

Toward a Human-Centric Demand Response Framework: Optimizing Energy Efficiency and Comfort for Aging People in the Built Environment

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Abstract— This paper presents an innovative strategy to improve the comfort of elderly people during demand response events. Despite the residential sector accounts around 30% of total energy consumption, demand response strategies prioritize system flexibility over occupant well-being, often overlooking comfort when optimizing energy consumption. One issue that is not take into account is the well-being of elderly, who may be particularly affected by such approaches. To address this issue, a Human-Centric Demand Response Framework that prioritizes the comfort of elderly people has been developed. A detailed analysis of each component of the framework is showcased, describing its role and highlighting the input and output data. Finally, a case study is presented to illustrate how the proposed framework is going to be implemented in a real-case scenario during demand response events, highlighting the importance of a Human-Centric approach to assess the comfort of elderly people. As demonstrated in this study, standard methods for evaluating thermal comfort in elderly are no longer accurate.

Keywords—comfort and well-being, aging people , demand response, energy consumption.

I. INTRODUCTION

In recent decades, the average age of the population has increased, and this trend is expected to continue in the coming years. For example, the proportion of the population aged 65 and over is projected to rise from 12.5% in 2021 to 16.7% in 2030, and 20% in 2050 [1]. The well-being of elderly people in the environments they inhabit is becoming an increasingly relevant issue [2]. Older adults tend to prefer living in their own homes rather than moving to nursing homes or specialized care facilities. This preference has led to the rise of the trend known as “ageing in place,” which refers to the possibility of living at the own house as long as adequate safety and comfort conditions are ensured [1]. Due to a weaker immune system and spending more time indoors, elderly people are particularly sensitive to changes in indoor conditions [3]. For this reason, measuring Indoor

Environmental Quality (IEQ) is essential to assess the comfort conditions tailored to their needs [4]. Comfort is a complex concept based on the sensory perception of occupants within an indoor environment [5]. It significantly influences both physical and mental health and has gained increasing attention due to its impact on well-being, performance, and building sustainability [1]. Comfort is therefore defined as a specific condition of psycho-physical well-being of an individual, in accordance with their sensory perception of the surrounding environment[1]. This perception is influenced by various factors, such as temperature, air humidity, noise levels, and lighting conditions. These aspects highlight the existence of different types of comfort that contribute to the overall well-being of occupants within an indoor environment.

Thermal comfort is a fundamental aspect of indoor well-being and, according to ISO 7730 and ASHRAE standards, is typically assessed through the Predicted Mean Vote (PMV), which is calculated with a combination of environmental and personal parameters, such as indoor and outdoor temperature, mean radiant temperature, relative humidity, and metabolic rate. However, when not all parameters are available, simplified models like Buratti’s sPMV [6], based solely on indoor temperature and relative humidity, offer a practical alternative for estimating thermal comfort. Despite being a subjective mental state, thermal comfort in this study is evaluated through the Thermal Sensation Vote (TSV), an index rated from +3 (too warm) to -3 (too cold). TSV is preferred over the widely used PMV, as Fanger’s model often fails to assess the thermal sensations of vulnerable groups, such as children and the elderly. In this framework, Artificial Intelligence (AI) plays a crucial role in enabling the development of personalized thermal comfort models. These models aim to capture individual-specific characteristics by monitoring occupants’ thermal responses and leveraging AI algorithms to generate tailored comfort predictions[7].

Alongside thermal comfort, Indoor Air Quality (IAQ) is crucial for health and well-being and is assessed by monitoring CO₂, VOCs, and particulate matter (PM)[8], [9]. Visual comfort [10], which ensures adequate lighting through parameters like illuminance, daylight factor, and glare index, and acoustic comfort [11], related to indoor noise levels and external noise intrusion, are also essential components.

Therefore, measuring and monitoring these parameters is essential to ensure a comfortable and living environment with optimal conditions, especially for elderly people who have specific needs.

The residential sector accounts for approximately 30% of total energy consumption [12], [13], and a significant portion of this energy is used to ensure comfortable living conditions within homes. For example, building heating, ventilation, and air conditioning (HVAC) systems are responsible for roughly 20% of total energy consumption in a building[14], [15]. In the context of promoting renewable resources and increasing end-user involvement, it is important to consider that the large-scale integration of renewable energy sources introduces a degree of uncertainty into the grid due to their stochastic nature, which is heavily influenced by local weather conditions[16].

As a result, demand and response (DR) strategies become necessary. Demand response refers to a strategy that involves managing energy demand in a flexible way to help balance the power grid. By modifying their energy usage, consumers can either increase, reduce, or adjust their consumption levels. This adjustment helps maintain grid stability, and in return, participants can earn financial rewards for their contribution [17]. DR is also described as a collection of time-based programs and pricing schemes aimed at reducing or shifting electricity consumption to different periods. DR systems offer mechanisms that promote load shedding or shifting, especially during peak demand times or when electricity prices are elevated, helping to alleviate strain on the electrical grid and optimize energy distribution[18].

However, DR strategies often overlook occupants' comfort. These strategies typically focus on optimizing energy consumption by reducing reliance on non-renewable sources and maximizing renewable energy production. Additionally, they may aim to minimize demand charges, lower total utility costs based on real-time electricity prices or take advantage of available financial incentives [17]. Also, some other strategies may involve adjustments in HVAC operational setpoints or lighting, thus opening up potential occupant comfort perception problems [14].

The DEDALUS project, funded by the EU under Horizon Europe, aims to enhance the efficiency and sustainability of residential buildings by integrating flexible energy consumption strategies. It leverages IoT sensors and demand response systems to optimize IEQ while ensuring occupant comfort, particularly for the elderly. The project focuses on energy efficiency, cost reduction, and community-driven energy management through a digital platform that enables smart energy management and the development of connected, energy-efficient homes.

In accordance with the most recent scientific findings and the emerging need of a comfort-oriented demand response strategy, this study aims to develop a Human-Centric Demand Response Framework that prioritizes the elderly

people's comfort while enhancing the energy performance of the building. By considering individual comfort preferences, such as TSV, within the apartment, this framework enables users to determine the optimal dispatch of comfort flexibility actions during DR events. Furthermore, the proposed framework is examined in detail, analyzing all its technical components and outlining the necessary measures for its implementation, with a specific focus on input data and outputs. The aim of this framework is to find a trade-off between energy efficiency and comfort, ensuring that optimal comfort conditions are maintained for elderly residents as much as possible during DR events.

The paper is structured as follows: Section II provides a detailed description of the DR framework proposed. Section III presents a concrete use case where this strategy has been applied and finally followed by Discussion and Conclusions in Section IV.

II. HUMAN-CENTRIC DEMAND RESPONSE FRAMEWORK

This section outlines the methodology adopted to develop the proposed DR strategy. It begins with the identification of the target audience for the digital service, followed by an in-depth exploration of its key components.

The service is designed for both *apartment residents* and *building or apartment managers*. Residents have the opportunity to sign contracts with the grid operator, who is the entity responsible for balancing electricity supply and demand, maintaining grid stability, and integrating renewable energy sources. By doing so, they can earn financial incentives in exchange for their availability to adjust their energy consumption when the grid requires flexibility. In addition, building and apartment managers can ensure a certain level of comfort for residents without requiring them to interact directly with the grid operator. Instead, the entire process can be delegated to an automated or intermediate management system, optimizing energy efficiency while maintaining occupant well-being.

To achieve this goal, an innovative strategy has been defined, highlighting the main components of the service and analyzing their interactions. Specifically, three key blocks have been identified, as illustrated in Fig. 1:

- **Building Level:** this represents the data acquisition phase, carried out through sensors installed in the building or apartment being analyzed.
- **Comfort Flexibility Model:** this is the phase where the collected data is processed to provide solutions that consider the building's various operating conditions, evaluating potential options for comfort flexibility.
- **Decision Phase:** this represents the phase where the results from the comfort flexibility model, combined with grid requests, converge toward the end user. At this stage, a decision is made to provide the optimal trade-off between comfort and energy efficiency.

A. Building Level

In this block, all data related to the environment of the areas of interest is measured and collected. This includes internal environmental parameters (such as temperature and humidity), external environmental data (e.g., outdoor temperature), and energy consumption/production. A critical

element is the collection of TSV from occupants, which is fundamental for improving perceived comfort. Although TSV is initially collected through questionnaires filled out by the occupants, the ultimate goal is to train a machine learning (ML) algorithm to predict the TSV based solely on environmental data (e.g., indoor temperature (T_{in}) and relative humidity (RH)). Through this process, the system will learn to recognize and associate environmental conditions with users' thermal perceptions, making it possible to estimate TSV automatically without the need for continuous user feedback.

Once collected, the data are processed and sent to the Comfort Flexibility Model for further analysis.

B. Comfort Flexibility Model

The Comfort Flexibility Model is the block responsible for calculating three potential solutions that balance occupant comfort with energy efficiency. It ensures the optimal dispatch of comfort flexibility actions. This model is divided into two main sub-blocks:

1) **Comfort Model:** the data used in this block include environmental parameters such as T_{in} , outdoor temperature (T_{out}), RH, particulate matter (PM10, PM2.5, PM0.5), CO₂ levels, and light intensity (as shown in Table I), along with the TSV, organized into a dataset on a hourly basis (Fig.1). These data are used to assess the residents' daily comfort conditions, considering the types described in the introduction: thermal comfort, indoor air quality and visual comfort, all assess according to the relevant standards [19], [20],[21]. As regards thermal comfort, TSV is used. Indeed, this DR strategy is defined as a human-centric approach since it is based on the end-users' thermal experience, enabling the environment to dynamically adapt to their needs. In this way, it will be possible to establish control actions for the heating and cooling system, ensuring optimal conditions for the elderly in any scenario while always placing the end-user at the center of the comfort strategy

2) **Optimization Algorithm:** the core of this block provides actionable and personalized recommendations, suggesting optimal internal conditions for the next day (i.e T_{in} and RH) based on historical T_{out} , forecasted T_{out} , historical environmental parameters, occupants' TSV, historical energy consumption and production, and forecast flexibility energy consumption and production for the following day. Within the context of this work and European Project, energy data are provided (i.e., historical energy consumption data and flexibility forecasts data) based on the type of available energy systems.

For the next day, the following sets of data are provided:

- Flexibility of renewable energy production [Wh].
- Flexibility of energy consumption in the apartment [Wh].

For each of these categories, three predictive curves are provided (Fig.2):

- *Baseline:* represents the standard forecast for energy production or consumption for the following day.
- *Flexibility Above:* indicates the maximum possible forecast production or consumption that could be reached.
- *Flexibility Below:* defines the minimum expected forecast production or consumption.

Based on these flexibility curves, the Pareto-efficient algorithm [22] is applied for identifying the optimal set of solutions (T_{in} and RH) for the following day while considering specific conditions.

The process consists of two main phases:

1. Calculation of performance indicators: energy consumption and production, CO₂ emissions and TSV.
2. Identification of the Pareto frontier, which includes the set of optimal solutions that simultaneously minimize/maximize energy performance, reduce CO₂ emissions, and guarantee comfort (i.e., TSV=0).

The process depends only on the forecasted T_{out} for the following day. Energy flexibility is integrated by comparing forecasted consumption and production data with historical data. Since the Pareto method searches for similar situations in historical data, the algorithm analyzes cases where T_{out} was similar to the current forecast. It then compares these scenarios with flexibility data to determine the best set of possible solutions (i.e. T_{in} and RH), which can be: absence of renewable energy production system or presence of renewable energy production system. The aim is to identify solutions that ensure the comfort of elderly people in accordance with the thresholds set by current regulations[19]. Since these regulations require that elderly occupants remain in comfortable conditions for at least 95% of the time, the solutions proposed below will always comply with the standards requirements but will aim to guarantee comfort in category I (individuals with particular needs), with different percentages of time depending on the chosen solution. Nevertheless, in all cases, the comfort of elderly individuals will always be ensured at category I, adopting an approach that prioritizes the well-being of elderly people.

In case there is no renewable energy production, flexibility management focuses only on energy consumption, CO₂ emissions reduction, and maintaining thermal comfort

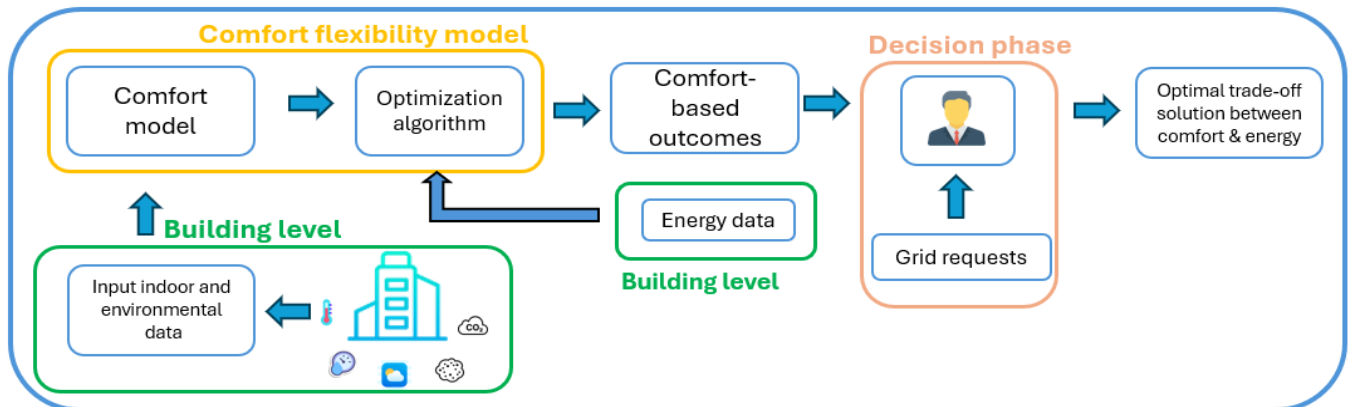


Figure 1: DR strategy proposed.

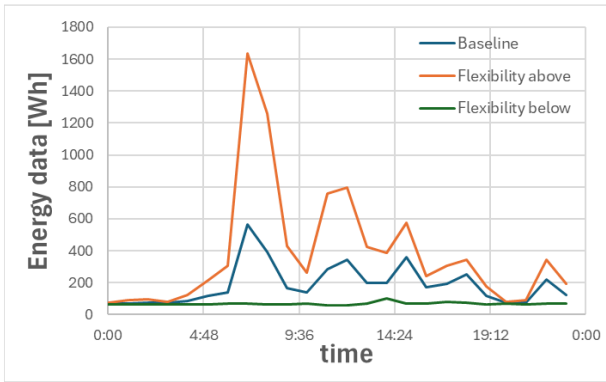


Fig. 2: example of energy flexibility consumption or production trend.

(i.e., TSV=0). The proposed solutions balance comfort and energy savings as follows:

- *Optimal comfort minimizing energy consumption:* this solution aims to ensure the highest possible level of comfort, guaranteeing that conditions remain within category I [19] for 99% of the time, while reducing energy consumption. The Baseline curve is used as a reference, representing the standard consumption forecast for the following day.
- *Acceptable comfort minimizing energy consumption:* in this scenario, a slight compromise on comfort is accepted with 97-98% of the time guaranteed within category I, to achieve a reduction in energy consumption compared to the standard scenario. The reference energy consumption is the average between Baseline and Flexibility Below, allowing for lower energy usage while maintaining adequate thermal comfort.
- *Minimization of energy consumption without prioritizing comfort:* in this scenario, the main objective is to maximize energy savings, even if this leads to a slight reduction in comfort with 95-96% of the time guaranteed within category I. The Flexibility Below curve is adopted, representing the lowest possible energy consumption for the following day, while still ensuring a minimal level of thermal comfort for residents.

The *Flexibility Above* curve is not considered, as scenarios where energy consumption exceeds the *Baseline forecast* are not relevant. The proposed strategy aims to optimize energy usage while maintaining an acceptable level of comfort, during DR events.

When the building has renewable energy production systems, flexibility management must account for both energy consumption and production. The proposed solutions are structured as follows:

- *Optimal comfort minimizing energy consumption:* this solution ensures indoor comfort within category I for 99% of the time, guaranteeing high standards of occupant well-being. The approach leverages a dual flexibility strategy: the Flexibility Above curve is employed to maximize the exploitation of on-site renewable energy sources, while the Flexibility Below curve is applied to minimize overall energy consumption. This integrated framework

simultaneously targets the reduction of grid dependency, CO₂ emissions, and TSV deviations.

- *Acceptable comfort minimizing energy consumption:* this solution accepts a slight compromise on comfort, ensuring category I conditions for 97-98% of the time. The adopted approach relies on the Baseline curve, which is maximized to increase on-site renewable energy usage and minimized to reduce energy consumption. This integrated framework simultaneously targets the reduction of grid dependency, CO₂ emissions, and TSV deviations.
- *Minimization of energy consumption without prioritizing comfort:* in this scenario the priority is maximizing energy savings, accepting a limited reduction in comfort, with 95-96% of the time guaranteed within category I. The renewable energy production is the lowest, therefore is used the Flexibility Below curve. The energy consumption curve used is the average between Baseline and Flexibility Below, to avoid excessive discomfort while maintaining an acceptable TSV level, reducing also CO₂ emissions.

By applying this approach, both cases aim to ensure adequate comfort levels while reducing energy consumption and CO₂ emissions as much as possible.

The recommendations (i.e., Tin e RH) are structured into three-hour windows, allowing end-users to adjust their environment accordingly. Moreover, the approach provides the optimal dispatch of comfort flexibility actions in each time window for the next day and this information converges to the *Decision phase* (Fig. 1).

C. Decision phase

In this phase, information about the optimal dispatch of comfort flexibility actions for the next day is provided to end-users, i.e., both apartment resident and building manager.

This is where the flexibility of comfort is implemented. The end user will select the solution that best suits their needs. However, if the grid operator requests a reduction in energy consumption below a certain threshold within a specific time window, the end user will choose the most suitable comfort solution proposed during the DR event. Finally, based on this choice, the building or apartment control system is configured accordingly.

III. USE CASE

Borgo Mazzini Smart Cohousing (BMSC) is in the historical town center of Treviso. BMSC hosts nearly 80 elderly residents living in 1-bedroom and 2-bedroom flats, each with a surface of 40-50 m². Each flat is provided with all necessary facilities for independent living: kitchen appliances and full-furnished bathroom in accordance with the Design4All principles[23], to accommodate people that might develop some form of disability in the future. BMSC flats present a high degree of comfort for their residents but the management of heating and cooling systems, as well as the supply of energy and water is conducted exclusively by Istituto per Servizi di Ricovero e Assistenza agli Anziani (ISRAA) which is the institution managing the buildings.



Fig. 3: internal view of an apartment of the *Italian pilot*.

TABLE I. DATASHEET OF THE SENSORS DEPLOYED

Sensor	Measured parameter	Accuracy
Temperature sensor	Air temperature [°C]	± 1.0 °C
Humidity sensor	Relative humidity [%]	$\pm 3\%$
CO ₂ sensor	CO ₂ concentration [ppm]	± 30 ppm
Lux meter	Light intensity [lux]	$\pm 1\%$
PM 10	Particular matter 10 [$\mu\text{m}/\text{m}^3$]	$\pm 10\%$
PM2.5	Particular matter 2.5 [$\mu\text{m}/\text{m}^3$]	$\pm 10\%$
PM4	Particular matter 4 [$\mu\text{m}/\text{m}^3$]	$\pm 10\%$
PM1	Particular matter 1 [$\mu\text{m}/\text{m}^3$]	$\pm 10\%$
PM0.5	Particular matter 0.5 [$\mu\text{m}/\text{m}^3$]	$\pm 10\%$

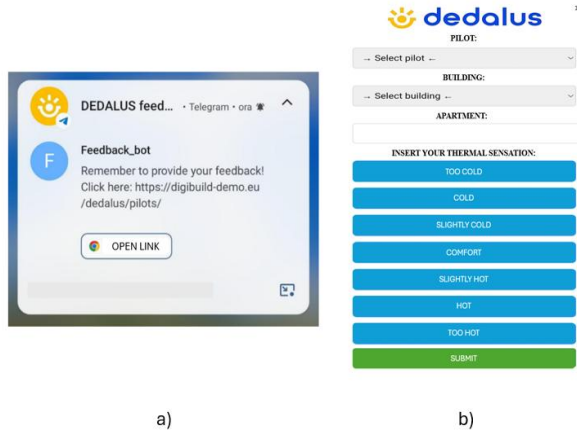


Fig. 4: on the left, notification sent to the users by Telegram app. On the right, questionnaire provided to the tenants to collect TSV.

This centralized management of the supplies and regulation of indoor temperature often risks creating differences in terms of perception and comfort between different residents who may have diverse needs. Within the context of this study, one building of the Italian pilot is considered and Fig. 3 reports the indoor environments characterizing the building under study.

In this building, a non-intrusive IoT sensor system was deployed to measure the IEQ parameters. Table I reports all the IoT sensors installed in each apartment of the building under study.

As previously explained in the Human-Centric DR Framework, sensor data are processed to assess the daily comfort of elderly residents in each apartment. To integrate

occupants' TSV into comfort assessment, a survey-based approach was implemented. A dedicated web page allows residents to submit their TSV by selecting their apartment and indicating their thermal sensation. The survey is distributed hourly via Telegram notifications, as shown in Fig.4 a), and special attention was given to designing a user-friendly interface suitable for elderly users, as shown in Fig.4 b). All collected TSV data will be used to train a ML model capable of predicting real-time TSV based only on environmental data, reducing the need to require it.

As shown in Fig. 5, which illustrates the trend of the TSV compared to the sPMV based on Buratti's model over the period from 23 October 2024 to 30 October 2024, the importance of ensuring thermal comfort for elderly occupants becomes evident. Although the sPMV suggests that thermal conditions remain within the comfort range throughout the entire period, the TSV reveals that, at certain times, the elderly individual experienced sensations of slight warmth or slight cold, highlighting occasional moments of discomfort.

The main objective of this framework is therefore to reduce the time the elderly person spends in discomfort, enhancing thermal comfort management in a more personalized, human-centric manner. Regarding the energy aspect, the responsible partner provided a historical dataset of energy consumption, recorded on an hourly basis from 1st of July 2024 to the 30th of October 2024 (Fig. 6). In addition, hourly forecasts of energy consumption flexibility for the following day (October 31, 2024) were provided. Fig. 7 highlights the three different flexibility curves previously described.

The Italian pilot lacks renewable energy systems, so comfort flexibility management focuses only on energy consumption. As explained earlier, energy flexibility curves are used to provide personalized recommendations for managing thermal comfort and energy consumption for the following day. These recommendations are shared with the end user (either the elderly resident or an ISRAA-designated manager), who selects the setup that best suits their needs. If the grid operator requests specific energy consumption during a given period, the building manager chooses the option that balances comfort preferences with grid requirements, ensuring optimal comfort for elderly residents.

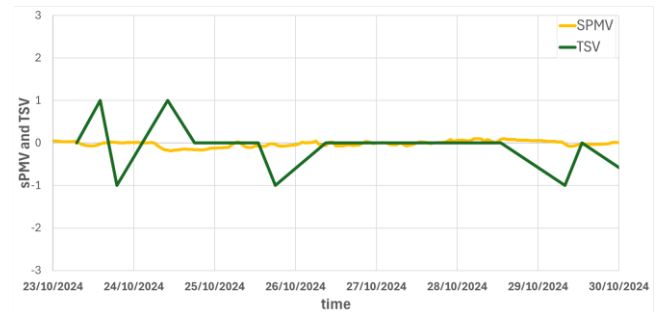


Fig. 5: comparison between the resident's TSV and sPMV measured in one apartment of the Italian pilot.

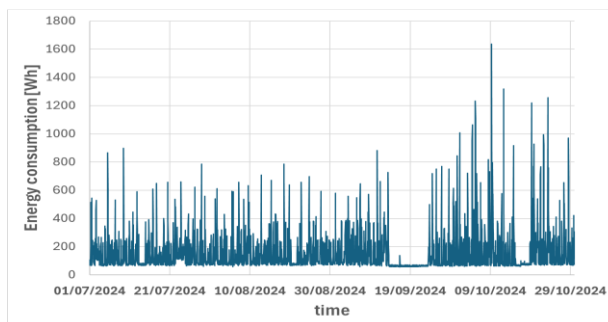


Fig. 6: Energy consumption measured in one of the Italian pilot's apartment .

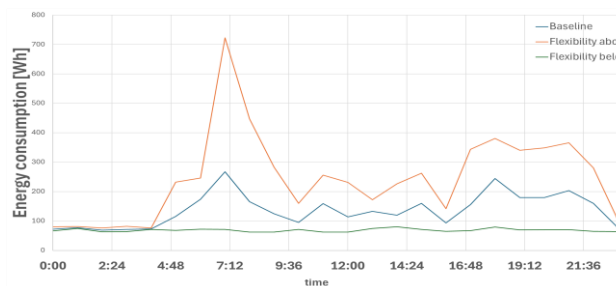


Fig. 7: Energy flexibility consumption forecasted for the next day (31/10/2024).

IV. DISCUSSION AND CONCLUSIONS

This paper presents a Human-Centric Demand Response Framework aimed at improving the comfort of elderly people during DR events, addressing their unique needs. The framework was developed to fill the gap between ensuring comfort for elderly residents and enhancing energy efficiency during DR events. While DR strategies typically focus on energy savings, they often overlook individual comfort, particularly for vulnerable groups like the elderly, who require specific conditions for well-being. This paper details the proposed framework, including its components, and presents an Italian pilot building as a case study where the strategy will be implemented. The case study highlights the importance of a human-centric approach, using subjective factors (TSV) rather than purely environmental metrics.

Ultimately, this paper not only explores a DR strategy specifically designed for elderly people but also emphasizes the importance of ensuring their comfort during DR events, particularly in light of the growing integration of renewable energy sources into the power grid.

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