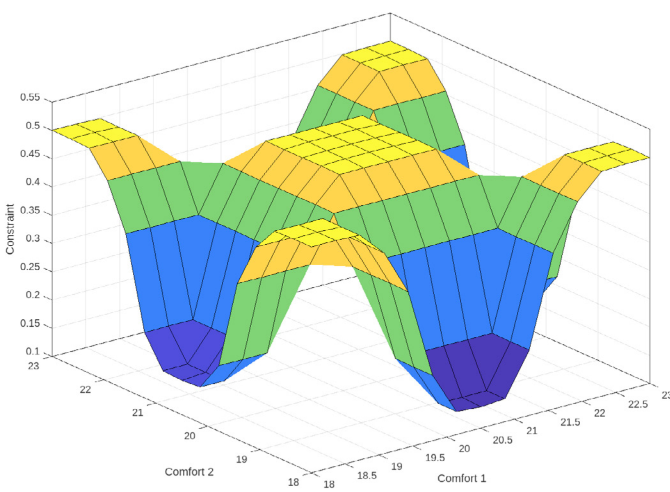

Fig. 5. Control surface of FIS

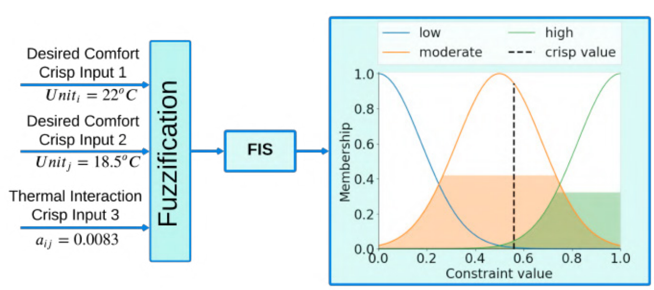

Fig. 6. Aggregate membership function and defuzzified crisp value

The optimization for the 24-hour day ahead scheduling is performed on *cvxpy* flatform (Boyd and Vandenberghe, 2009) by utilizing (4a) and (7a), shown in Fig. 7 denoted by *dashed* and *solid* lines, respectively. As we can clearly see, the aggregated profile of the building results in avoiding peak hour usage (6 AM to 9 AM and 4 PM to 8 PM) (Hydro-Québec, 2023a) and also maintains the temperature within the desired limits by exploiting the flexibility potential. Besides, on utilizing (7a), the aggregated profile

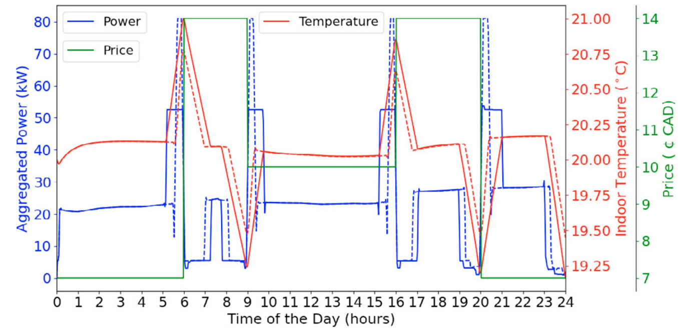

Fig. 7. Aggregated power profile of the building for a day with respect to desired temperature level and price signal

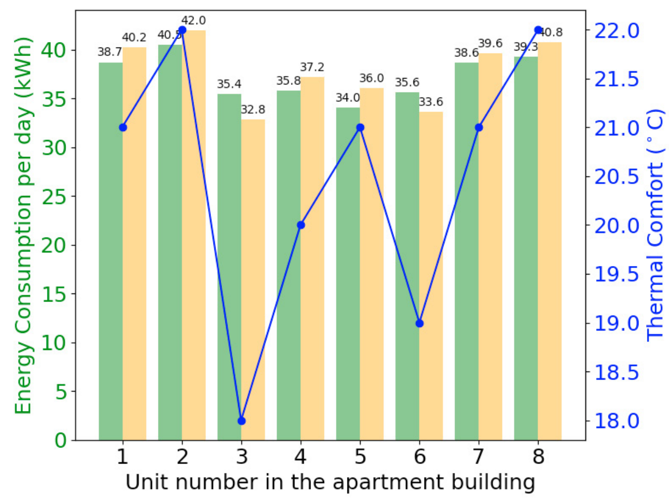

Fig. 8. Total energy consumption per day of each unit with the same comfort levels (green bars) and different comfort levels (yellow bars).

avoids the rebound peak after the high price signal period and tries to keep the profile flattened. This significantly reduces the load by modulating the indoor temperature to $\pm 0.75(^oC)$. Furthermore, Fig. 8 shows the difference in the energy consumption per day of each unit in the building, which is attributed to the different desired comfort and difference in the energy consumption managed by the proposed management equipped with fuzzy logic. The green bars show the energy consumption with the desired comfort kept the same for all the units to $20(^oC)$. On the other hand, upon changing the desired comfort levels of each unit, the difference in consumption (yellow bars) is a result of the fuzzy logic-based constraint for the optimization problem. That shows the effectiveness of the proposed setup to manage on a daily basis with the changing comfort and exploiting flexibility via consumption patterns of EBHs to respond to the TOU price signal.

4. CONCLUDING REMARKS

This paper proposed a management entity responsible for optimizing the energy consumption of a multi-unit apartment building and managing the energy utilization of each unit. It is equipped with an optimization formulation to minimize the energy cost in response to the utility price signal and fuzzy logic to assist the energy utilization of each unit with respect to their desired comfort levels. As a case study, a multi-unit apartment building in Trois-Rivières, Québec, Canada, is chosen and successfully modelled in EnergyPlus to obtain a data-driven thermal model with actual recent winter weather data. The optimization task was able to avoid the period of high price by preheating each unit without compromising on comfort $\pm 0.75(^{o}C)$. Besides, it was able to reduce the rebound peak by 30% via spreading the usage along the time instead of an instant power surge. The proposed strategy of exploiting the flexibility of a multi-unit apartment building will be highly useful in the demand response scenario with the dynamic pricing scheme, where an apartment building is billed in bulk and managed by a single entity responsible for optimization. In future work, a decentralized scenario will be analyzed and the proposed method will be extended to a game theoretic scenario where several other buildings in a neighbourhood participate in the demand response scenario with the grid side aggregator.

REFERENCES

Ahn, J., Cho, S., and Chung, D.H. (2017). Analysis of energy and control efficiencies of fuzzy logic and artificial neural network technologies in the heating energy supply system responding to the changes of user demands. *Applied Energy*, 190, 222–231.

Arcos-Aviles, D., Pascual, J., Marroyo, L., Sanchis, P., and Guinjoan, F. (2018). Fuzzy logic-based energy management system design for residential grid-connected microgrids. *IEEE Transactions on Smart Grid*, 9(2), 530–543.

Arcos-Vargas, A., Lugo, D., and Núñez, F. (2018). Residential peak electricity management. a storage and control systems application taking advantages of smart meters. *International Journal of Electrical Power and Energy Systems*, 102, 110–121.

Bay, C.J., Chintala, R., Chinde, V., and King, J. (2022). Distributed model predictive control for coordinated, grid-interactive buildings. *Applied Energy*, 312.

Boyd, S. and Vandenberghe, L. (2009). *Convex Optimization*. Cambridge University Press, New York.

CER (2023). Canadas energy future data appendices. *Canada Energy Regulator*.

Christensen, C., Courtney, A., Horowitz, S., Givler, T., and Barker, G. (2005). Beopt: Software for identifying optimal building designs on the path to zero net energy. *Proceedings of the Solar World Congress*, 1, 55–60.

Domínguez-Jiménez, J.A., Henao, N., Agbossou, K., Parrado, A., Campillo, J., and Nagarsheth, S.H. (2023). A stochastic approach to integrating electrical thermal storage in distributed demand response for nordic communities with wind power generation. *IEEE Open Journal of Industry Applications*, 4, 121–138.

Dong, W., Yang, Q., Fang, X., and Ruan, W. (2021). Adaptive optimal fuzzy logic based energy management in multi-energy microgrid considering operational uncertainties. *Applied Soft Computing*, 98, 106882.

Drgoňa, J., Arroyo, J., Cupeiro Figueroa, I., Blum, D., Arendt, K., Kim, D., Ollé, E.P., Oravec, J., Wetter, M., Vrabie, D.L., and Helsen, L. (2020). All you need to know about model predictive control for buildings. *Annual Reviews in Control*, 50(May), 190–232.

Fayaz, M. and Kim, D.H. (2018). Energy consumption optimization and user comfort management in residential buildings using a bat algorithm and fuzzy logic. *Energies*, 11(1), 1–22.

Foroozandeh, Z., Ramos, S., Soares, J., Vale, Z., and Dias, M. (2022). Single contract power optimization: A novel business model for smart buildings using intelligent energy management. *International Journal of Electrical Power and Energy Systems*, 135(August 2021).

Fournier, M., Leduc, M.A., and Nadrault, G. (2016). Winter demand response using baseboard heaters: achieving substantial demand reduction without sacrificing comfort. *Proceedings of ACEEE Summer Study on Energy Efficiency in Buildings (Pacific Grove, CA)*, 1–12.

Gökçe, H.U. and Gökçe, K.U. (2013). Holistic system architecture for energy efficient building operation. *Sustainable Cities and Society*, 6(1), 77–84.

Henao, N., Fournier, M., Kelouwani, S., and De, T. (2018). Characterizing Smart Thermostats Operation in Residential Zoned Heating Systems and its Impact on Energy Saving Metrics. *International Building Preformance Simulation Association*.

Hosseini, S.S., Vallianos, C., Agbossou, K., and Athienitis, A. (2022). Impact of Zoning Definition on Electrical Heating Systems Flexibility Potential in Residential Buildings: A Quebec Case Study. *Proceedings of the 5th International Conference on Building Energy and Environment*.

Hydro-Québec (2022). Annual report. *Hydro-Québec*.

Hydro-Québec (2023a). Using energy more wisely in cold weather. URL `https://www.hydroquebec.com`. Accessed on 04.05.2023.

Hydro-Québec (2023b). What is the breakdown of household electricity use? URL `https://www.hydroquebec.com`. Accessed on 05.05.2023.

IEA (2022). Canada 2022 - energy policy review. *International Energy Agency Publications*, 1–261.

Jang, J.S.R., Sun, C.T., and Mizutani, E. (2015). *Neuro-Fuzzy and soft computing: A computational approach to learning and machine intelligence*. Prentice Hall, New Jersey.

Kontogiannis, D., Bargiotas, D., and Daskalopulu, A. (2021). Fuzzy control system for smart energy management in residential buildings based on environmental data. *Energies*, 14(3).

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Aditi, M., and Thorne, P. (2021). Synthesis report of the ipcc sixth assessment report (ar6). *Intergovernmental Panel on Climate Change*.

Sharmin, T., Gül, M., Li, X., Ganev, V., Nikolaidis, I., and Al-Hussein, M. (2014). Monitoring building energy consumption, thermal performance, and indoor air quality in a cold climate region. *Sustainable Cities and Society*, 13, 57–68.

Wang, Z., Chen, Y., and Li, Y. (2019). Development of RC model for thermal dynamic analysis of buildings through model structure simplification. *Energy and Buildings*, 195, 51–67.

Yuan, X., Karbasforoushha, M.A., Syah, R.B., Khajehzadeh, M., Keawsawasvong, S., and Nehdi, M.L. (2023). An Effective Metaheuristic Approach for Building Energy Optimization Problems. *Buildings*, 13(1).