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Energy management of smart buildings during crises and digital twins as an optimisation tool for sustainable urban environment

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ABSTRACT

The COVID-19 pandemic underscored the need for resilient energy management systems in smart buildings, especially during crises. This study investigates the role of Digital Twins in optimising energy systems, analysing energy use in a residential complex in Cyprus under lockdown conditions. Advanced predictive models, including Skforecast, XGBoost, LightGBM, CatBoost, LSTM, and RNN, were employed to forecast energy demand. While gradient boosting models performed well, LSTM showed superior accuracy in capturing long-term patterns. These models are crucial for anticipating energy demand fluctuations, especially during unforeseen events such as the COVID-19 pandemic. The use of Digital Twins enabled real-time monitoring, proactive maintenance, and decision-making, significantly improving energy efficiency and resilience. This research underscores the importance of interdisciplinary collaboration and the integration of advanced technologies in building management. The findings advocate for a holistic, human-centric approach to energy management that prioritises adaptability, resilience, and sustainability in the face of ongoing and future challenges.

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Smart buildings; energy management; digital twins; predictive models; resilience; sustainability

1. Introduction

Contemporary energy consumption is a pressing global concern with significant implications for both society and the environment. A large portion of our energy comes from combustion processes that rely on non-renewable resources and emit harmful greenhouse gases (GHGs) into the atmosphere. This multifaceted issue has spurred global efforts such as the 'Go green' movement (Rathor and Saxena 2020), the Low Carbon Transition Programme in China (Wang et al. 2020), and Europe's Nearly Zero Building Strategy 2020 (Li et al. 2019), among others. These initiatives aim to enhance energy efficiency and drive energy conservation to mitigate negative impacts.

Rapid urbanisation and population growth have increased the complexity of energy requirements in cities. Existing systems are evolving to offer comprehensive solutions through an optimised approach. In the context of IoT-enabled smart cities, it is crucial to establish an optimised operational framework and deploy efficient sensors to meet increasing demands (Selvaraj, Kuthadi, and Baskar 2023). The building sector assumes a substantial role, accounting for nearly 40% of total

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energy consumption, 40% of greenhouse gas emissions, and a whopping 70% of electricity usage in industrialised nations (Minoli, Sohraby, and Occhiogrosso 2017). Buildings surpass both the transport and industrial sectors in terms of energy consumption, primarily due to heating, cooling, lighting, and electrical appliances. Legislation in many countries mandates that a significant portion of energy consumption by 2025 must come from renewable and carbon-neutral sources, spurring investments in smart grid technologies designed to minimise overall energy costs.

Governments worldwide have introduced various policies and action plans to combat greenhouse gas emissions and enhance energy efficiency in buildings. The International Energy Agency (IEA) introduced the Net Zero by 2050: A Roadmap for the Global Energy Sector, which emphasises a 50% reduction in building-related CO_2 emissions by 2030 through retrofitting, efficient appliances, and electrification (IEA 2021). The United Nations Environment Programme (UNEP) promotes the Global Alliance for Buildings and Construction (GlobalABC), fostering international collaboration to decarbonise buildings, particularly in developing nations (UNEP 2022). In the European Union, the Energy Performance of Buildings Directive (EPBD) serves as a cornerstone policy, requiring nearly zero-energy buildings (NZEBs) for all new constructions and mandating energy performance certificates for existing buildings (European Commission 2021). In Japan, the Definition of ZEB and Future Measures Proposed by the ZEB Roadmap Examination Committee outlines a strategy for a gradual increase in net-zero energy buildings in the residential and non-residential sectors by 2030 (METI 2016). Furthermore, Australia's National Construction Code 2022 introduces mandatory energy efficiency measures for new buildings, highlighting the global trend toward stringent regulatory frameworks for sustainable construction (Australian Building Codes Board 2022).

Achieving carbon neutrality in the built environment requires not only the adoption of energy-efficient technologies but also the implementation of comprehensive assessment tools that measure a building's smart readiness (Chatzikonstantinidis, Giama, Fokaides, et al. 2024). However, optimising these technologies to improve building energy performance remains an open challenge (Giama et al. 2024).

Another pivotal challenge resides in the proliferation of alternative energy sources, exemplified by photovoltaic cells, wind turbine parks, geothermal installations, and tidal wind turbines. These alternatives must harmonise their coexistence with conventional energy sources such as oil, coal, nuclear, or hydraulic power. Energy flexibility is a critical aspect of modern building management, particularly in regions with distinct seasonal variations such as the Mediterranean. This flexibility allows buildings to adapt their energy consumption in response to external conditions, which is essential for optimising energy use and reducing costs (Chantzis, Giama, Papadopoulos 2023). Economic imperatives further compel stakeholders to explore avenues for minimising the costs associated with energy consumption. Over the years, energy strategies on the consumer front have centred on automation and control optimisation, epitomised by the incorporation of Building Automation Systems (BAS) and Home Automation. Demand response has emerged as a pivotal tool for decarbonisation, especially during energy transitions, highlighting the role of smart technologies in managing energy resources efficiently (Chantzis, Giama, Nižetić, et al. 2023). Technology has bestowed upon us the means to construct a coherent framework for research and development, fostering innovation in energy efficiency and operational cost reduction.

Effectively researching smart energy requires profound insights into both energy systems and Information and Communications Technologies (ICT). This synergy leverages digital transformation opportunities. ICT advancements, including the Internet, Ubiquitous Computing, Big Data, Wireless Sensor Networks, and microservices, enable new functionalities in energy management systems (EMS). Artificial intelligence is pivotal in smart energy, contributing to tasks such as monitoring, analysis, and decision-making. Smart energy objectives must be balanced with goals of improving quality of life and service quality, ushering in the era of a 'smart environment.' Common 'smart scenarios' include 'smart buildings,' 'smart homes,' 'smart health,' and 'smart cities,' viewed as interconnected ecosystems (Aguilar et al. 2021).

In smart buildings, the integration of Digital Twins (DT) stand as a cornerstone innovation, fundamentally transforming energy management, especially in times of crisis. DTs, sophisticated digital replicas of physical buildings, enable unprecedented monitoring, analysis, and prediction, facilitating real-time decisions that optimise energy use and operational efficiency. Their importance cannot be overstated, particularly when swift adaptive measures are needed in response to sudden changes in occupancy patterns, energy supply, demand, or environmental conditions. Through continuous data collection and analysis, DTs offer a dynamic, holistic view of a building's performance, allowing stakeholders to identify inefficiencies, predict future trends, and implement preventive maintenance strategies. This proactive approach is invaluable during crises like the COVID-19 pandemic, where traditional energy management practices may fall short. Furthermore, DTs serve as essential tools for scenario planning, enabling the simulation of various crisis impact scenarios and testing different energy management strategies without risking actual building operations. By leveraging DTs, smart buildings can navigate crisis-induced challenges, becoming more resilient, efficient, and aligned with sustainability goals. This approach heralds a new era of smart building operation, prioritising adaptability and resilience (Billey and Wuest 2024).

2. COVID-19 and smart buildings

On March 11, 2020, the World Health Organization (WHO) declared COVID-19 a pandemic, marking a significant turning point in global health. As reported by the WHO, the COVID-19 pandemic has infected nearly 625 million people and tragically claimed over 6 million lives worldwide (Amirzadeh et al. 2023). Beyond the high mortality rate, the pandemic has triggered ongoing challenges and widespread disruptions profoundly impacting people's lives in multifaceted ways (Shakil et al. 2020).

The COVID-19 pandemic has brought transformative changes to our lives, prompting extensive mitigation measures, including restrictions that have significantly altered societal norms and lifestyles. This novel coronavirus represents the paramount global health crisis of our era, comparable only to the challenges posed during the Second World War. Beyond its public health repercussions, the pandemic has also unleashed a devastating socio-economic crisis. The World Bank reports that approximately 97 million people were thrust into poverty in 2020, an unprecedented surge. Furthermore, the International Labor Organisation estimates that nearly 205 million people may have lost their jobs in 2022 (UNDP 2020).

During the pandemic, most countries imposed 'lockdowns,' curtailing daily activities and confining individuals to their residential buildings. These measures, essential for public health, have unintentionally resulted in heightened energy consumption within residential buildings. Increased energy demand in households not only amplified energy costs for residents but also necessitated adjustments to electricity distribution strategies within homes. Of particular concern was the alteration of load patterns for distribution transformers, which could lead to potential overloads. Consequently, grid load reduction became imperative. Additionally, enhancing hygiene and sanitation in medical facilities became paramount, with hospital buildings emerging as the frontline against the virus. Given the potential for rapid airborne virus transmission, improving indoor air quality and ventilation systems within buildings gained prominence. Finding viable solutions to meet these new requirements became imperative. The challenges posed by the COVID-19 pandemic demand prompt, comprehensive, and adaptable solutions.

The COVID-19 pandemic has revealed the critical importance of integrating smart technologies into Building Management Systems (BMS) to ensure resilience during crises. In this context, the concept of 'smart buildings' has emerged as a fitting response. Recent research has highlighted how smart buildings can effectively manage water resources during lockdowns, emphasising the importance of real-time monitoring and adaptive management systems in mitigating the impacts of such unprecedented events (Chatzikonstantinidis, Giama, Chantzis, et al. 2024). Smart buildings leverage information technology to connect various subsystems that traditionally operate independently, enabling these systems to share data and optimise overall building performance. The genesis of the smart building concept can be traced to the widespread use and dissemination of computers and the internet. These technologies facilitate the organisation and monitoring of buildings as digital systems (Xie, Ramakrishna, and Manganelli 2022).

2.1. Impact of COVID-19

Throughout the COVID-19 pandemic, one of the most pervasive responses to curbing the virus's spread has been the imposition of 'lockdowns' in numerous countries, which confined individuals to their residential buildings and limited their daily activities. Paradoxically, this measure gave rise to a new challenge: a notable increase in energy consumption within residential buildings. Additionally, given the virus's rapid spread through airborne particles, ensuring high indoor air quality within various types of buildings has become a critical concern.

These containment measures, including stay-at-home and teleworking policies, significantly impacted energy usage patterns. This led to notable changes in household energy profiles and consumption patterns worldwide, as demonstrated by several studies (Cheshmehzangi 2020; Santiago et al. 2021; Bielecki et al. 2021). Some of the key observations and insights from these research efforts are summarised below:

- In China, a discernible surge of 40% in domestic culinary activities was observed, along with changes in leisure pursuits. There was a noteworthy 60% increase in the use of climate control systems for temperature regulation, a 40% rise in the use of lighting, and a significant increase in energy expenditure, with energy bills increasing by 22% to 95% during the study period.
- In Spain, there was a 13% reduction in national electricity consumption. This resulted in changes to the morning and evening peak electricity demand, with shifts in timing and load distribution among households.
- In Poland, there was no significant change in the maximum load, but the distribution of load profiles widened among the nearly 7,000 sampled households.
- In Australia, weekdays saw similar load profiles, but there was an increased evening peak.
- In social housing in Québec, Canada, major alterations in energy usage were observed in April and May, with minor changes in June and July.

One notable change was a 40% increase in household cooking during lockdown compared to the pre-lockdown period. However, after the lockdown, there was a significant decrease in cooking at home, indicating that cooking habits did not return to pre-pandemic levels but remained lower. People seemed to prefer recovering from months of continuous indoor cooking by seeking outdoor dining options during the post-pandemic recovery phase. Similar patterns were observed for home entertainment, which almost tripled during lockdown but reverted to normal levels afterward. The closure of outdoor recreational activities during lockdown prompted people to seek entertainment alternatives within their homes, leading to short-term increases in household energy consumption.

While there were no statistically significant findings suggesting long-term transitions in energy use, the substantial increases in household energy demand for activities like cooking and home entertainment during lockdown challenged conventional assumptions and expectations (Li, Guo, and Kauffman 2015). Seasonal variations were also evident, with an estimated 60% increase in cooling and heating, as well as a 40% increase in lighting between January and February 2020 alone (Xinye and Wei 2019). This surge in domestic energy use reflected higher consumption patterns, increased usage of household appliances, and greater energy consumption for cooling, heating, and lighting (Chen et al. 2020).

Furthermore, it is imperative to acknowledge the profound ramifications of the COVID-19 pandemic on energy provisioning and electrical supply networks, encompassing the entirety of the continuum from power generation to end-user consumption. The cessation or partial curtailment of industrial operations precipitated a conspicuous reduction in the requisites for electrical power and energy resources. On a global scale, economically developed nations witnessed a noteworthy decrease in both energy and electricity requisition, quantifying at a range of 5% to 6%. Notably, the United States and European Union member states were the most significantly impacted, registering reductions of 9% and 11% respectively in their energy and electricity demands (Zhongming et al. 2020). This overall reduction, coupled with growing interest in low-carbon energy sources and decreased demand in coal, gas, and oil industries, contributed to an 8% reduction in global carbon emissions (Norouzi et al. 2020).

2.2. Challenges during the COVID-19 lockdown on energy management

As mentioned before, the COVID-19 lockdown brought about significant changes in energy and water demand and imposed several challenges in terms of occupancy and patterns of use of buildings. These challenges have had significant implications for both residential and commercial buildings, leading to changes in the way spaces are used and managed (Selvaraj, Kuthadi, and Baskar 2023; Wang, Huang, and Li 2022). In the context of managing resources, especially during crises, it is crucial to identify the challenges and have robust risk assessment and mitigation strategies in a holistic manner, particularly in the face of emerging global challenges (Zafeiriou et al. 2024). Some main of the key challenges and their consequences that arose during the COVID-19 lockdowns are presented below:

(1) **Reduced Commercial and Industrial Energy Demand:** A substantial portion of the commercial and industrial landscape witnessed temporary closures or scaled-down operations in response to lockdown measures and social distancing protocols. Consequently, this engendered a marked reduction in energy demand emanating from these sectors.
(2) **Modified Working Patterns:** The prevailing modus operandi of the workforce underwent transformation, with remote work gaining prevalence as the standard practice. This metamorphosis in conventional office work paradigms resulted in unoccupied or partially occupied office spaces, thereby diminishing the necessity for office-related amenities and resources such as climate control, lighting, and sanitation services. One of the key challenges during the COVID-19 pandemic was the effective management of building spaces to adapt to the widespread adoption of teleworking. DT technologies have demonstrated significant potential in optimising space utilisation and ensuring operational efficiency in such scenarios. As highlighted in the Lazio Region Headquarters case study, DT models enabled real-time data collection and analysis, allowing building managers to monitor occupancy patterns and adjust space allocation dynamically. This approach not only enhanced energy efficiency but also ensured compliance with safety guidelines, such as maintaining social distancing in shared spaces (Piras, Muzi, and Tiburcio 2024). In the Architecture, Engineering, Construction, and Operations (AECO) sector, space management has become a critical component for balancing smart working needs with operational goals. By leveraging DT platforms, the sector has embraced innovative strategies to address the demands of flexible working environments, ensuring that buildings are not only efficient but also resilient to future disruptions. These findings underline the importance of integrating advanced technologies into smart building frameworks to support sustainable and adaptive practices in the post-pandemic era.
(3) **Increased Residential Energy Demand:** The widespread adoption of remote work and remote learning routines by numerous individuals and households precipitated a surge in residential energy utilisation. Residences served a multifaceted role, functioning not merely as abodes but also as workplaces and educational spaces, leading to heightened electricity usage for illumination, temperature regulation, and the operation of electronic devices.
(4) **Shift in Peak Energy Demand:** The customary diurnal apexes in energy demand, typically linked to commercial and industrial undertakings, underwent displacement. Instead of

traditional daytime peaks, utility providers experienced more equitably distributed and protracted peaks across the day, reflective of the augmented residential energy demand.

(5) **Impact on Renewable Energy:** The overarching attenuation in total energy demand exerted discernible repercussions on the economic dynamics of renewable energy ventures. Particular renewable energy sources, such as wind and solar power, confronted challenges given their reliance on grid demand and pricing fluctuations.

(6) **Safety and Health Concerns**: Building occupants and management faced concerns regarding indoor air quality, sanitation, and virus transmission. Buildings needed to adapt by implementing enhanced cleaning protocols, improving ventilation, and ensuring adequate spacing to meet safety guidelines. Investments in air filtration and touchless technology became a priority.

(7) **Challenges in maintaining energy supply for critical facilities**: Maintaining energy supply for critical facilities like hospitals during the COVID-19 pandemic posed challenges due to increased demand for continuous operation, the need for reliable backup power systems, and ensuring fuel supply and regulatory compliance. Hospitals had to carefully allocate resources and develop comprehensive emergency plans to ensure uninterrupted patient care while managing energy-related risks.

(8) **Supply Chain Disruptions**: The integrity of supply chains suffered disruptions that reverberated throughout the availability of essential building materials and maintenance requisites. The resultant delays in maintenance and repair activities, precipitated by scarcities in materials, engendered the potential for escalated operational expenses and safety apprehensions.

(9) **Energy Management Challenges**: The administration of energy resources assumed a heightened degree of complexity, necessitating building operators to navigate the delicate equilibrium between energy efficiency and the preservation of secure and comfortable indoor environments. Certain buildings bore witness to fluctuations in energy consumption, typified by heightened energy utilisation in residential precincts and diminished energy use in commercial edifices. Consequently, adjustments to heating, cooling, and illumination systems became imperative.

(10) **Remote Building Management**: Building operators found themselves compelled to remotely oversee and supervise building systems, ensuring optimal efficiency and safety. The indispensability of remote building management solutions prompted investments in technological infrastructure and training initiatives to ensure the continued security and functionality of buildings.

3. Materials and methods

This section outlines the methodological approach adopted in this study to investigate energy management in smart buildings during the COVID-19 pandemic, with a particular focus on the application of DTs as an optimisation tool for sustainable urban environments. The chapter details the selection of the case study, the development of the DT, data collection processes, and the setup for predictive modelling. These methods form the backbone of the study, providing the necessary tools and data to explore how smart buildings can adapt to crisis-induced changes in energy consumption.

The selection of a representative case study was a critical step in this research. The chosen site, a residential complex in Larnaca, Cyprus, was selected due to its ability to provide a microcosm of the broader urban energy landscape during the COVID-19 pandemic. The complex consists of multiple residential units with varying occupancy levels, making it ideal for analysing the impact of the pandemic on energy consumption. The diversity in unit types and occupancy patterns allowed for a comprehensive examination of how different residential behaviours influenced energy usage under lockdown conditions.

The residential case study was chosen to investigate how smart building technologies can address common challenges in energy efficiency, occupant comfort, and environmental sustainability in the residential sector. Residential buildings represent a significant portion of energy consumption, making them a critical area for implementing and evaluating smart solutions. The findings of this case study are intended to provide insights into the potential of smart technologies for broader applications across other building typologies.

Larnaca was specifically chosen for its Mediterranean climate, characterised by hot summers and mild winters, which requires significant energy usage for heating, cooling, and ventilation. This climate provided a rich dataset for examining seasonal variations in energy consumption, particularly under the constraints imposed by the pandemic. Additionally, the availability of historical energy consumption data for the complex allowed for a comparative analysis, contrasting energy usage patterns before, during, and after the lockdown periods.

The development of a DT for the Larnaca residential complex was central to this study's methodology. A DT is a virtual replica of a physical asset, in this case, the residential buildings, which is used to simulate, monitor, and optimise real-world performance. The DT was developed using advanced Building Information Modelling (BIM) software, which allowed for the precise modelling of the complex's structural, mechanical, and electrical systems.

The adoption of DT technology in this study was driven by its ability to provide a real-time, dynamic representation of the physical environment. DTs not only allow for continuous monitoring but also enable predictive maintenance by simulating various operational scenarios. This capability is crucial in crisis situations, such as during the COVID-19 pandemic, where energy management must be both proactive and responsive. The integration of real-time sensor data into the DT presented some challenges, particularly in ensuring data accuracy and system integration, but these were overcome through careful calibration and testing.

To create the DT, comprehensive data were collected from the physical buildings, including architectural plans, HVAC system specifications, and electrical layouts. This data were then used to construct a detailed BIM model, which served as the foundation of the DT. The DT was further enhanced by integrating real-time data feeds from sensors installed throughout the complex. These sensors were strategically placed to monitor critical aspects of energy consumption, including electricity usage, HVAC operations, and lighting.

The BIM model developed in this study provided a detailed representation of the structural and mechanical systems of the residential complex. Unlike standard 3D models (e.g. DWG, DXF), which primarily capture geometric and visual information, BIM integrates metadata, including material properties, energy performance, and system specifications. This integration enables dynamic simulations and data exchange, forming the foundation for the DT.

A significant distinction between BIM and a Digital Twin lies in their operational scope. While BIM is static and primarily used in the design and planning phases, a DT evolves dynamically, integrating real-time sensor data to provide continuous monitoring and predictive analysis. In this study, the DT was enhanced with real-time data from IoT-enabled sensors deployed throughout the complex. The integration of HVAC systems into the DT was achieved through sensors that collected temperature, humidity, and airflow data from strategically placed sensors. These inputs allowed the DT to simulate energy demands, optimise system performance, and adjust HVAC operations dynamically, improving both energy efficiency and occupant comfort.

The integration of sensor data into the DT allowed for real-time monitoring and analysis of energy consumption patterns. The DT provided a dynamic platform for simulating various scenarios, such as changes in occupancy or external temperature, and their impact on energy use. This capability was particularly valuable during the pandemic, as it allowed for the modelling of different lockdown scenarios and their potential effects on energy demand.

Figures 1 and 2 provide visual representations of the physical complex and its corresponding DT. Figure 1 shows the layout of the buildings within the complex, while Figure 2 illustrates the digital model created in BIM software. These figures underscore the complexity and detail involved in developing a DT that accurately reflects the real-world performance of the residential complex.

Data collection was a crucial component of this study, as it provided the empirical foundation for analysing energy consumption patterns. The data collection period spanned from June 2021 to June

Figure 1. Examined complex of buildings.

Figure 2. Visualised iModel of the Larnaca pilot buildings.

2022, covering multiple phases of the COVID-19 pandemic, including strict lockdown periods, gradual easing of restrictions, and the return to more typical conditions.

Energy consumption data were continuously collected using the sensors installed throughout the complex. These sensors captured detailed information on electricity usage, including data from HVAC systems, lighting, and other electrical appliances. The data were transmitted in real-time to a central database, where they were stored and later analysed.

Data collected from the sensors required extensive preprocessing to ensure accuracy and reliability. This included handling missing data, correcting anomalies, and ensuring synchronisation across different data streams. Given the variability in energy usage patterns due to the pandemic, special attention was paid to maintaining the temporal integrity of the data, allowing for accurate time-series analysis.

To ensure the robustness of the analysis, the collected data were divided into three sets: training, validation, and testing. The training set comprised the majority of the data and was used to develop initial predictive models. The validation set was used to fine-tune these models, ensuring that they could accurately predict energy consumption under different conditions. Finally, the testing set was used to evaluate the performance of the models, providing an independent assessment of their accuracy and reliability.

In addition to energy consumption data, supplementary data on weather conditions and occupancy levels were also collected. Weather data, including temperature, humidity, and solar radiation, were obtained from local meteorological stations, while occupancy data were estimated based on surveys and occupancy sensors. These additional data streams were essential for understanding the external factors influencing energy consumption and for improving the accuracy of the predictive models.

To forecast energy consumption and identify potential issues before they arise, several predictive models were employed. The predictive modelling process began with the use of the Skforecast library, which integrates seamlessly with Scikit-learn regression models. Skforecast was chosen for its ability to handle time-series forecasting, a crucial requirement given the temporal nature of the energy consumption data. The models were trained using the historical data collected from the sensors, with particular attention paid to identifying and incorporating significant lag variables. These lags represented previous time steps in the data, which were expected to influence future energy consumption.

To further enhance the predictive capabilities of the models, gradient boosting techniques were employed. Models such as XGBoost, LightGBM, and CatBoost were selected due to their robustness in handling large datasets and their ability to incorporate non-linear relationships between variables. These models were particularly well-suited for the complex and multifaceted nature of energy consumption data, which can be influenced by a wide range of factors, from external weather conditions to internal occupancy patterns.

The choice of predictive models, including Skforecast and various gradient boosting techniques was guided by their proven effectiveness in handling complex, non-linear data patterns typical of energy consumption datasets. These models were selected to provide a comprehensive analysis, with each bringing unique strengths in handling different aspects of the data, such as time-series forecasting or the incorporation of exogenous variables.

Each model underwent a rigorous hyperparameter tuning process, utilising grid search methods to identify the optimal configuration for each set of data. This process involved testing various combinations of parameters, such as the number of trees in the model or the learning rate, to maximise the accuracy of the predictions. The models were then validated using the validation dataset, ensuring that they could generalise beyond the training data.

Exogenous variables, including weather data and occupancy levels, were incorporated into the models to improve their predictive performance. These variables provided additional context, allowing the models to account for external factors that could impact energy consumption. The inclusion of these variables was particularly important during the pandemic, as changes in occupancy and unusual weather patterns had significant effects on energy usage.

Data visualisation was employed throughout the study to facilitate the interpretation and communication of the results. The visualisations were created using a variety of tools, including Python libraries such as Matplotlib and Seaborn, which allowed for the creation of detailed and informative plots. The visualisations focused on illustrating key trends and patterns in the energy consumption data. Time-series plots were used to show changes in energy usage over the course of the study period, highlighting the impact of the pandemic on consumption patterns.

4. Results

This chapter presents the results obtained from the study, focusing on the energy consumption patterns of the residential complex in Larnaca, Cyprus, during the COVID-19 pandemic. The analysis is carried out through various predictive models, including Skforecast, XGBoost, and deep learning approaches like LSTM and RNN. Each section includes a detailed examination of the figures, explaining the significance of the results and how they contribute to the overall findings of the study.

4.1. Forecasting time series with Skforecast, Scikit regression model

Skforecast, is a library that contains necessary functions and classes adapting with any Scikit-learn regression model to forecast problems. Based on the Scikit-learn regression model, a forecast model was implemented using data from Onset sensors located in our complex of buildings in Larnaca. The dataset consists of the total energy consumption (kWh) from 2021-06-16 to 2022-06-15. Data are divided into 3 sets: training, validation, and test, as shown in Figure 3.

This figure illustrates the fluctuating energy consumption in the complex, with clear seasonal variations. The highest peaks occur during the summer months, which is consistent with the increased use of air conditioning in response to higher temperatures. The data indicates that external temperature is a major driver of energy consumption in the building. The seasonal pattern observed here underscores the need for energy management strategies that account for temperature-related demand. This could involve the integration of renewable energy sources like solar power, particularly during peak summer months, to offset increased energy consumption and enhance sustainability.

Figure 4 compares the actual total power consumption with the predicted values generated by the Skforecast model. The close alignment between the observed and predicted values indicates the model's accuracy in forecasting energy consumption based on historical data. This figure compares the actual energy consumption with the values predicted by the Skforecast model. The close alignment between the observed and predicted values demonstrates the accuracy of the model, with a percentage error of 3.025%. The Skforecast model shows robustness in its predictions, making it a reliable tool for anticipating energy needs in smart buildings. This accuracy is particularly crucial for planning and optimising energy resources during periods of fluctuating demand, such as during the pandemic.

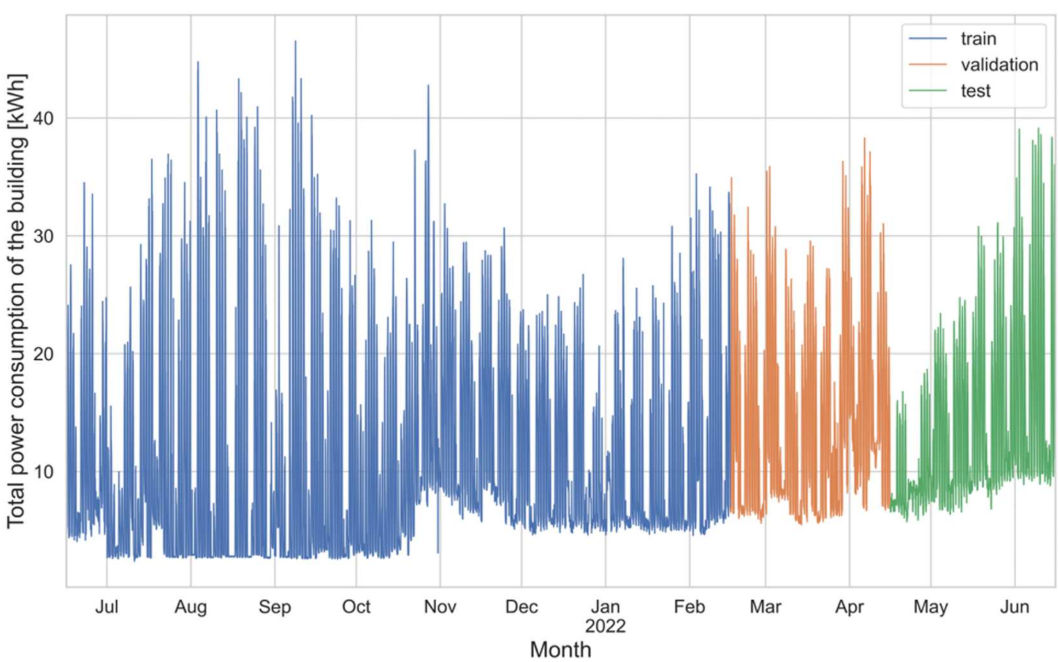

Figure 3. Total power consumption of the building [kWh].

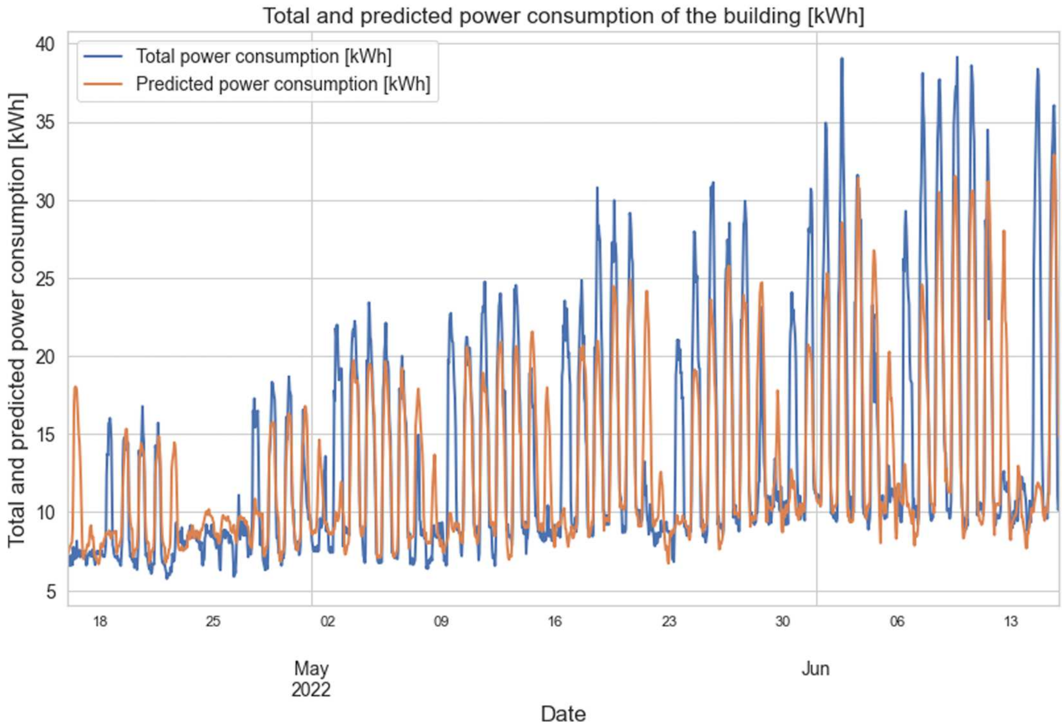

Figure 4. Total and predicted power consumption of the building [kWh].

Following the optimisation of lags and hyperparameters, the model's prediction accuracy improved, reducing the error margin to 2.864%. This figure demonstrates the enhanced alignment between the actual and predicted energy consumption after the model was fine-tuned. The improvement in prediction accuracy highlights the importance of model optimisation in predictive analytics. By fine-tuning the model, it becomes better equipped to handle the complexities of real-world energy consumption data, leading to more accurate and actionable insights.

Figure 5 introduces prediction intervals, providing a range within which the actual consumption is expected to fall. These intervals offer a measure of the model's uncertainty, allowing for more nuanced planning and decision-making. The inclusion of prediction intervals is a significant enhancement, as it allows building managers to prepare for potential variations in energy demand. This is particularly useful in crisis situations, where demand can be unpredictable.

4.2. Forecasting time series with XGBoost

The XGBoost model was also employed to forecast energy consumption, offering a different approach to handling the data. Figures 6–9 present the results of this model. XGBoost library contains the XGBRegressor class which follows the scikit learn API. It is compatible with skforecast. According to the XGBoost library, a forecast model was implemented using data from Onset sensors located in our case study. The dataset consists of the total energy consumption (kWh) from 2021-06-16 to 2022-06-15.

The following figure shows data divided into training and test. Figure 7 distinguishes between the data used for training the model and the test data used to evaluate its predictive performance. The training data covers a majority of the timeline, while the test data represents a smaller, more recent period. The separation of training and test data is essential for validating the model's

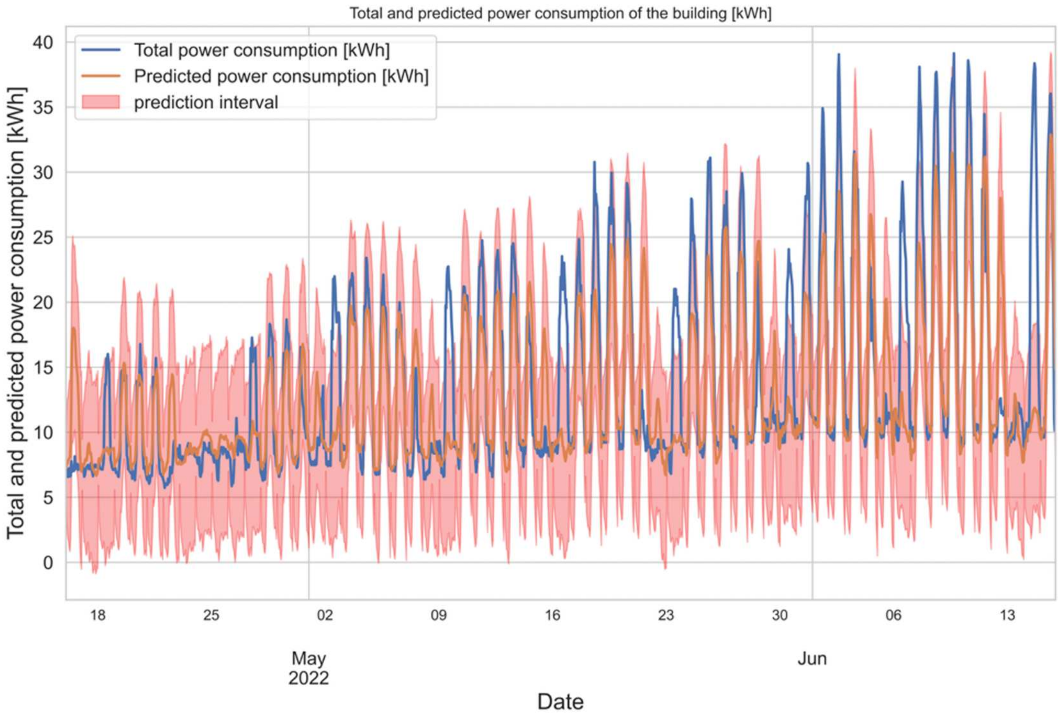

Figure 5. Total and predicted (intervals) power consumption of the building [kWh].

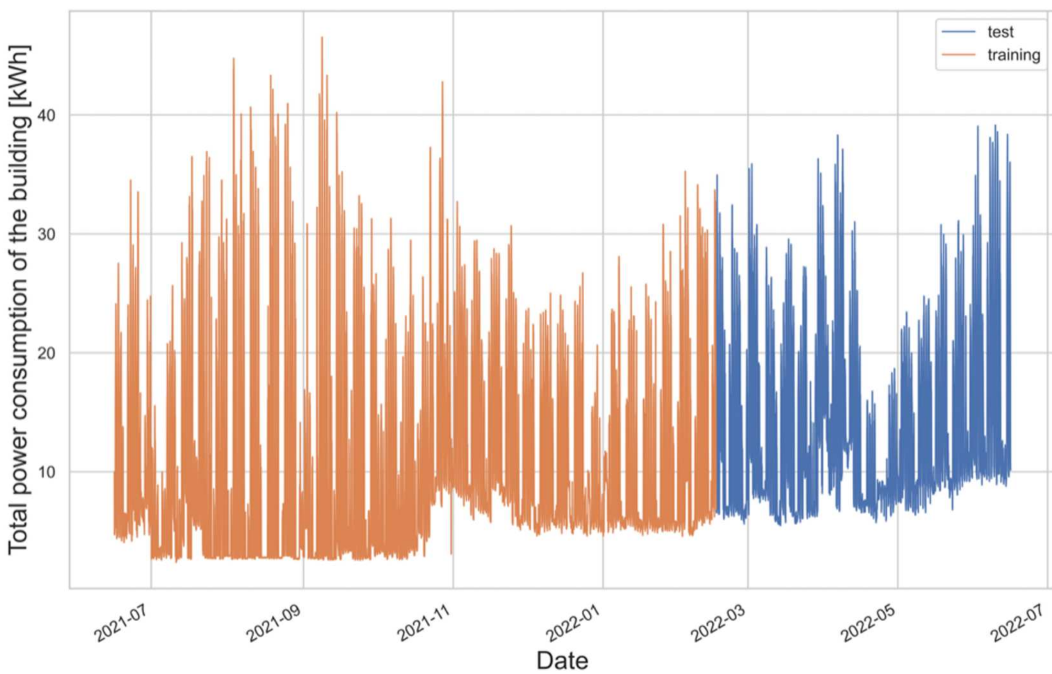

Figure 6. Total power consumption of the building [kWh], train and test dates.

predictive capability. By focusing on the model's performance on the test data, the study ensures that the results are generalisable and not just a reflection of overfitting to the historical data.

Figure 7 compares the actual energy consumption with predictions made by the XGBoost model. Here, the XGBoost model's predictions are plotted against the actual energy consumption data. The figure demonstrates the model's performance, showing how well it can predict energy consumption using advanced machine learning techniques. XGBoost's ability to handle non-linear relationships in the data makes it particularly effective in capturing the complex patterns of energy consumption in a smart building environment. The model's performance, with a slightly higher error margin than the optimised Skforecast model, suggests that while XGBoost is powerful, it may require further tuning or the inclusion of additional exogenous variables for enhanced accuracy. While XGBoost effectively captures non-linear relationships in the data, it may benefit from additional optimisation or the inclusion of more exogenous variables to improve accuracy. This model's performance suggests that different algorithms may be better suited to different aspects of energy consumption prediction.

Figures 8 and 9 highlight specific days where the model's predictions were either most accurate (February 27, 2022) or least accurate (June 2, 2022). These figures show the best and worst-performing days of the model's predictions. The best day shows excellent alignment with the actual consumption, while the worst day exhibits significant deviations. By analysing these outliers, the study can gain insights into the conditions or factors that lead to model inaccuracies. The significant difference in model performance between the best and worst-predicted days could be due to unforeseen events or extreme weather conditions that were not fully accounted for in the model. Understanding these outliers is crucial for improving the model's robustness, especially in environments with highly variable energy demands.

4.3. Forecasting time series with gradient boosting, Skforecast, XGBoost, LightGBM, CatBoost

Gradient boosting models stand out within the machine learning community for best results. As a result, they achieve in a multitude of use cases, both regression and classification. Based on gradient

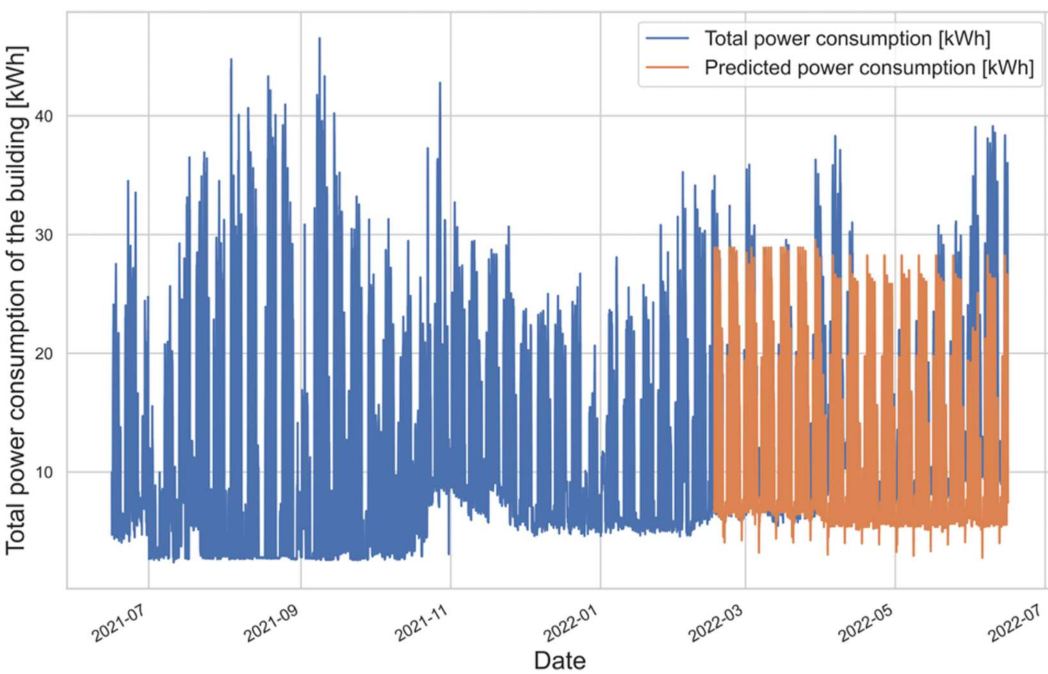

Figure 7. Total and predicted power consumption of the building [kWh].

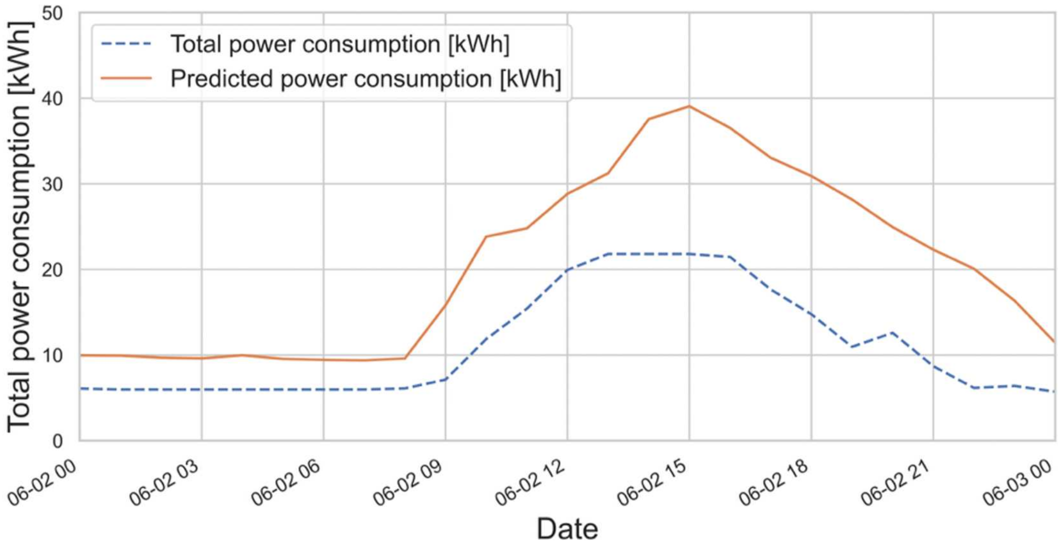

Figure 8. June 2, 2022 – Worst Predicted Day.

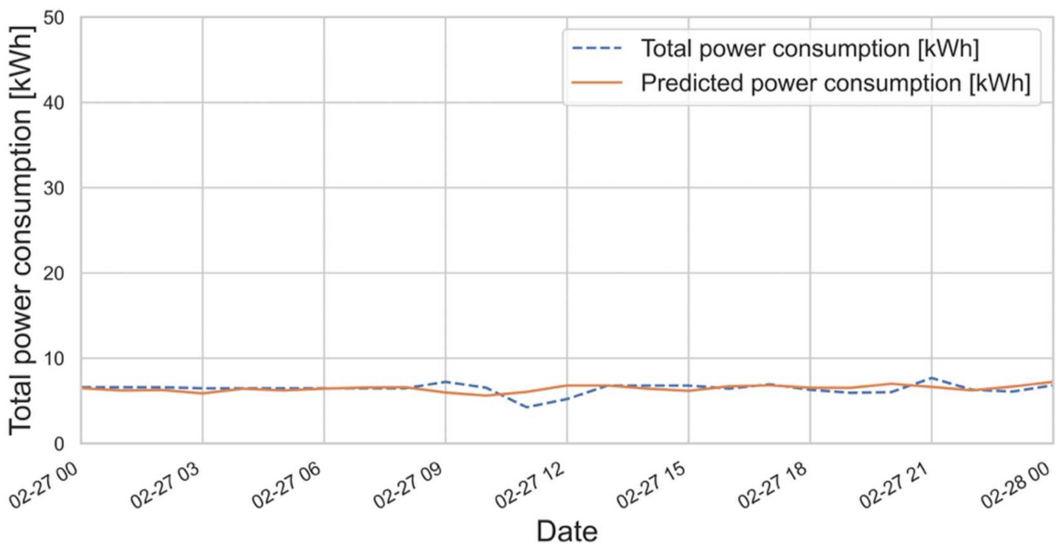

Figure 9. February 27, 2022 – Best predicted day.

boosting models, XGBoost, LightGBM and CatBoost, forecast models were implemented using data from Onset sensors located in the complex. The dataset consists of the total energy consumption (kWh) from 2021-06-16 to 2022-06-15.

Figure 10 presents the predictions from various gradient boosting models. The results from XGBoost, LightGBM, and CatBoost are compared against actual energy consumption. The comparison of different gradient boosting models provides valuable insights into which model is best suited for this type of data. The slight variations in prediction accuracy highlight the strengths and weaknesses of each model. Among the models, CatBoost shows the lowest error margin, suggesting it is particularly well-suited for this dataset, especially in handling categorical variables such as calendar effects.

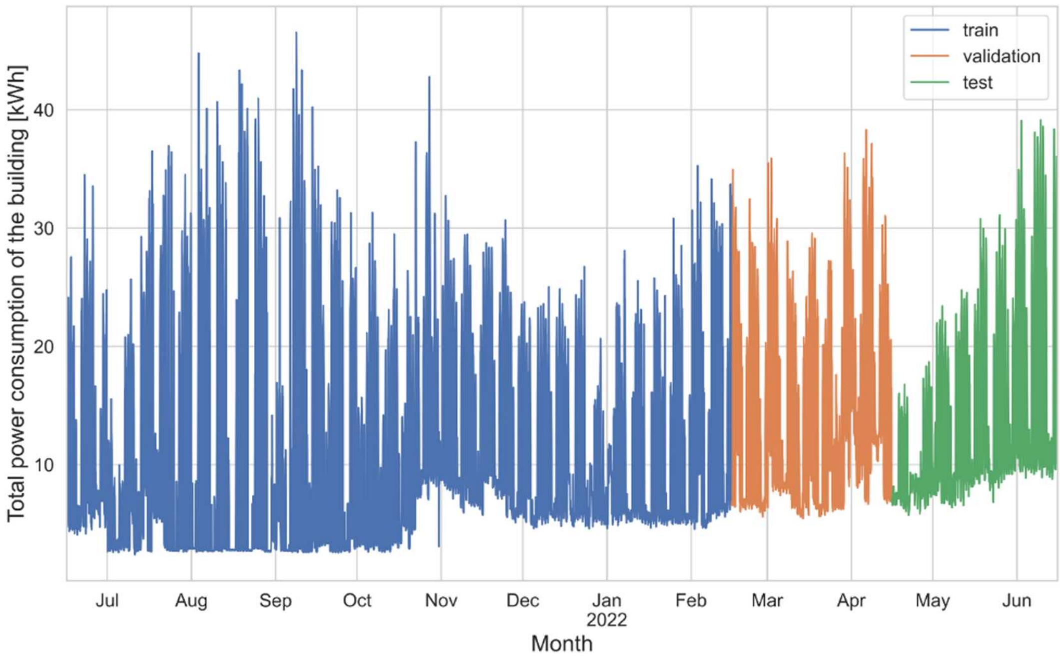

Figure 10. Total power consumption of the building [kWh].

4.3.1. XGBoost

XGBoost is an optimised distributed gradient boosting library that contains machine learning algorithms under the Gradient Boosting framework. As a first approach, an autoregressive model is trained. Model uses past values (lags) of the response variable itself as predictors. Given the high number of hyperparameters that gradient boosting models have, a grid search strategy combined with back-testing is used to identify the configuration resulting in the best predictions.

Once the best combination of hyperparameters has been identified using the validation data, the predictive capacity of the model is evaluated when applied to the test set. In order to simulate the prediction process (every 36 hours), the backtesting_forecaster function is used. The percentage error of the back test is 21.579%.

Figure 11 reiterates the results from the XGBoost model but includes additional context, such as the impact of incorporating exogenous variables. The use of exogenous variables such as temperature and calendar effects significantly improve the model's accuracy, as seen by the reduction in prediction error. This finding underscores the importance of a holistic approach in predictive modelling, where external factors are considered alongside historical consumption data.

4.3.2. Exogenous variables

Furthermore, to using autoregressive predictors obtained from the past of the response variable itself, it is possible to add other exogenous variables. In this case, information on the calendar (month, day of the week, time, holidays, etc.) as well as weather variables (temperature) is available.

Figure 12 illustrates how categorical data, such as day of the week or holidays, was stored and used in the models. Such data types are essential for capturing recurring patterns in energy consumption. The integration of categorical data enhances the model's ability to predict energy consumption more accurately. By considering the cyclic nature of energy use (e.g. weekdays vs. weekends), the models can better anticipate demand fluctuations, leading to more effective energy management strategies.

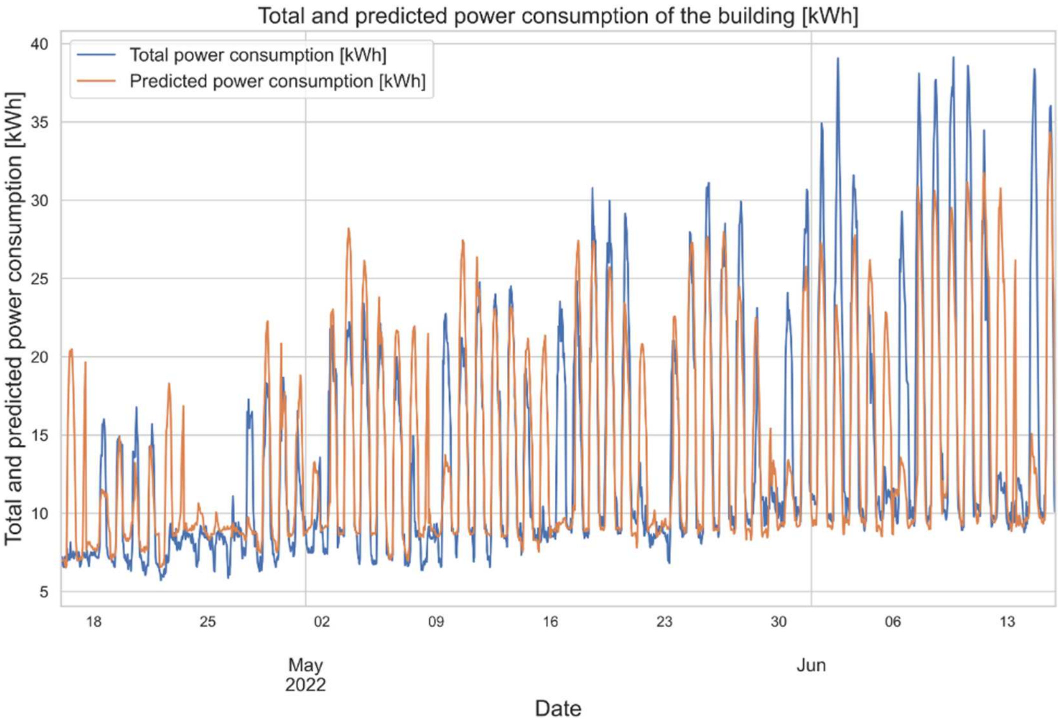

Figure 11. Total and predicted power consumption of the building [kWh].

Date	Total	temp	holiday	weather_clear	weather_cloudy	weather_fair	weather_fog	weather_heavy rain	weather_heavy rain shower	weather_rain	...	weekday_43.0
2021-06-16 01:00:00	4.710476	18.5	0.0	1	0	0	0	0	0	0	...	0
2021-06-16 02:00:00	4.718253	18.2	0.0	1	0	0	0	0	0	0	...	0
2021-06-16 03:00:00	5.482294	18.0	0.0	1	0	0	0	0	0	0	...	0

3 rows × 77 columns

Figure 12. Stored data as category type.

By including exogenous variables as predictors, the prediction error has been decreased. The percentage error of the back test is 19.928%.

4.3.3. LightGBM

LightGBM is a gradient boosting framework that uses tree-based learning algorithms. It is developed by Microsoft. An autoregressive model is trained. Model uses past values (lags) of the response variable itself as predictors. Given the high number of hyperparameters that gradient boosting models have, a grid search strategy combined with back-testing is used to identify the configuration resulting in the best predictions. The percentage error of the back test is 21.737%.

4.3.4. CatBoost

CatBoost is a high-performance open-source library for gradient boosting on decision trees developed by Yandex. It is a readymade classifier in scikit-learn's conventions terms that would deal with categorical features automatically. Using CatBoost model, the percentage error of the back test is 17.157%.

Therefore, as seen in the preceding cases, including exogenous variables as predictors can greatly improve predictive performance. CatBoost gradient boosting model yields substantially better results than the other two libraries in this situation.

4.4. Time series forecasting with long-short term memory (LTSM) deep learning model

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Based on Long-Short Term Memory (LTSM) deep learning model, a forecast model was implemented using data from Onset sensors located in the buildings. The dataset consists of the total energy consumption (kWh) from 2021-06-16 to 2022-06-15.

Figures 13 and 14 present the results from the LSTM model, a deep learning approach designed to handle sequential data. The figures show the actual vs. predicted energy consumption. The LSTM model's performance demonstrates the potential of deep learning techniques in energy forecasting, particularly for capturing long-term dependencies in the data. The model's ability to adapt to changes in energy consumption patterns over time makes it a valuable tool for dynamic environments like smart buildings.

Figure 13 shows the energy consumption predictions made by the LSTM model, which is designed to capture long-term dependencies in sequential data. The LSTM model effectively

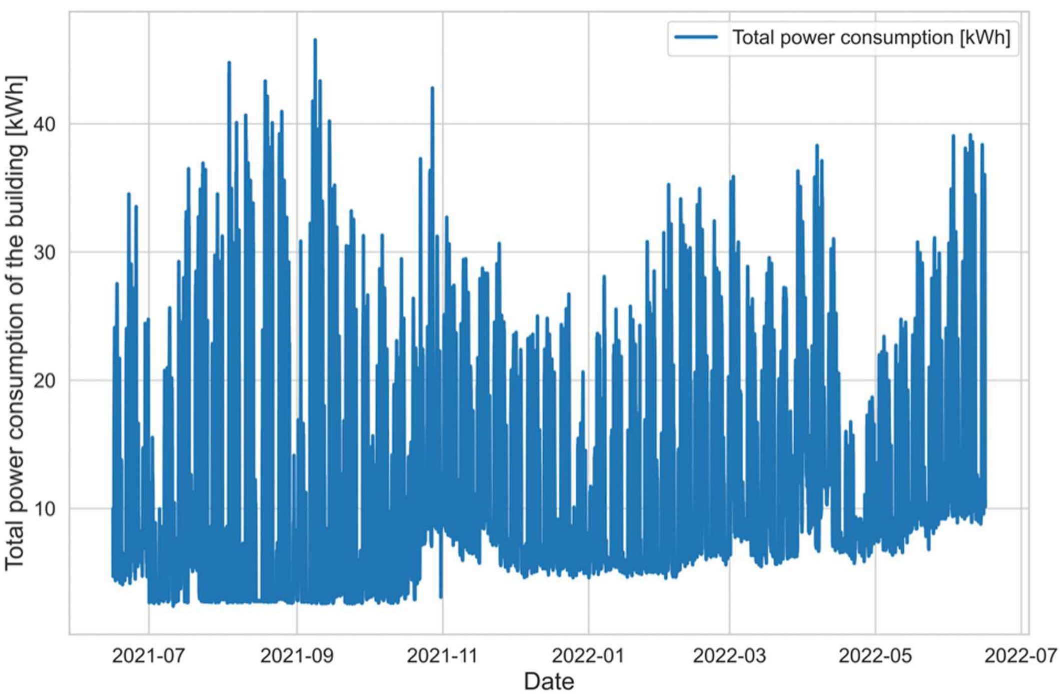

Figure 13. Total power consumption of the building [kWh].

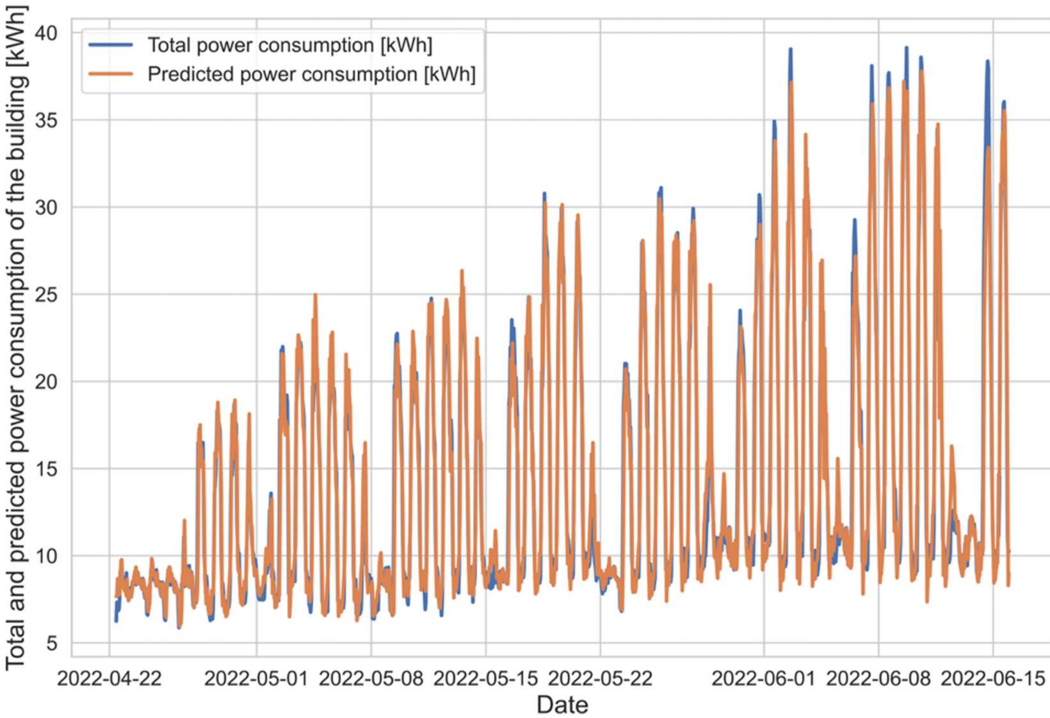

Figure 14. Total and predicted power consumption of the building [kWh].

handles the temporal nature of energy consumption data, making it a strong candidate for long-term energy forecasting in dynamic environments like smart buildings.

Figure 14 compares actual consumption with LSTM predictions, highlighting the model's ability to adapt to changing patterns over time. The LSTM model's performance is particularly strong in scenarios with significant historical influence, such as during the COVID-19 pandemic when past occupancy and behaviour patterns greatly influenced energy use.

4.5. Predicting energy consumption using recurrent neural network (RNN) and long-short term memory (LTSM)

A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed or undirected graph along a temporal sequence. According on both deep learning models, forecast models were implemented using data from Onset sensors located in the complex of buildings.

Figures 15 and 16 compare the predictions from RNN and LSTM models, highlighting their respective strengths in handling time-series data. While both RNN and LSTM models are designed for sequential data, LSTM typically outperforms RNNs in capturing longer dependencies and avoiding issues like vanishing gradients. The results suggest that LSTM is better suited for predicting energy consumption in scenarios where historical data significantly influences future trends.

4.5.1. RNN model

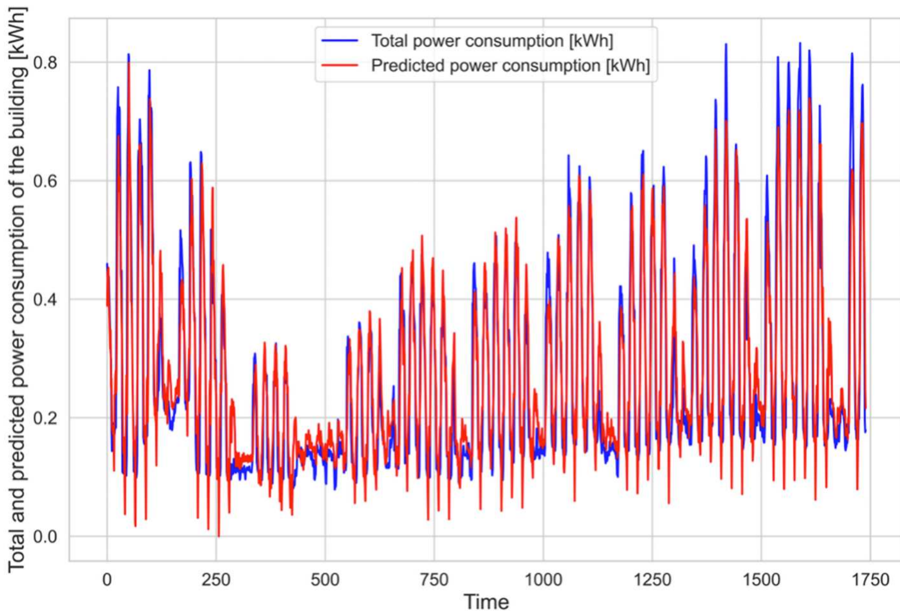

Figure 15. Predictions made by RNN model.

4.5.2. LSTM model

Figure 17 synthesises the predictions from both LSTM and RNN models, providing a direct comparison of their performance. The comparison reveals that LSTM generally produces more accurate predictions, particularly in capturing the nuances of energy consumption patterns over extended periods. This insight is critical for future studies focusing on improving predictive accuracy in smart building environments.

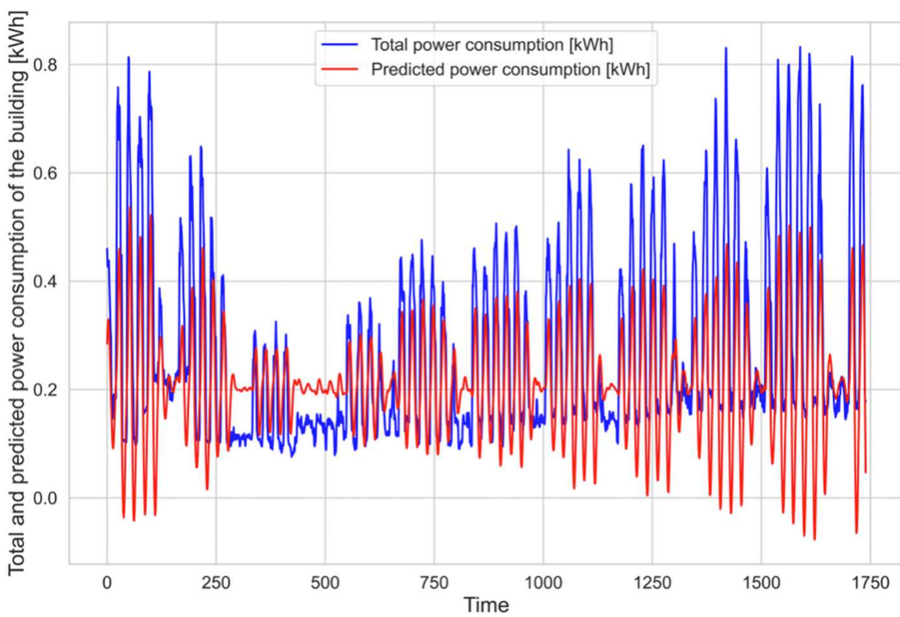

Figure 16. Predictions using LSTM model.

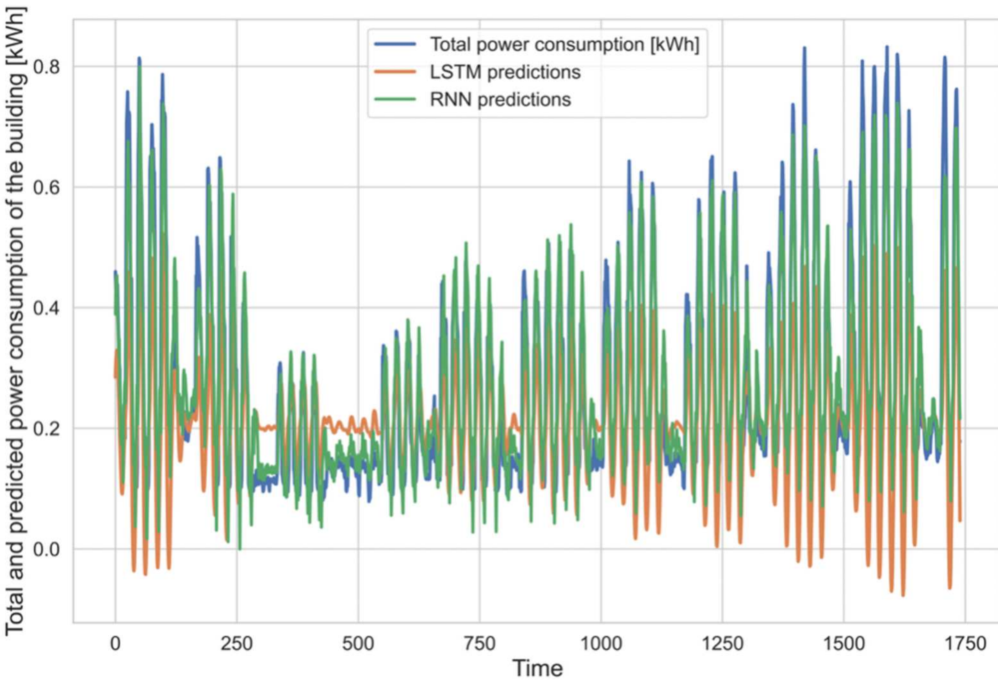

Figure 17. LSTM and RNN – Total and predicted power consumption of the building [kWh].

5. Discussion

The COVID-19 pandemic posed unprecedented challenges, fundamentally altering the dynamics of energy management in buildings during crises. This study delved into the intricate interplay between smart building technologies, energy management strategies, and the exigencies of crisis situations. A multifaceted approach was undertaken, encompassing a thorough literature review, in-depth analysis of real-world case studies, and the application of advanced technologies such as DTs. These methodologies aimed to illuminate pivotal strategies and innovative solutions for optimising energy resources in smart buildings during crises.

The pandemic served as a catalyst, highlighting the need for resilient and adaptable smart building technologies. The research demonstrated a paradigm shift in energy consumption patterns within residential buildings, driven by lockdown measures and the resulting changes in occupancy rates. The findings indicate that smart buildings, equipped with IoT sensors, BEMS, and data analytics, are indispensable tools for adapting to these dynamic circumstances.

One of the key innovations explored in this study was the integration of DTs into the energy management framework of smart buildings. By creating virtual replicas of physical buildings, DTs allow for in-depth analysis and simulation of energy usage under various scenarios, including unexpected ones like a pandemic-induced lockdown. This technology proved invaluable in providing insights into how changes in occupancy and usage patterns impact energy demand. It also allowed for real-time optimisation of systems, enhancing efficiency and reducing costs. Moreover, the predictive capabilities of DTs facilitated proactive maintenance, identifying potential issues before they escalated into major problems, ensuring that energy systems operated at peak efficiency.

The case study of a residential complex in Larnaca exemplified the dynamic interplay between external crises and resource consumption within urban settings. The substantial rise in energy consumption during the lockdown period, especially within residential buildings, underscored the multifaceted role homes played during the pandemic. Residences transformed into living spaces, workplaces, and educational hubs, driving up electricity usage for lighting, temperature control, and electronic devices. Seasonal spikes in energy consumption during the holiday season and hot summers further reinforced the need for adaptable energy management practices in smart buildings.

A critical component of this research was the implementation of various predictive models to forecast energy consumption within smart buildings. These models included traditional machine learning approaches like Skforecast, XGBoost, LightGBM, and CatBoost, as well as advanced deep learning models such as Long-Short Term Memory (LSTM) and Recurrent Neural Networks (RNN). Each of these models provided unique insights into the complex, non-linear relationships that drive energy consumption.

The LSTM and RNN models were particularly effective in capturing the temporal dependencies within the energy consumption data. These models are designed to handle sequential data, making them well-suited for time-series forecasting where past values have a significant impact on future outcomes. The LSTM model demonstrated its ability to accurately predict energy consumption over longer periods, accounting for both short-term fluctuations and long-term trends. This capability is crucial in dynamic environments like smart buildings, where energy demand can vary significantly based on occupancy, weather conditions, and other external factors. The RNN model, while also effective, showed slightly less accuracy compared to LSTM, which can be attributed to its simpler architecture and susceptibility to issues like vanishing gradients in longer sequences.

The integration of DTs into the energy management framework of smart buildings presented a transformative opportunity. By creating virtual replicas of physical buildings, DTs allowed for in-depth analysis and simulation of energy usage under various scenarios, including unexpected ones like a pandemic-induced lockdown. This technology provided invaluable insights into the impact of changes in occupancy and usage patterns on energy demand, allowing for real-time optimisation of systems, enhancing efficiency, and reducing costs. Moreover, the predictive capabilities of DTs facilitated proactive maintenance, identifying potential issues before they escalated into major problems, ensuring that energy systems operated at peak efficiency.

The study also highlighted several challenges encountered during the pandemic, ranging from fluctuating occupancy levels to data anomalies and communication hurdles. In response, innovative solutions were proposed, such as real-time monitoring, predictive maintenance, touchless fixtures, and user engagement. These solutions not only optimised resource utilisation but also enhanced occupant safety, demonstrating the crucial role of technology in crisis mitigation.

This research has provided valuable insights into the symbiotic relationship between technology and crisis management in smart buildings. It underscored the importance of data-driven decision-making, seamless integration of building systems, and proactive emergency preparedness. Moreover, the study emphasised the need for interdisciplinary collaboration, involving architects, engineers, data scientists, and policymakers, to foster holistic solutions.

The predictive models employed in this study, including Skforecast, XGBoost, LightGBM, CatBoost, LSTM, and RNN, each contributed unique strengths to the forecasting of energy consumption during the COVID-19 pandemic. The LSTM model stood out for its superior performance in capturing long-term dependencies in the data, making it particularly valuable for forecasting energy use in dynamic environments. Its ability to maintain accuracy over extended periods provided a robust framework for anticipating energy demand fluctuations. The RNN model, while also effective, was somewhat less accurate in comparison, highlighting the importance of model selection based on the specific characteristics of the data being analysed.

The success of these models, particularly the deep learning approaches, demonstrates the potential for advanced predictive analytics in optimising energy management within smart buildings. By leveraging these models, building managers can make informed decisions that enhance energy efficiency, reduce costs, and improve overall building resilience during crises.

Despite the promising results obtained in this study, the integration of DT technologies into building EMS revealed several technical challenges. Interoperability issues between DT platforms and existing BMS were a significant limitation, particularly for legacy infrastructures with proprietary data exchange protocols. To address this, custom middleware solutions were required, increasing the complexity and cost of implementation. Real-time data processing demands also posed challenges, as the computational resources required for dynamic modelling and simulation were substantial, potentially limiting scalability for larger systems. Moreover, sensor inaccuracies and data inconsistencies affected the reliability of the predictive models, necessitating frequent calibration and validation. Modelling occupant behaviour introduced additional complexity, as human activity patterns are dynamic and influenced by various external factors. These limitations underscore the need for future research focused on developing standardised protocols, enhancing sensor technologies, and creating robust algorithms for dynamic behaviour modelling. Addressing these challenges will be crucial to realising the full potential of DT technologies in sustainable building energy management.

DTs emerged as a pivotal optimisation tool in the energy management of smart buildings during crises. By enabling real-time monitoring, analysis, and decision-making, DTs facilitated proactive resource management and enhanced the resilience of smart buildings. The study's exploration of these technologies, alongside predictive models, provides a comprehensive approach to managing the complex challenges of energy consumption in the face of crises like the COVID-19 pandemic.

As we navigate an uncertain future, harnessing the power of technology, informed decision-making, and adaptive strategies will be paramount in building resilient, sustainable, and resource-efficient communities. The findings of this study suggest several directions for future research and practice. Future research should explore the broader application of DTs across various aspects of building management, integrating them with other smart technologies like IoT devices and AI to create more responsive and efficient systems. Continued refinement of predictive modelling techniques is necessary, particularly in incorporating more comprehensive datasets and improving model accuracy. Hybrid models that combine the strengths of different algorithms could offer more robust predictions. The insights from this study should also inform policy frameworks, industry standards, and academic curricula, fostering a collective approach toward building resilience in the face of unforeseen challenges.

6. Conclusions

The findings of this study highlight the transformative potential of Digital Twins (DTs) as an integral component of energy management in smart buildings, particularly during crises such as the COVID-19 pandemic. By bridging physical and digital systems, DTs have demonstrated their capability to provide actionable insights for real-time optimisation, predictive maintenance, and efficient resource utilisation. These technologies address critical challenges such as fluctuating energy demand, changing occupancy patterns, and operational inefficiencies, offering a robust framework for resilient and adaptive energy systems.

In conclusion, the COVID-19 pandemic has presented an unprecedented backdrop against which resource management in smart buildings has come to the fore. This study transcends the confines of traditional energy management paradigms. It not only underscores the pivotal role of smart building technologies in crisis scenarios but also advocates for a holistic, human-centric approach. By embracing innovative solutions, fostering interdisciplinary collaboration, and prioritising occupant well-being, smart buildings can evolve into dynamic, adaptable ecosystems capable of navigating the complexities of our ever-changing world.

Despite the promising advancements, several technical and operational challenges remain. Issues such as data inconsistencies, sensor inaccuracies, and the computational intensity of real-time modelling highlight areas for further development. These findings suggest the need for continued research into hybrid predictive models, standardisation of data exchange protocols, and the integration of DTs with IoT and AI technologies. Addressing these gaps will enhance the scalability and accessibility of these systems, enabling broader adoption in diverse building typologies.

The implications of this research extend beyond the realm of academia, shaping the future of sustainable urban living and resilient infrastructure. By leveraging the insights and methodologies outlined in this study, stakeholders can foster innovations that redefine the future of smart buildings and urban ecosystems. In these turbulent times, harnessing technology, informed decision-making, and adaptable strategies is imperative for a sustainable and resource-efficient future.

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No potential conflict of interest was reported by the author(s).

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Data availability statement

All data used in this study are available upon request.

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