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Efficiency in building energy use: Pattern discovery and crisis identification in hot-water consumption data

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ABSTRACT

As global challenges such as climate change and pandemics increasingly disrupt urban systems, the need for efficient and resilient management of energy resources has become critical. The energy used to prepare domestic hot water (DHW) takes a large proportion of residential buildings' total thermal energy demand. However, it is often overlooked in research due to its stochastic nature and high dependence on user behaviour. This study explores the identification of the crisis and its severity level in the DHW consumption data and the corresponding control actions necessary to mitigate its impact. To identify crisis severity, we utilised the mobility data of retail/recreation activities and transit stations, making the results generalisable for any crisis. In addition, we used power consumption for DHW preparation data from 10 residential apartment buildings located in Kaunas city to develop a machine learning-based hybrid ensembling stacking classifier (ESC) capable of predicting the crisis and its severity level. Finally, we applied principal component analysis (PCA) and k-means clustering to categorise DHW consumption hours throughout the day for each severity level. The results showed that the developed ESC classifier significantly outperforms ($R^2 = 0.99$) the baseline LGBMC classifier ($R^2 = 0.92$). Combining the classifier with extracted daily consumption patterns and clusters allows the optimisation of control actions on the supply, distribution, and demand side of the DHW system.

1. Introduction

With increasing global temperatures, the need to optimise energy use and reduce carbon emissions from energy generation has become critical [1]. Ensuring energy is used efficiently, produced and delivered precisely when and where it is needed is one of the key aspects of tackling climate change [2]. Given that producing certain types of energy for end users is often an inert process, it is necessary to anticipate the energy demand in advance. For example, building heating energy consumption can be predicted using its strong correlation with weather patterns [3]. In contrast, domestic hot water (DHW) demand is a highly stochastic process [4], which is strongly dependent on user behaviour, making it a compelling area for further research. In addition, fluctuations in hot water consumption can reveal changes in factors such as population density and occupancy, which, in turn, may signal changes in urban use patterns [5]. The share of thermal energy used to prepare domestic hot water accounts for a significant portion of the thermal energy consumed by households. According to the Lithuanian Data Agency, between 2009 and 2018 this share increased from 10.4 % to 18.6 % of the total thermal energy [6].

DHW systems are vulnerable to various crises triggered by different factors, such as natural disasters, pandemics, or economic downturns. For example, during the COVID-19 pandemic, many people had to switch to home offices, leading to significant changes in domestic water use [7]. However, to apply targeted control actions, it is important to identify the crisis and determine its severity level. In some cases, it might be beneficial to adjust control measures aiming for comfort or economic benefits; in others, it might even be necessary to prioritise certain areas over others to maintain service levels [8].

Identifying the change in energy consumption patterns is also economically significant for consumers, as the energy market is not fixed [9] and can offer more favourable rates during certain periods. To make

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use of that, the DHW control systems should be adjusted to account for current consumption patterns in relation to the energy price. For example, by combining energy demand forecasts with energy storage solutions [10], a more sustainable consumption model can be achieved. Similarly, hot water production, supported by mature technologies, can integrate energy storage with renewable energy sources [11].

To improve the accuracy of hot water demand forecasts under crisis conditions, it is essential to identify factors that signal potential changes in DHW usage. In previous studies, the number of daily cases of COVID-19 was used as a factor [12]. However, such input data highly limit the applicability of the study to a specific pandemic event. In contrast, factors such as variation in mobility within urban areas allow the identification of various crises that result in urban mobility change.

Reduced mobility flows suggest that more people are spending time at home, which in turn increases the hot water demand for activities like household chores, cooking, and personal hygiene. Under normal conditions, these fluctuations can be observed across different times of the year (e.g., school versus non-school periods) and different days of the week (e.g., weekdays versus weekends). A notable example occurred during the COVID-19 pandemic, when significant shifts in mobility were observed over a relatively short period [12]. Therefore, data from the COVID-19 pandemic period can serve as input in training forecasting models to identify different modes of DHW system operation.

Given the importance of accurately predicting and adapting to DHW consumption patterns, multiple stakeholders are affected by these variations. Understanding how changes in hot water usage influence different sectors underscores the need for comprehensive analysis and data-driven decision-making. The following points highlight the key stakeholders affected by the fluctuations in DHW demand.

- **Energy and water utilities providers:** Accurate DHW consumption patterns are essential to optimise water distribution and energy supply planning. Sudden usage changes, such as those caused by lockdowns, can affect demand forecasting and operational efficiency.
- **Policy makers:** Understanding variations in DHW usage helps inform policies related to energy efficiency, water conservation, and crisis response planning. This is particularly relevant for regions transitioning to renewable energy sources.
- **Building engineers and facility managers:** Detailed insights into DHW demand fluctuations enable better system optimisation, predictive control, and efficient scheduling to reduce energy waste and improve system performance.
- **Real estate developers:** Data on DHW consumption trends can inform sustainable building design, ensuring that infrastructure adapts to both normal conditions and crisis scenarios.
- **Manufacturers of DHW systems:** Insights from consumption pattern changes can guide the development of more adaptive, energy-efficient DHW systems, improving their responsiveness to varying demand levels.
- **The research community and energy planners:** Integration of demand patterns in energy planning, particularly for renewable-based DHW systems, is crucial to optimise resource allocation and ensure grid stability. In regions where solar thermal or heat pump systems are predominant, understanding peak demand shifts is critical for energy storage and distribution strategies.

In this study, we employ Community Mobility Reports [13] data collected by Google on retail/recreation and transit stations to categorise the crisis severity levels. Further, we develop a hybrid ensembling stacking classifier (ESC) that can predict the crisis and its severity level based on DHW consumption data collected from 10 residential apartment buildings located in Kaunas, Lithuania. Finally, we perform PCA using the mean and STD values of hourly DHW consumption for each severity level and cluster them using the k-means algorithm. The proposed method combines predictive modelling and consumption patterns extraction to enable targeted control actions in distinct parts of the DHW system, aiming for more resilient and efficient systems.

The main novelty of this work can be attributed to the following points. First, it addresses an often overlooked aspect of DHW consumption by focussing on crisis identification and predicting the severity of these events, which is typically challenging due to the unpredictable nature of user behaviour. Secondly, it incorporates mobility data from retail, recreation, and transit stations, allowing the model to become adaptable to various crises and making it applicable to broader contexts beyond just energy management. Third, the study introduces a new classification approach (a hybrid ensembling stacking classifier (ESC)) that performs significantly better than standard models, achieving high levels of accuracy in crisis and its severity level prediction. Fourth, using techniques such as PCA and k-means clustering enables categorisation of energy usage patterns, allowing targeted control actions for DHW systems supply, distribution and demand side management.

This article is structured as follows. Section 2 presents the previous work done on the power consumption for DHW preparation forecasting and identification of changes in daily consumption patterns during crisis conditions. Section 3 introduces the case study building and data used in this research. Section 4 provides all the information required to reproduce the results presented in this article, including the methods for crisis and severity levels forecasting, daily DHW consumption petterns identification, and consumption hours clustering. Section 5 explores the results obtained from the analysis and discuss their application for DHW control enhancement. Section 6 concludes the work and Section 7 offers recommendations for areas of future research.

2. State of the art

The COVID-19 pandemic impacted several industries, and the energy sector was no exception. The study of crisis severity in DHW consumption mirrors broader pandemic-driven research, including the prediction of healthcare needs [14] or the public sentiment of COVID-19 [15], highlighting the importance of data-driven approaches in addressing global health challenges. In most European countries, a state of emergency was declared in March 2020 and lasted several months thereafter, with a stricter period of lockdown observed from mid-March 2020 through April 2020 [16–18]. One of the most notable effects was the transition to working from home, which decreased industrial energy consumption but increased residential/domestic consumption in some countries [19]. Several researchers took to analysing the effect of the pandemic on energy demand within European countries [20,21] and other nations such as Canada [16,19], Brazil [22], the USA [23], among others [19,24].

Rayash et al. [16], for example, performed a comprehensive analysis of the hourly energy demand for the province of Ontario, Canada, for April pre-COVID (2019) and during COVID (2020) with the assumption that the heating energy data are equivalent to the electrical load. The results proved that the pandemic impacted electricity demand, with a total decrease of 14 % and a further reduction in demand over the weekend, reaching 15–25 %. In addition, the researchers found that the electricity demand during 2019 increased throughout the week but decreased over the weekend, while in 2020, the peak would be reached by midweek and decline throughout the rest of the week [16].

Similarly, Rouleu et al. [25] analysed the impact of the COVID-19 pandemic on energy consumption, not only considering electricity, but also taking into account hot water and space heating. The case study was conducted on a 40-unit apartment building in Quebec City, which relies on a district heating hot water loop that provides heat to the building and uses natural ventilation during the hot months. The authors found that the peak hot water consumption was reached at 7 PM in the control period. In contrast, in the COVID period, the peak was reached in the afternoon hours with an increase 103 %, indicating that the lockdown period during the pandemic influenced the hot water consumption pattern [25].

Researchers in Qatar [24] used machine learning techniques to compare the actual usage of electricity and the simulated usage of electricity, then used these data to predict energy consumption in the years 2021 and 2022. The pandemic was found to have a negative effect on electricity consumption in the residential sector in that it increased during the pandemic due to the stay-at-home policy. Electricity is free for Qatari citizens and the application of charges to it could decrease the demand for energy in domestic areas and curb the effects of crises on the energy sector. By analysing the effects of a crisis such as the COVID-19 pandemic, researchers and policy makers can predict, similarly to the work of Abulibdeh et al. [24], energy consumption patterns and better prepare for future disruptions.

Nepal et al. [26] analysed building electricity data using the K-means approach; instead of randomly selected centroids, the researchers chose initial centroids based on the hourly distribution of electricity data for one year. The percentile method was used to select the initial centroids, where the cumulative density was divided into $(k + 2)$ equally separated percentiles (k being the number of clusters). The results showed that the patterns among the six buildings analysed were similar, with an increase during the day and a decrease in electricity consumption at night. The author determined the accuracy of the proposed method by applying the methodology on four different real-world data sets and found that the technique resulted in much higher accuracy than the randomly selected centroid for K-means clustering.

To understand the full impact of the crisis, it is necessary to investigate all aspects of energy consumption. DHW usage is often overlooked due to its stochastic nature and high dependency on user behaviour [25]. However, neglecting this aspect can lead to inaccurate energy management strategies.

2.1. Power consumption for domestic hot water preparation daily patterns prediction

Several factors, including geographic location, outdoor conditions, indoor conditions, number of occupants, and occupant behaviour, influence DHW use. In other cases, these factors can extend to cultural behaviour or socioeconomic behaviour [27–29]. Moreover, as described in the literature, advanced forecasting methods can provide useful insights for improving the management of DHW systems, aiding in the prediction of crisis severity and enhancing the allocation of energy resources in residential settings [30–32]. In residential buildings, DHW accounts for 14–25 % of total energy consumption [4,12,28,33]. Typically, daily DHW patterns have two peaks in the morning and evening [28], which are largely contributed by the fact that occupants either go to school or work in the morning and then return around the evening to continue domestic activities such as showering and cooking. In the design process, most of these peaks are often estimated values. Empirical models are a common method for estimating DHW demands, where, as an example, standards like EN 12831-3 provide equations based on per capita water consumption and system efficiency factors [28] to determine the demand. Indicators of the DHW system in the design stage, such as peak power and thermal energy demand, can be determined using relevant standards [34]. However, dynamic simulations should be used more as they offer more details by incorporating several elements, aside from the theory-based calculations as shown by Rashad et al. [35] through the use of TRNSYS for analysing energy demand.

Understanding peak power consumption from DHW usage is important in predicting the impact of crises conditions on daily patterns. However, owing to the various factors influencing peak power demand, the DHW systems are often not designed to meet the requirements of such fluctuating needs, which usually leads to inefficiencies, increased operational costs or system failures, especially in multiple occupancy buildings such as apartments. As discussed in the review by Fuentes et al. [28], most DHW systems are designed based on standards and not real data, and as such, many systems are often oversized or undersized. Several modelling tools [36] are used in designing DHW systems with consideration of occupancy and usage patterns through representative days; however, this approach doesn't take into account the dynamic nature of water consumption. Amanowicz [37] highlights the need to be attentive to peak power selection, which, as the author describes, affects cost, size and efficiency of DHW systems. The author used three different methods to analyse peak power consumption and found that the method with the highest confidence of results is the Sander's method which uses hot water volume flowing from the water device, temperature of water and time use to determine energy requirements. Rubina et al. [38] emphasized the importance of understanding peak water flow rates in the design of DHW systems, which also influences factors like pipe design. The authors used a new empirical calculation of the water flow estimation and compared actual water flows with the new design water flow values and found that the method resulted in a reduction in energy demands for water heating, as well as a reduction in pipe size, which ultimately reduces the cost of manufacturing.

User behaviour plays an important role in power consumption of DHW, and generally, this criteria is not considered fully in the design of the systems and as such would affect the prediction of hot water usage in crisis or non-crisis conditions. Hansen et al. [39] conducted an interesting study to determine how occupation, age, income, and other can affect the peak power usage of a building. It was found that households with white-collar workers had higher morning peaks, whereas pensioners' homes had lower and later peaks. Households with ages 41–50 years had higher morning peaks with 4.5 kWh in the 7th hour, whereas age groups 18–40 years and 51–60 years had a lower power consumption with 4 kWh in the 7th hour as well. High-income households exhibited higher consumption in the morning and evening peaks, whereas lower-income groups presented much flatter peaks. These results indicate that peak power consumption is affected by occupants and their behaviour, and as such, it should also be considered in design and management of utilities.

Cao et al. [33] predicted hot water demand using seven occupants' hot water usage behaviour by collecting shower data. The researchers trained the data using the Support Vector Machine (SVM), a data mining technology, to analyse the showering habits of the occupants. They found that it was possible to predict the hot water usage and implement a hot water supply strategy. However, this predictive model achieved a root mean square error (RSME) of 77.63 when the shower habits of the occupants were analysed individually versus the RSME value of 58.65 when the data were aggregated, which led the researchers to conclude that a separate analysis provided better accuracy. The researchers also note that the different choice of evaluation criteria is the main reason for this difference.

To form more accurate predictive models of DHW consumption, it is necessary to perform an extensive data review when analysing larger data sets to remove any outliers. Sonnekalb et al. [40] used neural networks and Gaussian processes to evaluate data sets to learn and predict human behaviour concerning DHW to adapt heating times to reduce energy consumption. The initial data for the hot water preparation were presented in minutes; therefore, data pre-processing was necessary to convert the data into hourly intervals and add other specific features. Incomplete data sets were eliminated and the results showed that it would be possible to reduce the window of hot water preparation, thus reducing the energy consumption of hot water preparation by up to 33–85 %.

Maltais et al. [4,41] used model predictive control (MPC) relying on data provided by neural networks that were trained from real data for the energy management of DHW for single-family residential units. It was found that the long-term predictions from machine learning models can show higher inaccuracies compared to the theoretical approach [4]. However, these models can still be used to predict DHW demand, and if used together with a storage tank, where the MPC is inaccurate, a supply would still be present to meet the demand. The author also suggested that prediction inaccuracies are reduced by increasing the time interval to 2 h.

Clustering is not limited to analysing building electricity data, as mentioned earlier. Ritchie et al. [42] used clustering and statistical analysis to model DHW usage. The researchers created clusters and sub-clusters of time, volume, and flow rates, and the generated model determined the probability of occurrence of these clusters over the specific distribution. The model showed high accuracy compared to the measured data. With that in mind, the authors proposed that the model could be used for energy management strategies as the energy drawn from the grid can be predicted.

DHW forecasting models can potentially optimise system control, leading to energy savings and economic benefits. However, developing robust models that can account for the stochastic nature of user behaviour and disruptive events remains a challenge. Therefore, training these models to recognise and respond to crises is crucial.

2.2. Changes in daily patterns during crisis conditions

A national or global crisis can occur at any moment. Recessions, pandemics, or natural disasters are all examples of crises. Policymakers and governments can learn from crises such as the COVID-19 pandemic and better prepare by creating forecasting and prevention strategies in various disciplines to mitigate future disasters [43]. Generally, energy consumption during the COVID-19 pandemic saw a change in daily patterns. The prepandemic conditions had a peak energy consumption in the morning hours of the weekday and significantly lower values on weekends; however, during the pandemic, no typical morning peaks were observed, and the energy consumption was lower [17].

Zhang et al. [20] simulated the impact of the COVID-19 pandemic on energy demand in a building matrix in Sweden using the UMI tool. The buildings were divided according to their archetype, where occupancy and DHW, among other parameters, were considered. The researchers showed that the average system energy demand, which includes heating, cooling, and domestic water, decreases in a range of 7.1 % to 12.0 %. It was also concluded that increasing confinement constraints increase the DHW energy demand in residential buildings; however, less heating is required due to greater internal heat gains [20].

Kim et al. [12] analysed real data from an apartment complex in South Korea to determine changes in DHW demand during the pandemic. Unlike most European countries, the state of emergency in Korea was issued on 20 January (2020), almost two months before it was issued in Europe. Data were collected at hourly intervals and included DHW accumulated energy, flow rate, supply temperature, outdoor temperature, and city water temperature. The analysis identified a significant increase in DHW demand after the pandemic, which is due to changes in the daily consumption patterns of the occupants as a result of the stay-at-home policy, similar to what was identified by Rouleu et al. [25].

Abu-Bakar et al. [44] used clustering to determine the impact of the COVID-19 pandemic on water consumption patterns in England. The patterns were divided into four clusters: the evening peak, the late morning, the early morning, and multiple peaks, which were identified using the “elbow” method. The researchers found that there was an increase in water demand in each of the clusters during the lockdown period defined as January to May 2020. Using K-means clustering from May 2019 to October 2020 (considering workdays, weekends, and holidays), Dziminska et al. [45] revealed that the patterns obtained for three different buildings were similar, differing only in volume of water consumption in a given hour. A change in the morning and evening peak is observed, with a shift of about two hours later in the morning hours and about two hours earlier during the night. There is also increased usage during the afternoon.

2.3. Identified challenges in managing DHW consumption under crisis conditions

The state-of-the-art review revealed that recent research has addressed changes in energy consumption patterns, including crises such as the COVID-19 pandemic, which significantly altered daily routines and subsequently affected residential energy use. Studies have demonstrated how mobility restrictions during lockdowns influenced DHW demand and other utilities, noting shifts in peak consumption times and increased residential demand due to stay-at-home policies. In particular, researchers have used machine learning techniques to predict energy consumption and categorise usage patterns, integrating data from both environmental factors and user behaviour. However, several gaps remain unaddressed:

- **DHW demand analysis under crisis conditions.** While various studies have explored general energy consumption during the pandemic, few have focused specifically on DHW demand [16,24,26]. DHW consumption is highly variable and user dependent, making it challenging to manage, especially in crisis conditions [25]. More research is needed to identify the change in DHW consumption daily patterns during crisis and segregate them based on the severity level.
- **Model generalisability to various crises.** Existing studies often rely on specific data related to pandemics, such as COVID-19 case counts, limiting their applicability to similar crises [12]. This reduces the generalisability of the prediction models to other crisis scenarios. There is a need for models that can leverage broader indicators, such as urban mobility data.
- **Control optimisation based on crisis severity level.** Current models focus on forecasting energy demand [30–32], but further discussion on targeted control actions based on the results is lacking. Effective crisis management in energy systems should include dynamic control strategies that respond to predicted changes in demand, particularly considering the intermittent nature of renewable energy sources [35].

3. Case study introduction

3.1. Case study buildings

Ten residential apartment buildings in Kaunas (Lithuania) were selected as a case study (Fig. 1). The urban block has clear boundaries of intensive streets and natural elements. It contains multi-flat housing built from the 1960s to the late 1980s, accommodating diverse social groups. Several multi-flat residential buildings have been modernised by increasing the thermal resistance of the building envelope and applying autonomous room temperature control. The basic description of building service systems is as follows.

- **Heating system.** Buildings are heated by thermal energy supplied through a centralised district heating (DH) network operated by the city’s thermal energy provider. The DH network in Kaunas city covers all the major populated areas. For all buildings, the thermal energy supply for heating is regulated according to the outdoor temperature by a sensor.
- **Water system.** The cold water supply and sewerage systems follow the same principle, i.e. district (centralised) supply and disposal by the city’s water services provider. Hot water is prepared within the

Fig. 1. Arrangement of selected multi-flat residential buildings.

Table 1
Characteristics of selected multi-flat residential buildings.

Building no.	Useful area (m^2)	Number of apartments	Average apartment area (m^2)	Number of taps	Number of occupants
92	1042	32	32.6	64	32
90	1524	32	47.6	64	44
89	891	18	49.5	36	26
88	1511	32	47.2	64	44
87	812	18	45.1	36	23
86	1416	32	44.3	64	41
82	1517	32	47.4	64	44
80	1530	32	47.8	64	44
79	1423	87	16.4	87	87
75	1400	86	16.3	86	86

building's heating unit, heated through a dedicated heat exchanger, and distributed throughout the building's hot water network for consumption. Since the buildings contain many flats, location and distance between the pipelines are significant factors. To address this, recirculation loops are installed in the system. These parallel and additional pipelines, along with the recirculation pump and other necessary equipment, continuously circulate hot water through the system to ensure a timely hot water supply at the most inconvenient (furthest) point (tap) from the heat exchanger. Hot water is prepared using the same thermal energy sourced from the DH system at the building's heating distribution plant. All buildings are equipped with instantaneous domestic hot water heat exchangers, without storage tanks. The principal schemes of the system are defined by the energy provider [46].

The useful (heated) area of the buildings varies from 812 m^2 to 1795 m^2, which corresponds to between 18 and 87 apartments with corridors and basement spaces. The number of occupants ranges from 23 to 87 and the number of taps for food processing and hygiene activities ranges from 26 to 87 (Table 1). The information provided is based on data from the State Enterprise Centre of Registers information system [47].

3.2. Building data description

Data on energy consumption for hot water preparation and maintenance have been collected from separate smart metres, which are installed in the heat distribution plants of buildings and measure the thermal energy consumption at 1-h intervals. In addition, smart metres measure the temperature of the inlet and outlet heat agents and the flow rate. The data collection period for pilot case buildings ranges from 2 to 10 years between 2011-10-01 and 2021-09-30. The whole set consists of 480,580 entries (timestamps) of thermal energy for hot water measured in kWh.

Data were retrieved from smart metres in the CSV (Comma Separated Values) data format. Subsequently, it had to be treated accordingly by filtering, cleaning, aggregating, and interpolating. To ensure data comparability for objective evaluation and analysis, normalisation was applied based on the most significant influencing factor: the number of occupants. By dividing the energy consumption for hot water preparation by the number of occupants (Table 1), a derived unit of kWh/occupant is obtained, eliminating the influence of building size.

Fig. 2 shows the normalised daily thermal energy consumption for DHW preparation. The data collected from all buildings and used for this analysis span from 01/01/2018 to 30/09/2021. The vertical red transparent bars mark the lockdown periods: the first from 16/03/2020 to 16/06/2020, and the second from 7/11/2020 to 30/06/2021. The green vertical bars indicate the corresponding periods prior to the lockdowns. The blue curve represents the total daily energy consumption, while the orange curve shows the average monthly daily energy consumption, highlighting a clear seasonal trend.

The increase in energy consumption during the heating season can be attributed to the lower temperature of cold water, as more thermal energy is required to reach the hot water set-point temperature, i.e. 55 °C. In addition, occupant consumption habits and the recirculating hot water loop contribute to higher energy demand during the heating season due to a slight decrease in indoor temperature. During the heating season, the indoor temperature tends to be lower than during the non-heating season period, which increases the heat loss to the environment from the circulating hot water loop pipes and thus the energy demand, even though the hot water loop is used continuously. Comparing the same periods before and during lockdown, the plot does not indicate significant differences in energy consumption. However, there are recurring outliers with values of 0 or significantly lower values during the warm season. This is likely due to the annual maintenance of the building's heating and hot water systems when they are temporarily shut down.

3.3. Mobility data description

In response to the COVID-19 pandemic, Google developed Community Mobility Reports [13] to provide public health officials with aggregated anonymised mobility data for informed critical decision making. These reports tracked movement trends across various geographic regions and categories, including retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential areas.

In this study, data specific to Kaunas city were extracted and analysed, with a focus on changes in mobility patterns in response to COVID-19 related policies. Changes were examined in two key categories: retail and recreation activities (including places such as restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres) and transit station activities (encompassing public transport hubs such as bus stations). The categories of retail recreation and transit stations were chosen due to their significant impact on urban mobility and public behaviour during the COVID-19 pandemic. Retail and recreation activities serve as key indicators of economic activity and social interaction, reflecting changes in consumer behaviour and adherence to public health measures such as lockdowns or social distancing guidelines. Meanwhile, transit station activities provide critical insights into public transport usage, which is directly correlated with mobility patterns, access to essential services, and the broader functioning of the urban economy. By concentrating on these two categories, the study aimed to capture the most influential aspects of daily life in Kaunas affected by COVID-19 related policies. The data, provided in the form of time series, span from February 2020 to December 2021.

Mobility data, including the categories of retail / recreational and transit stations from Google mobility reports, clearly indicates the start of both lockdown periods in Kaunas, Lithuania, during the COVID-19 pandemic (Fig. 3). The percentage change from baseline, depicted in the graph, highlights the sharp declines in mobility corresponding to the onset of the first and second lockdown periods. These lockdown periods are reflected in the different severity levels of restrictions, represented by colour-coded bands ranging from baseline (normal activity) to severity 5 (the most stringent restrictions). The data show that mobility decreased significantly at the beginning of the pandemic, especially

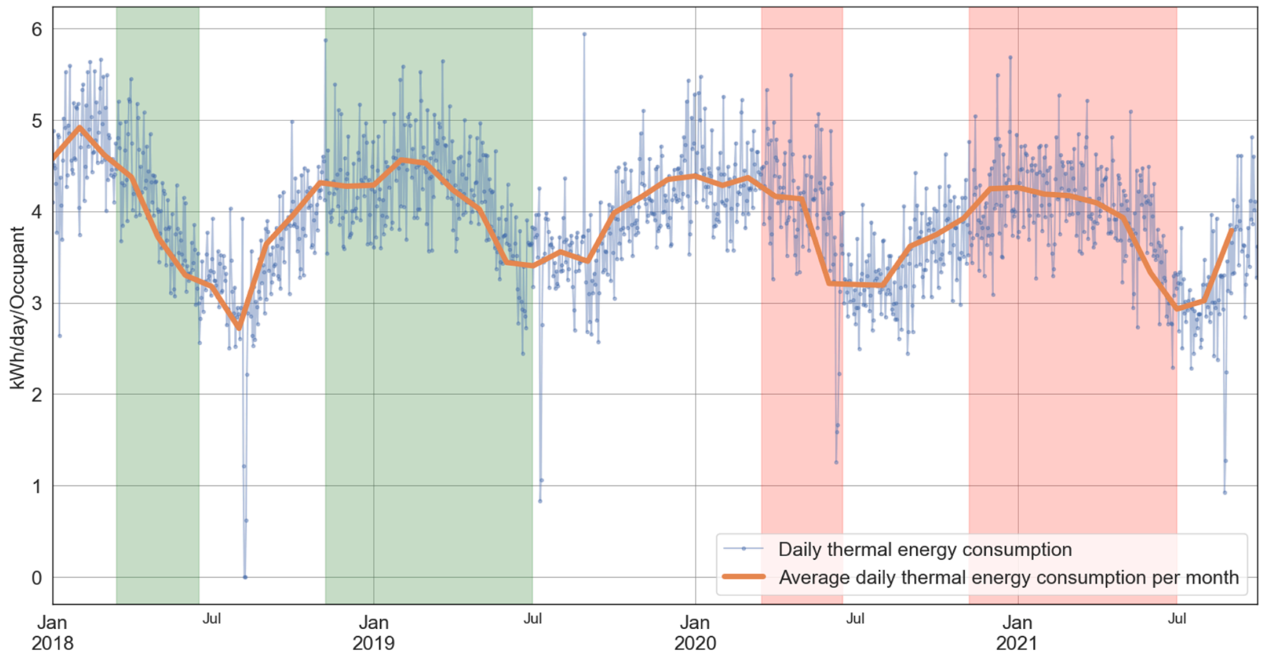

Fig. 2. Normalised daily thermal energy consumption for domestic hot water preparation.

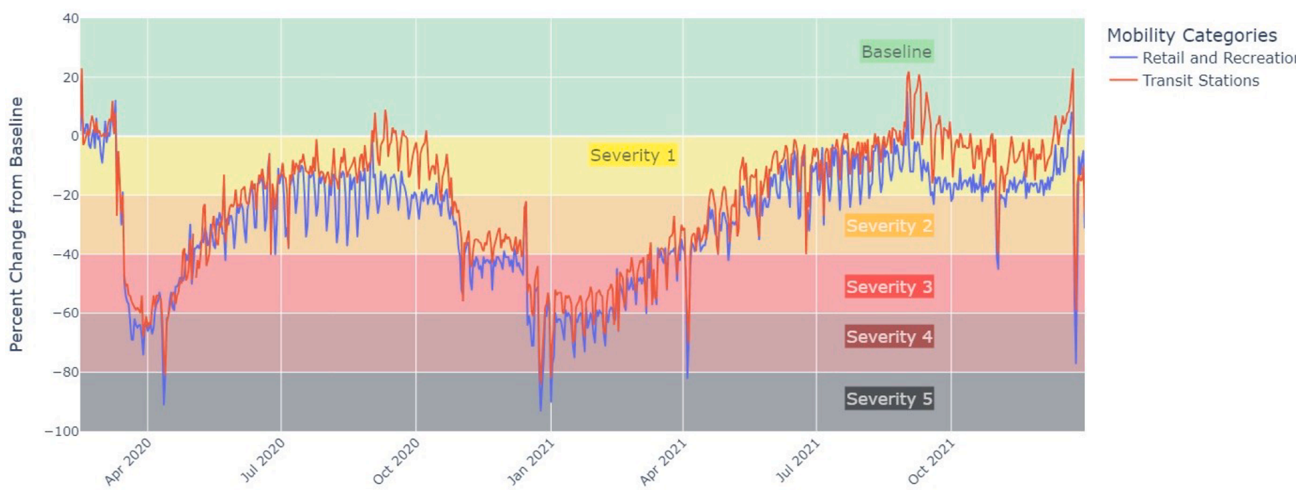

Fig. 3. Mobility changes in retail/recreation activities and transit stations in relation to crisis severity levels.

during the strictest lockdown phases, before gradually recovering in line with the easing of restrictions. However, mobility levels remained below baseline throughout the study period, indicating a prolonged impact of the pandemic on public activity, particularly in transit and recreational spaces. The extraction of the Severity levels are further detailed in the Methodology section.

4. Methodology

The overall research approach is illustrated in Fig. 4. It consists of three main parts: data collection and preparation, crisis and severity forecasting, and pattern extraction and clustering. The first part involves data from two main sources: 10 case study buildings in Kaunas (Lithuania) and Google Community Mobility Reports [13]. In this phase, the building data undergo the usual data cleaning, normalisation, and pre-processing steps. Crisis severity levels are extracted from the datasets on retail/leisure activity and transit stations collected in the Google Community Reports. Finally, the pre-processed data are merged into a single dataset that includes additional temporal features.

In the next phase, the ESC classifier is used to forecast the crisis and its severity level. The forecasting model is further cross-validated to ensure its reliability and accuracy.Further, daily DHW consumption patterns are extracted for each of the crisis severity levels. Additionally, PCA and k-means clustering are used to define the clusters of daily consumption hours.

The results of forecasting, pattern extraction and clustering acts as an input for DHW systems control optimisation. Each part of the methodology is further detailed in this chapter.

4.1. Data collection and preparation

4.1.1. Calculation of hot water consumption

The collected raw data pertain the amount of thermal energy used for hot water preparation. However, to determine the distinct hot water consumption patterns, the DHW consumption data are needed. The main factor determining the amount of thermal energy is the temperature of the cold water to be heated, which varies throughout the year due to the changing temperature of the outdoor air. However, the cold water temperature variation is significantly influenced by the thermal inertia

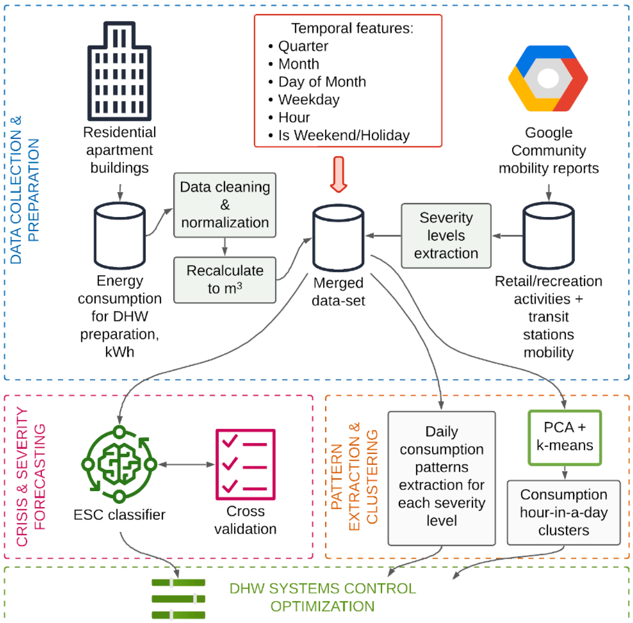

Fig. 4. Research approach.

of the ground (soil), as the supply pipelines are laid at a depth of at least 1,8 m underground to prevent freezing during the coldest periods of winter. The average depth of the pipelines in Kaunas varies between 2 and 2.5 m.

Kaunas (central Lithuania) is in the cold-temperature zone, with moderately warm summers and cold winters. The city of Kaunas has an average long-term outdoor temperature of around 7–8 °C. The average outdoor temperature in July is around 17 °C, and in winter around −5 °C. Lithuania has relatively hot summers, daytime highs above +35 °C, and cold winters, with nighttime lows below −30 °C.

Therefore, the amount of hot water consumed V_{hw}, m^3 knowing the thermal energy consumed Q_{hw}, J was calculated using Eq. (1).

$$V_{\rm hw} = \frac{Q_{\rm hw}}{C_v \cdot (\theta_{\rm hw} - \theta_{\rm cw})} \tag{1}$$

where:

- C_v is the volumetric heat capacity of the water. The standard value is $4,160,000\,\mathrm{J/(m^3\,°C)}$.
- θ_{hw} is the standardised hot water temperature (°C). A temperature of 55 °C should be maintained, considering the Building Regulations' requirements.
- θ_{cw} is the supplied cold water temperature (°C), which varies between 4 °C and 16 °C over the year.

The cold water temperature in the network throughout the year is determined based on the average daily outdoor temperature. To take into account the thermal inertia of the soil, i.e. the variation in outdoor temperature, which is normally most significant over 24 h, a moving average method was adopted. The relationship between the cold water temperature and the moving average outdoor temperature is based on the cold water temperature measurements declared by the provider, where a lower limit of −4 °C water temperature corresponds to an outdoor temperature of −20 °C and an upper boundary of −16 °C corresponds to +25 °C. The cold water and outdoor air temperature measurements were used to apply a linear regression method and derive the Eq. (2).

$$\theta_{cw} = \theta_{out} \cdot 0.2667 + 9.3333 \tag{2}$$

where:

- θ_{out} is the 24-h moving average of daily outdoor temperature, °C.

Table 2
Lockdown severity characterization based on mobility changes (Kaunas).

Labels	Description
Baseline	Percentage change equal or greater than 0
Severity1	Percentage change between −1 % and −20 %
Severity2	Percentage change between −20 % and −40 %
Severity3	Percentage change between −40 % and −60 %
Severity4	Percentage change between −60 % and −80 %
Severity5	Percentage change between −80 % and −100 %

Fig. 5 shows the variation of the cold water temperature in the supply networks according to the fluctuation of the outdoor air temperature. The results are plotted for the period, starting from 2016 to the end of September 2021.

4.1.2. Characterisation of severity based on local mobility patterns

Google mobility data include percentage changes measured against a baseline that represents typical mobility levels before the COVID-19 pandemic. Using predefined thresholds, a characterisation scheme was implemented for these deviations to illustrate the varying levels of departure from baseline mobility patterns (Table 2):

- If the mobility change for retail/recreation and transit stations was the same, this value was assigned to the subsequent label.
- If the mobility change differed, only the mobility change value for retail/recreation was used as the subsequent label.

The Google mobility data begins in February 2020, while the water usage volume data begins in February 2019. Hence, all data points for 2019 were labelled with the "Baseline" label to distinguish the pre-COVID-19 period when mobility patterns were unaffected by lockdowns.

This characterisation determines the severity of COVID-19 lockdowns and the general restrictions imposed on local residents. The "Baseline" label represents normal conditions, i.e. indicating the pre-COVID level of mobility. In contrast, severity levels (Severity 1 through Severity 5) denote increasing levels of restricted mobility correlating with the intensity of lockdown measures and other restrictions in the urban area of Kaunas. Although mobility changes are recorded daily, the characterisations were applied to represent conditions for all subsequent hours of each day. Fig. 6 shows an aggregated view of the hourly counts of COVID-19 quarantine severity levels impacting mobility data for each month from January 2020 to May 2021. It is highlighted that there is a clear rise in hours characterised as more severe in terms of the lockdown effect, particularly in April 2020 and December 2020, where the most instances of Severity 5 are recorded, which is in line with the historical timeline of the austerity of the lockdown measures.

4.1.3. Combined dataset and feature extraction

Following the characterisation scheme for each timestamp described in Section 4.1.2, the resulting hourly labels were merged with the hourly domestic water volume intake data. Consequently, the combined data set spans from February 6, 2019, to September 29, 2021, for each building.

The domestic water volume intake data for each of the ten buildings (as described in Section 4.1.1) were sequentially combined into a single dataset. Using the characterisation scheme outlined in Section 4.1.2 for each timestamp, the resulting hourly labels were merged concurrently with the corresponding water intake data.

For the analysed dataset, time was incorporated as a feature by splitting the timestamp into categorical values to create additional temporal features. In addition to standard temporal features, such as the hour of the day, day of the week, and month, specific features were synthesised based on the unique characteristics of our dataset, reflecting the location of the case study. Lithuanian holiday data for 2019 to 2021 were included using the 'holiday' Python library. An additional feature

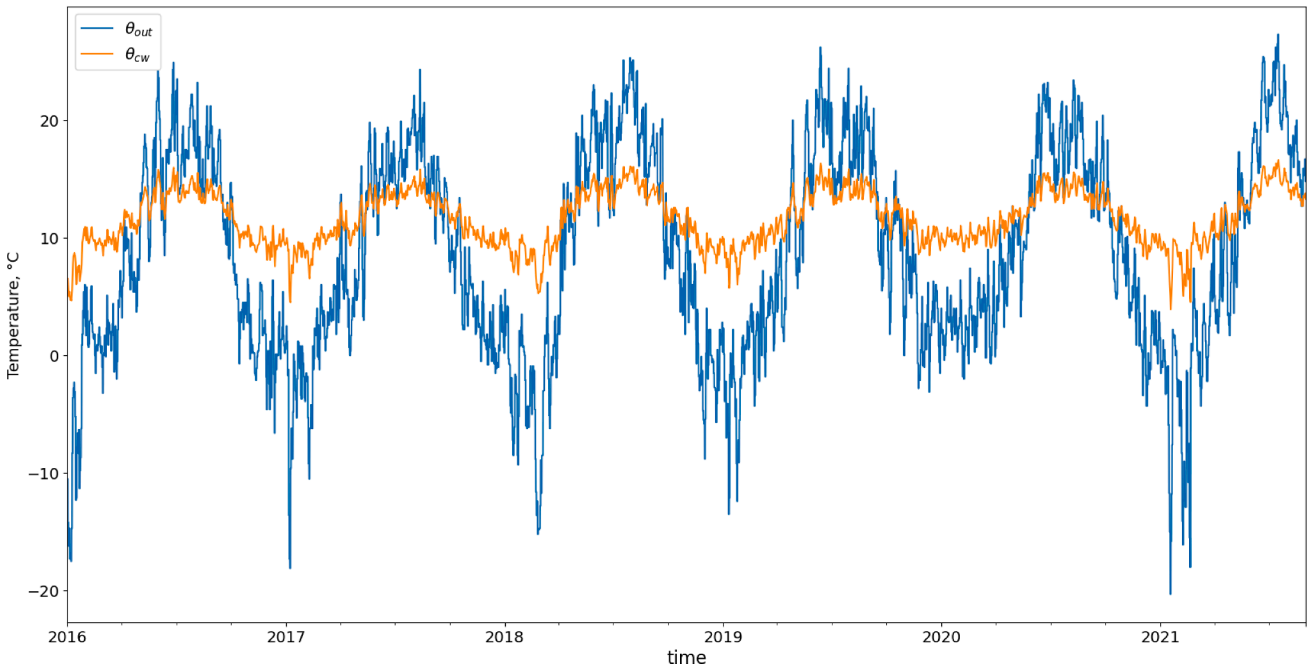

Fig. 5. Relationship between outdoor air temperature and cold water temperature in supply networks.

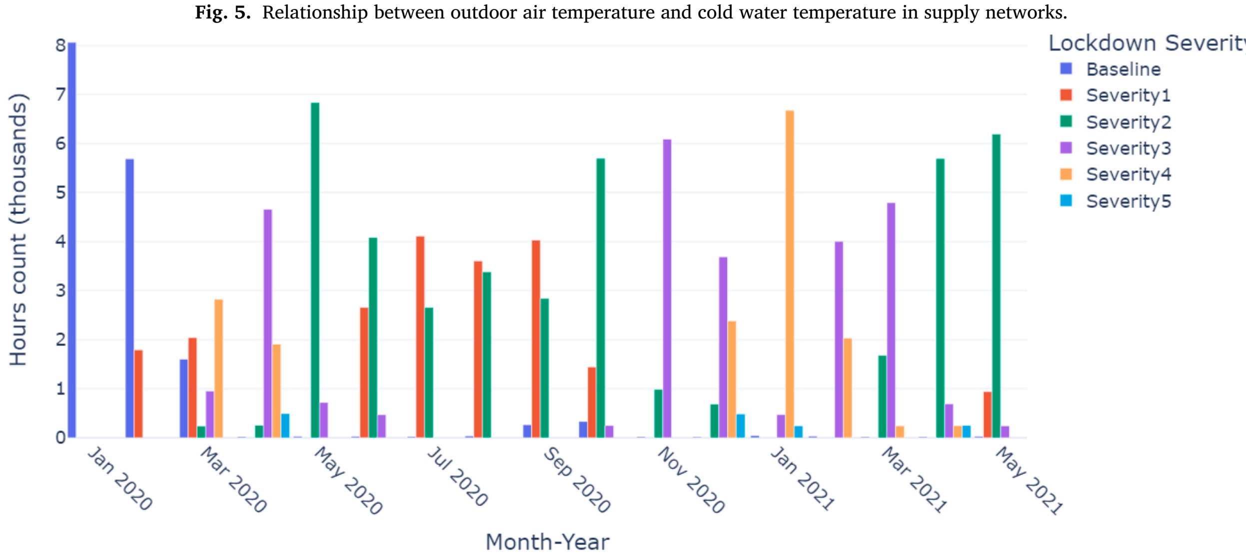

Fig. 6. Quarantine severity characteristic instances (hourly count).

Table 3
Predictive modelling: features description.

Feature	Labelling
lockdSeverity	Baseline: 0, Severity1: 1,…Severity5: 5
W_vol	Water intake for each building (m^3)
Quarter	1 to 4
Month	1 to 12
DayofMonth	1 to 31
Weekday	0 to 6
Hour	0 to 23
IsWknd_Holiday	0, 1

(IsWknd_Holiday) was created to identify whether a given date falls on a Saturday or Sunday and coincides with any Lithuanian holiday.

An outlier detection strategy was applied to the water volume data, identifying values above the 99.99th percentile for each of the ten buildings and replacing them with the maximum value corresponding to this percentile.

The final data set for the ESC forecast was divided into training and test sets, with 80 % training and 20 % for testing [48].

4.2. Crisis and severity forecasting

4.2.1. Predictive modelling of lockdown-type emergencies

As indicated in the relevant literature, the COVID-19 lockdown and its consequences on daily routines directly affected residents' energy and hot water consumption patterns. Therefore, it has become critical to identify such abrupt future emergencies so that utility providers can make immediate adjustments and preparations to ensure that no severe disruptions occur for tenants.

In this study, a data-driven pattern recognition mechanism was developed to identify potential future irregularities in residential water demand under unforeseen circumstances resembling a lockdown event, such as the post-COVID-19 period. Using severity level labels, a machine learning-based classifier was created to predict whether such an emergency might be imminent and, if so, to estimate the expected severity of the situation. To achieve this, a hybrid ensemble stacking classifier (ESC) was implemented. This meta-ensemble learning model combines the strengths of multiple individual classifiers through a two-level stacking approach, enhancing predictive accuracy for irregular demand patterns.

The first layer consists of two base classifiers: LGBMClassifier (LGBMC) and HistGradientBoostingClassifier (HGBC). The LGBMC classifier optimises the following objective function:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, f(x_i; \theta)) + \Omega(f) \tag{3}$$

where:

– $L(\theta)$ is the overall loss function.
– l is the loss function.
– y_i is the true label.
– $f(x_i; \theta)$ is the predicted value.
– $\Omega(f)$ is the regularisation term to avoid overfitting.

HistGradientBoostingClassifier uses the gradient boosting framework:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \tag{4}$$

where:

– $F_m(x)$ is the current model at iteration m.
– $F_{m-1}(x)$ is the previous model.
– γ_m is the learning rate.
– $h_m(x)$ is the base learner at iteration m.

The second layer, the meta-learner, integrates the output from the base-level classifiers. The meta-learner chosen is XGBClassifier (XGBC). The XGBoost classifier can be formulated as follows:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, f(x_i; \theta)) + \sum_{k=1}^{K} \Omega(f_k) \tag{5}$$

where:

– $L(\theta)$ is the overall loss function.
– l is the loss function.
– y_i is the true label.
– $f(x_i; \theta)$ is the predicted value.
– $\Omega(f_k)$ is the regularisation term for the kth tree.

The stacking process involves two layers:

- First layer:

$$\hat{y}_{LGBMC} = LGBMC(X) \tag{6}$$

$$\hat{y}_{HGBC} = HGBC(X) \tag{7}$$

- Second layer (meta learner). The meta-learner $XGBC$ uses the predictions of the base classifiers as its input:

$$\hat{y}_{meta} = XGBC([\hat{y}_{LGBMC}, \hat{y}_{HGBC}]) \tag{8}$$

4.2.2. Cross-validation

All models were used for one-step (i.e. 1 h) forecasting. Additionally, the ESC employs 5-fold cross-validation during the training of the meta-learner (Eqs. (9) and (10)). The data were split into 5-equal folds in 5-fold CV and hence in each fold, 20 % of the data is available. One fold is left for testing, and the remaining four folds are used for training. The decision to use 5-fold cross-validation is commonly made because it achieves a good balance between computational efficiency and model evaluation reliability. It is less computationally expensive than higher-fold cross-validation, especially when dealing with large data sets or complex models such as meta-learning.

$$CV_{ESC} = \frac{1}{K} \sum_{k=1}^{K} \hat{y}_{meta}^{(k)} \tag{9}$$

where:

– K is the number of folds (in this case, 5).
– $\hat{y}_{meta}^{(k)}$ is the prediction of the meta-learner on the kth fold.

Table 4
ESC hyperparameters.

Classifier	Hyperparameters
LGBMC	reg_alpha = 0.7, reg_lambda = 0.7 learning_rate = 0.07
HGBC	max_leaf_nodes = 30, learning_rate = 0.07
XGBC	max_depth = 6, subsample = 0.8

Combining the base classifiers and meta-learner in a two-level stacking framework can be expressed as:

$$\hat{y} = XGBC([\hat{y}_{LGBMC}, \hat{y}_{HGBC}]) \tag{10}$$

Here $\hat{y}$ is the final prediction of the ESC model. The hyper parameters for each base classifier were carefully selected to balance bias and variance, aiming to reduce over-fitting. Specific values were determined using grid or random search methods along with selected trial and error compiles, ensuring optimal performance on the test sets (Table 4).

4.3. Pattern extraction and clustering

For the five defined crises severity levels and the baseline (normal conditions), daily patterns for DHW consumption were extracted using the mean values for each hour of the day. The standard deviation (STD) was calculated to evaluate the possible high variation in the data. In addition, weekends and holidays were excluded, while daily patterns were extracted based on observations during data exploratory analysis.

The data points corresponding to each severity level and the baseline were split into six data sets that were further used for clustering. Each data set included 24 rows representing values of hot water consumption for each hour of the day; however, the number of dimensions differed for each data set since not all months showed the six severity levels. The structure and months included in each data set are presented in Table 5.

Principal component analysis (PCA) and the k-means method were used to cluster separate hours in a day of energy consumption for DHW preparation. The data set used included mean and STD values for all investigated buildings. Using the mean and STD allowed us to consider possible strong discrepancies between separate buildings' hot-water consumption patterns.

5. Results and discussion

5.1. Predictive modelling results

The performance metrics considered for the tested classifiers are Accuracy, Precision, Recall, and F1 Score (Table 6). Overall, the developed ESC exhibits very good performance, achieving high accuracy. The accuracy of the test data is aligned with the accuracy of the training data, indicating that the model is not overfitting and generalises very well to unseen data. The high precision, recall, and F1 scores in both datasets underscore the robustness of the model and its ability to classify positive instances correctly. Compared to a base classifier, the ESC significantly outperforms the LGBMC in all performance metrics. Although LGBMC and HGBC are gradient-boosting algorithms, they optimise differently and have different biases. Combining their outputs through a meta-learner like XGBC, a powerful boosting algorithm, allows the ESC to learn more complex patterns in the data. An overview of ESC performance is also illustrated in a confusion matrix (Fig. 7); it represents the results of a classification task, dividing test samples into four categories, depending on their true and predicted labels: true positives (TP), true negatives (TN), false positives (FP), false negatives (FN). The only misclassifications are limited to Label 0 (Baseline), while there are no misclassifications for any of the severity levels.

Table 5
Dataset structures used for PCA.

Dataset	Baseline	Severity 1	Severity 2	Severity 3	Severity 4	Severity 5
Number of rows	24	24	24	24	24	24
Number of dimensions	24	16	20	16	10	6
Months included	1–12	2,3,5-10	3–12	1–6,11,12	1–4,12	1,4,12

Table 6
Predictive model performance metrics.

Dataset	Model	Accu.	Prec.	Recall	F1
Test	LGBMC	0.9203	0.9229	0.9203	0.9204
Test	ESC	0.9946	0.9946	0.9946	0.9946
Training	LGBMC	0.9196	0.9224	0.9196	0.9197
Training	ESC	0.9956	0.9956	0.9956	0.9956

5.2. Pattern discovery

5.2.1. Daily patterns based on severity levels

The extracted daily hot water consumption patterns for each crisis severity levels are illustrated in Fig. 8. To simplify the comparison of changes between different severity levels, daily profiles for each severity are expressed as a percentage of the peak observed at 3 PM during the highest severity. Across all severity levels, except Severity level 5, a consistent pattern emerges during the night (between midnight and 5AM), where the lowest consumption is observed. However, during the same period, the highest crisis level shows an increase in DHW consumption of approximately 10 %. For normal conditions (baseline), the morning peak appears at 7 AM. However, with the increasing severity of the crisis, consumption around this time decreases significantly. The baseline consumption at 7 AM is around 35 % higher than the consumption of Severity 5.

At the same time, the morning peak for each severity level appears later in the day, with the highest severity reaching its peak at 3 PM. Here, between noon and 3 PM, the increase in consumption at Severity 5 is up to 30 % higher than in Severity 4 and up to 50 % higher than in the Baseline. Changes in consumption patterns are also observed in the evening, especially compared to the highest severity pattern, where consumption is almost as low as during the night. Between 6 and 10 PM, the difference between the Baseline and Severity 5 is approximately 20 %. However, by 11 PM, DHW consumption appears to be similar across all severity levels.

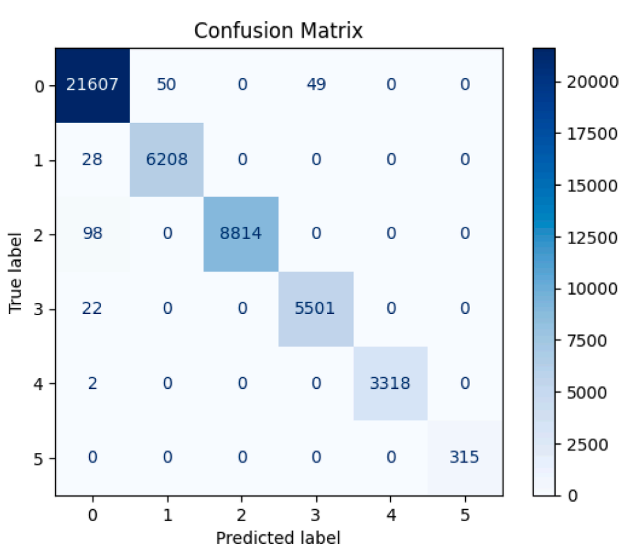

Fig. 7. ESC model performance: confusion matrix.

The highest severity level also shows the highest STD for the extracted daily pattern. This reveals that the greatest uncertainty in hot water consumption is present during the most severe crisis conditions. The error bars in Fig. 8 show the spread of the data points around the mean. At 3 PM, the deviation from the mean reaches almost 50 %.

5.2.2. Comparison of daily, weekly, and annual patterns

As highlighted earlier, DHW consumption is highly dependent on various factors, with occupant behaviour playing a central role. Crisis situations, such as COVID-19, which impose mobility restrictions, alter occupants' daily routines. However, other factors, such as seasonality, also have a significant impact on occupant behaviour. Therefore, it is crucial to quantify the effects of a crisis in comparison to other major influencing factors, such as seasonality.

Fig. 9 illustrates the daily profiles for different periods, including the crisis situation during the lockdown, the crisis period without restrictions, and the pre-COVID period. As was also seen in the daily profiles for different severity levels, the morning peak significantly shifted to later hours in a day. Fig. 10 represents the weekly profiles, generally indicating an approximate 10 % increase in consumption during the lockdown period. It is important to note that the lower consumption during the non-lockdown period is also influenced by seasonality, as most of the data for this period was collected during the summer months. Finally, Fig. 11 presents the yearly profiles, emphasising the strong influence of seasonality. During the pre-COVID period, the difference between the peak consumption and the lowest point was less than 20 %. Overall, the yearly consumption pattern remains consistent, showing no significant changes in total DHW consumption.

Comparing the change in mean hourly DHW consumption between daily and yearly patterns, we observe that both seasonality and crisis conditions have similar effects. The largest difference in daily consumption patterns between pre-COVID and lockdown conditions is approximately 15 %. However, a comparable change is also observed in the yearly patterns for the pre-COVID period when comparing winter and summer seasons. While both seasonality and lockdown severity influenced DHW consumption, the lockdown had a more pronounced short-term effect, causing immediate shifts in peak demand timing and usage habits. In contrast, seasonality had a more gradual and predictable impact on overall consumption levels. This distinction is crucial for energy management strategies, as control systems need to adapt dynamically during crisis scenarios rather than relying solely on seasonal adjustments.

5.3. Cluster identification

5.3.1. PCA results

PCA was run separately for each of the datasets, including data from different levels of crisis severity, as presented in Table 5. Before performing the PCA, the values were scaled to ensure that each feature contributed equally to the analysis. The results showed that by selecting only three principal components, between 82.7 % and 98 % of the variance could be explained across all datasets (Table 7). For all data sets, more than 91 % of the explained variance can be reached with the inclusion of five principal components. Considering only the first principal components, it was evident that more available data corresponded to higher explained variance. The normal conditions (baseline) dataset contained the most data, as these conditions were present throughout all months of the year, given that the dataset spans multiple years. For

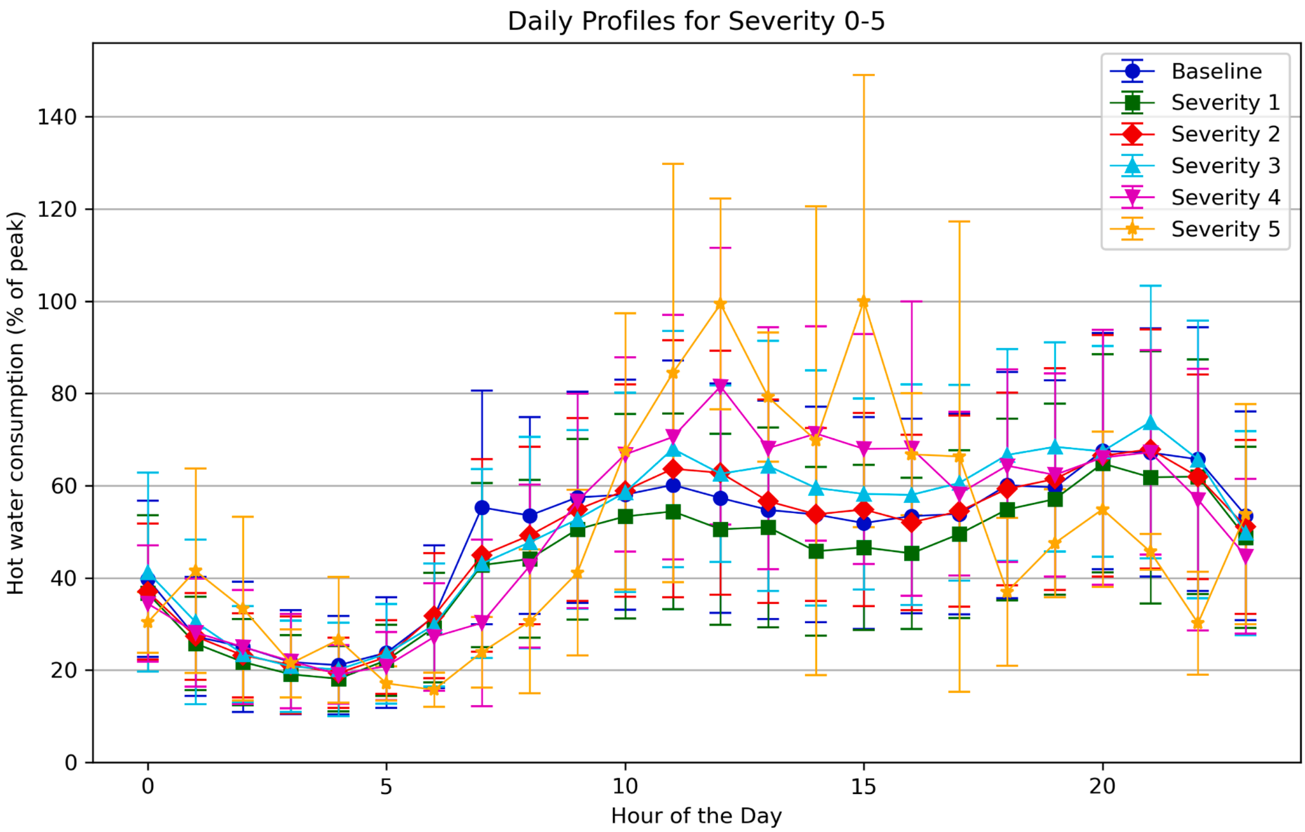

Fig. 8. Extracted daily profiles based on crisis severity level.

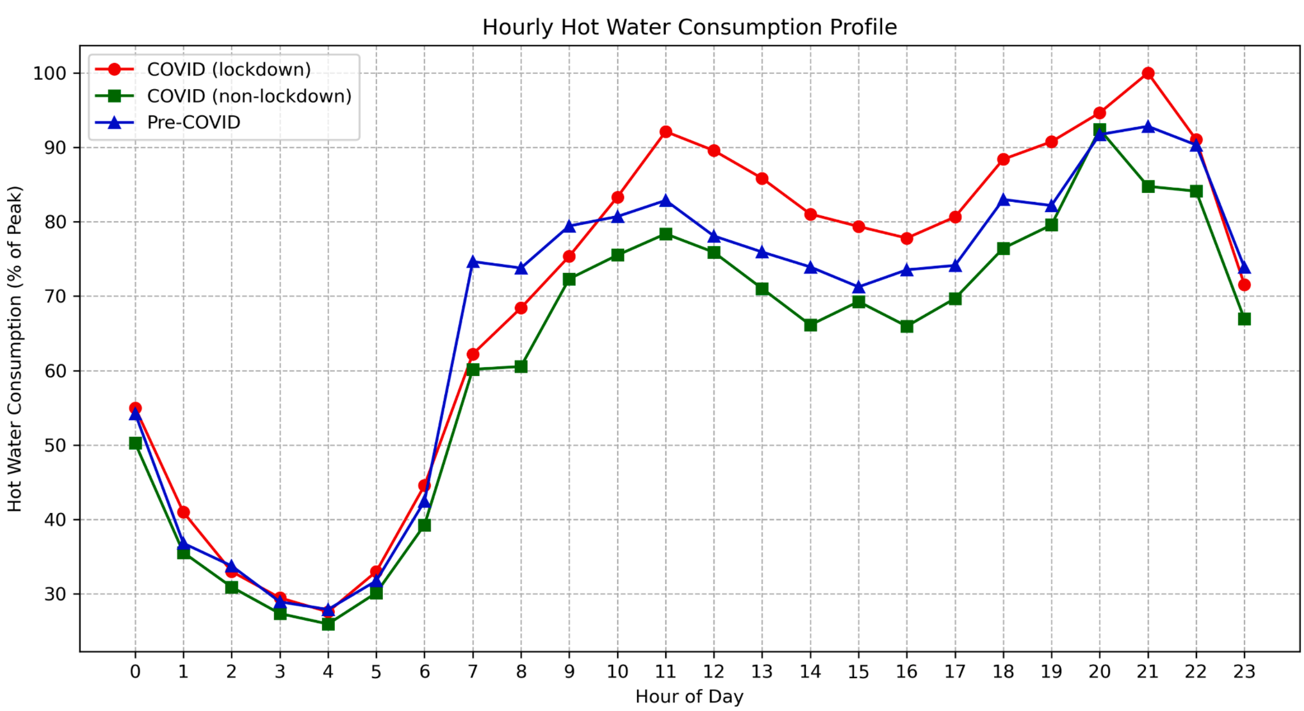

Fig. 9. Daily profiles during different periods.

the Severity 1, 2, and 4 datasets, the first principal component explained 70 % to 75 % of the variance. However, for the Severity 3 dataset, the first principal component accounted for only 63.8 % of the variance, although it had a similar number of dimensions as the other severity datasets, indicating greater variability in these data. Overall, the analysis demonstrated that PCA significantly reduces the number of variables in the data, providing a strong foundation for further clustering.

5.3.2. *K-means clustering*

PCA and k-means were used to identify the thermal energy consumption required for the preparation of hot water at different times of the day under normal conditions and at varying severity levels (Fig. 12). The “elbow” method was used to determine the optimal number of clusters, however, it did not yield significant results; therefore, four clusters were chosen as they capture the best

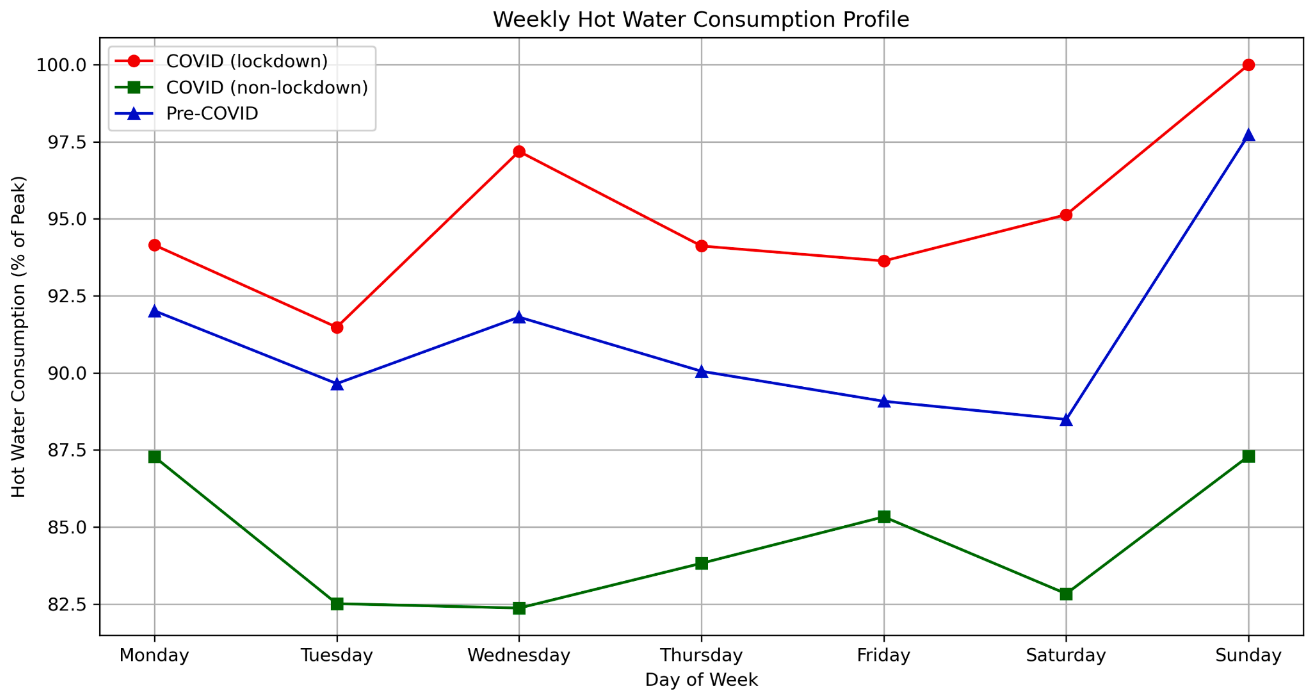

Fig. 10. Weekly profiles during different periods.

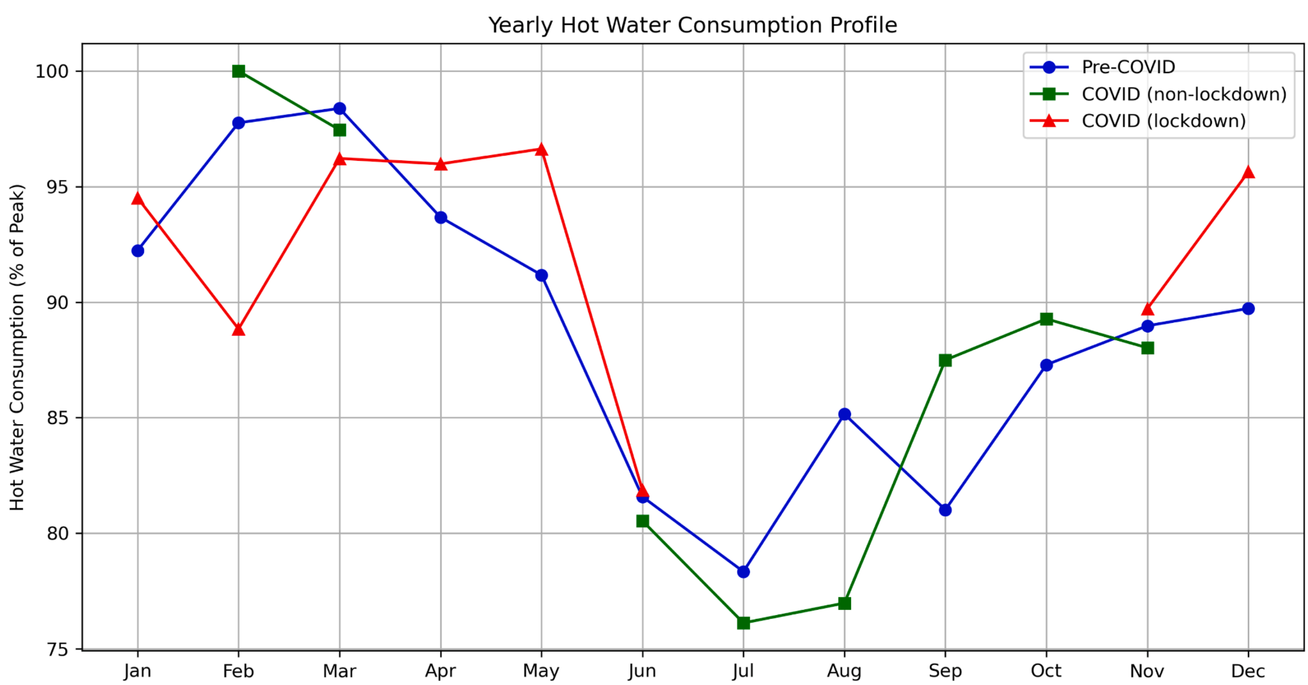

Fig. 11. Annual profiles during different periods.

the low consumption night hours, morning, mid-day and evening peaks.

At baseline, low-consumption night hours are clearly distinguished in the green cluster, with 6 AM forming a separate cluster where consumption remains low but is approaching medium levels. The medium consumption hours, where residents are normally at work or school, form the largest yellow cluster; whereas the consumption peaks appearing in the morning and evening hours are in the blue cluster. At Severity 1, a noticeable shift in the hourly clustering patterns emerges. The low-consumption night hours are still clearly distinguished in a blue cluster (6AM here is a part of this cluster); however, the remaining hours in a day form another 3 clusters, each containing nearly equal numbers of data points, reflecting a more uniform distribution of daily consumption levels.

At Severity 2, the low consumption night hours (blue cluster) shift back to the right side of the plot. Here, the highest consumption appearing at hours 11, 18, 20–22 forms the green cluster, and the remaining hours, except for 19, form the biggest medium consumption (purple)

Table 7
Cumulative explained variance ratio of principal components, %.

	Baseline	Severity 1	Severity 2	Severity 3	Severity 4	Severity 5
PC1	81.8	75.0	72.4	63.8	70.4	42.5
PC2	86.4	81.7	79.4	76.0	80.5	74.2
PC3	89.3	86.5	84.9	82.7	88.7	96.0
PC4	91.9	90.4	88.5	88.4	93.9	98.3
PC5	93.5	93.0	91.2	93.5	96.3	99.2
PC6	95.0	96.7	93.4	95.4	98.1	100
PC7	96.3	98.0	95.3	97.0	99.1	–
PC8	97.3	98.8	96.5	97.8	99.6	–
PC9	98.0	99.2	97.6	98.5	99.8	–
PC10	98.5	99.5	98.4	99.0	100	–
PC11	98.9	99.7	98.9	99.3	–	–
PC12	99.2	99.9	99.2	99.6	–	–
PC13	99.4	100	99.5	99.8	–	–
PC14	99.6	100	99.6	99.9	–	–
PC15	99.7	–	99.8	100	–	–
PC16	99.8	–	99.9	100	–	–
PC17	99.9	–	99.9	–	–	–
PC18	100	–	100	–	–	–
PC19	100	–	100	–	–	–
PC20	100	–	100	–	–	–
PC21	100	–	–	–	–	–
PC22	100	–	–	–	–	–
PC23	100	–	–	–	–	–
PC24	100	–	–	–	–	–

cluster. Hour 19 stands alone, forming its own cluster, indicating an intermediate consumption level between the peak and mid-consumption hours. In contrast, for Severity 3, all hours descend almost equally between the clusters. This shows a fairly stable consumption throughout the day.

Significant changes are observed for the Severity 4 clusters. Some night hours shift from the lowest-consumption (purple) cluster to the low- to mid-consumption (green) cluster. High consumption peaks appear during hours 12, 16, and 22, forming the yellow cluster. The remaining hours exhibit relatively stable consumption and are grouped into the largest cluster (blue), indicating consistent demand across these periods.

At Severity 5, distinct patterns with pronounced peaks emerge. Here, the night hours, early morning and late evening form the largest low-consumption (purple) cluster. The highest peaks at hours 12, 16 and 17 are in the green cluster, and the mid-consumption is represented in the blue cluster at hours 13–15. Interestingly, the lowest consumption is observed here during hour 23, separated in the yellow cluster. However, hour 11 AM is also grouped in the yellow cluster, despite showing medium consumption levels that align more closely with the blue cluster, suggesting occasional discrepancies based on available data. Since Severity 5 was observed for only three months, this dataset included only six dimensions, representing the mean and standard deviation for each month.

5.4. Discussion on results application for DHW control

To mitigate the crisis impact on DHW preparation, understanding the main system components and possible control actions is essential. Fig. 13 illustrates the DHW system, divided into supply, distribution, and demand. The supply includes a solar collector and a boiler/district heat pump, while distribution consists of supply/return water systems and DHW storage. The demand side features an additional controller. According to ISO 52120-1:2021 [49], DHW storage charging can be managed via direct or integrated electric heating, solar collectors, or supplementary heat generation on both the supply and demand sides. Additionally, hot water generation can regulate storage charging on the supply side, and DHW circulation pumps can be controlled within the distribution system. Control actions range from simple on/off mechanisms to advanced automated solutions integrating multiple sensors and predictive models.

The observed changes in daily DHW consumption patterns dictate the need to assess these changes in relation to hot water preparation systems. Therefore, DHW system control strategies should be adapted to account for altered consumption patterns during lockdown periods. Fig. 9 shows that during the lockdown period (red curve), the duration of increased DHW consumption lasted approximately 11 h (from 10:00 to 21:00) compared to the non-lockdown period. All periods show two daily peaks in DHW demand; however, these peaks are more pronounced during lockdown.

In optimising the hot water production process, the main objective is to ensure the required hot water flow for a certain period, and this must be achieved with a minimum energy that is directly related to the amount of resources consumed from traditional energy sources (e.g., district heating). This implies that if we can accurately forecast periods of increased consumption, we can optimise DHW preparation and reduce heat losses in storage tank-type systems. This approach would be beneficial for the integration of renewable energy sources and the improvement of net balance options.

This quantification is particularly important for stakeholders such as energy and water utilities, policy makers, building engineers, facility managers, and real estate developers, as it provides data-driven insights for strategic planning. For example, water management boards and energy planners require accurate demand patterns to optimise resource allocation and infrastructure development, particularly in regions where DHW systems rely heavily on renewable energy sources. The findings of this study support long-term planning for sustainable energy integration and resilient water management strategies.

For renewable energy sources (solar, wind, hydro), characterised by intermittent generation, control strategies must account for energy fluctuations while minimising carbon footprint. This is especially critical during high-severity lockdowns, where hot water production requires greater adaptability. Optimising control should be guided by forecasts of both DHW demand and renewable energy generation. The ESC classifier, designed to predict DHW crisis severity, supports proactive maintenance by optimising control actions based on detected patterns. This aligns with prescriptive maintenance strategies aimed at improving equipment reliability and operational efficiency in both residential and industrial settings [50].

By analysing mobility and DHW consumption patterns, this study enables faster, more effective responses to crises like pandemics, economic shifts, and extreme weather events. Integrating data from retail centres and public transport stations, the model detects early crisis indicators, supporting rapid decision-making. Its flexibility extends beyond energy crises, making it applicable in various sectors where external factors impact resource use.

Anticipating energy crises can lead to significant cost savings for both consumers and utilities. Consumers benefit from lower energy bills through optimised usage, while utilities improve resource allocation, reducing reliance on costly backup systems. Over time, these efficiencies can reduce operating costs and contribute to more affordable energy.

6. Conclusions

This study investigated the impact of lockdown during crises conditions on DHW consumption patterns, evaluating changes in these patterns based on the severity of the crisis, with the goal of improving control over energy production and distribution. In this regard, a case study of ten residential apartment buildings in Kaunas (Lithuania) was analysed. The main conclusions of the study are as follows:

- Google Community Mobility Reports facilitated the classification of crisis severity levels, allowing for generalisation to any crisis involving reduced citizen mobility. The analysis showed significant changes in mobility patterns during COVID-19, with extremely low mobility at the start of lockdowns and gradual increases toward their end.

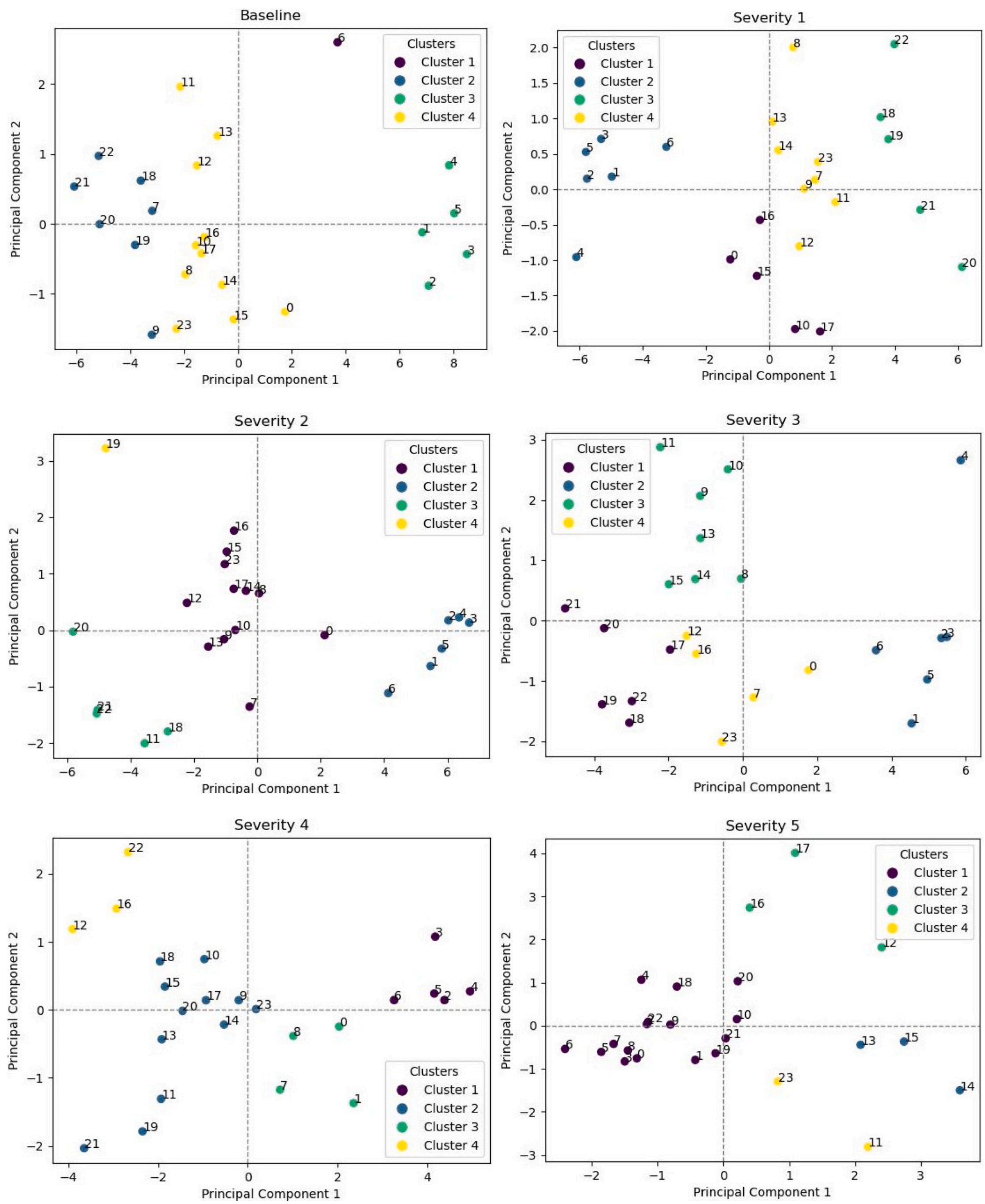

Fig. 12. Normalised thermal energy consumption for hot water preparation clusters of different daily hours.

- The extracted DHW daily consumption patterns for each mobility level exhibited significant discrepancies compared to the baseline (normal conditions), with changes reaching up to 50 % at the highest severity level. Analysis of daily, weekly, and yearly DHW consumption patterns across different periods—pre-COVID, COVID during lockdown, and COVID without mobility restrictions—revealed that seasonality has a more significant impact on total consumption. However, lockdown severity had a more pronounced short-term effect, causing immediate shifts in peak demand timing and usage habits.
- PCA and k-means were used to identify DHW consumption clusters for each hour of each day across all severity levels. The results indicated that these clusters vary significantly with each severity level, revealing distinct shifts in hourly consumption patterns that align with changes in occupant routines and mobility restrictions.

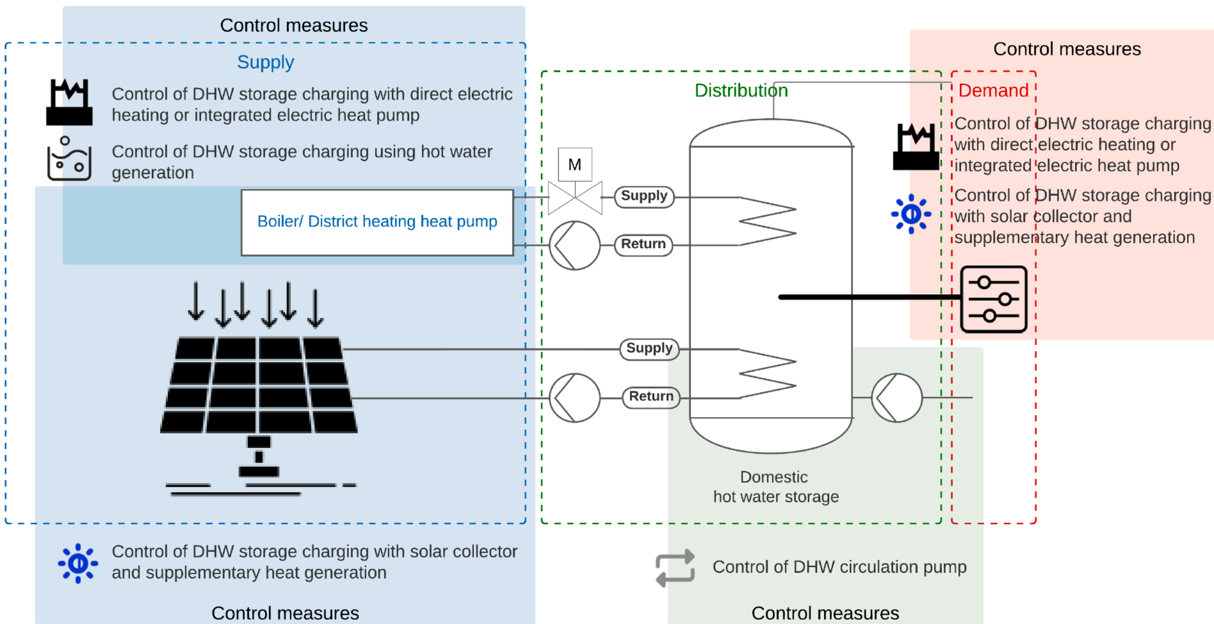

Fig. 13. DHW system and control. Adapted from [49].

- The developed ESC classifier demonstrated high accuracy (R^2 = 0.99) on both training and test datasets, indicating a strong generalisation with minimal overfitting. The predicted severity levels serve as input for utility managers, building owners, and other stakeholders, allowing targeted control actions based on the extracted DHW consumption patterns for each severity level.

7. Limitations and future work

A key limitation of this study is the relatively small amount of data available for modelling. Newer metering systems that can distinguish between hot water used for everyday activities and heating have only been introduced in recent years. As a result, the amount of data for training the models was limited, which made it challenging to fully develop and refine certain models, especially those designed to predict hot water demand over time.

In the future, more extensive data collection is needed to improve the accuracy and performance of the models. This could include collecting data over a longer period and incorporating additional factors such as weather, user habits, or building occupancy. Expanding the data set in this way would help the models perform better, especially when dealing with unexpected events or disruptions.

Furthermore, the study was conducted and focused only on residential buildings, but hot water consumption patterns during crisis periods in other types of buildings (industrial, commercial, service, office, etc.) would be relevant and encouraged as future work.

Further research should also explore how well these models can be applied to different types of buildings, such as commercial or mixed-use, and in different regions. Developing more advanced methods for predicting DHW use, such as time series models that track changes over time, could also make the system more effective. By addressing these possible research areas, the study findings could become even more useful and widely applicable.

The changed daily patterns of hot water consumption during the crisis period are relevant in terms of thermal energy production using different sources. These cases have recently become particularly popular when thermal energy is produced from electricity using heat pumps. Primary energy is obtained from solar, wind, or hydro sources, but it causes significant fluctuations in the demand/production balance and energy prices. Balancing different types of energy is becoming a necessity for many modern buildings; therefore, the research conducted serves a further perspective, i.e. to explore the possibilities of controlling the building's heating system by varying between different energy sources, taking into account the energy prices on the market in real time.

Data availability

The datasets used and analyzed in this study are openly available in Mendeley Data at https://data.mendeley.com/datasets/f22hz7hxbn/3, under the **Creative Commons Attribution (CC BY 4.0)** license. Additional supporting information can be obtained upon request from the corresponding author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CRediT authorship contribution statement

Lina Morkunaite: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization; **Darius Pupeikis:** Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation, Conceptualization; **Nikolaos Tsalikidis:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization; **Marius Ivaskevicius:** Writing – original draft, Investigation, Formal analysis, Conceptualization; **Fallon Clare Manhanga:** Writing – original draft, Methodology, Investigation, Conceptualization; **Jurgita Cerneckiene:** Writing

– original draft, Methodology, Investigation, Conceptualization; **Paulius Spudys:** Writing – review & editing, Methodology, Data curation, Conceptualization; **Paraskevas Koukaras:** Writing – review & editing, Supervision, Resources; **Dimosthenis Ioannidis:** Writing – review & editing, Validation, Resources, Project administration, Conceptualization; **Agis Papadopoulos:** Writing – review & editing, Validation, Resources, Project administration; **Paris Fokaides:** Writing – review & editing, Validation, Resources, Project administration, Funding acquisition.

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