Analysis and Design of Smart Components in Digital Energy Twins

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Abstract: The energy crisis, energy demand growth, and dependence on fossil fuels worldwide have made urgent action necessary for us to seek sustainability in energy production and use. Digital technologies, especially Digital Energy Twins, have immense potential to reduce energy consumption, thereby reducing environmental impacts, particularly in the building sector. This paper presents the development of a digital energy twin that supports sustainable energy consumption analysis and optimization. Our study begins with a comprehensive analysis of the energy consumption data, the weather data, and the building plans as a solid basis for the analysis. We identify key energy consumption trends and patterns across different timescales and device-specific details that could be optimized, such as base load consumption and device-specific inefficiencies. A key part of our work is forecasting energy consumption using time series models, such as the ARIMA model, which promises to be useful in identifying patterns for improving energy efficiency. Overall, our study provides valuable insights into energy optimization and could form the base for further advances in digital energy twins at OTH Regensburg, helping to contribute to its sustainable development goals and smart campus initiatives.

1 INTRODUCTION

The current energy crisis is one of the most significant global challenges. The increasing energy demand, coupled with the widespread use of fossil fuels, has led to a significant rise in energy prices and increased uncertainty regarding energy availability. In 2021, the European Union imported more than 45% of its natural gas, highlighting its dependence on external energy sources (International Energy Agency, 2024). In addition, using fossil fuels is a major contributor to the increase in carbon dioxide (CO2) emissions that drive climate change (Farghali et al., 2022). These circumstances emphasize the urgency of rethinking global energy consumption patterns and developing sustainable energy systems to achieve long-term climate targets and ensure energy security (Farghali et al., 2023).

A decisive step towards transforming the energy sector in Germany was taken with the Heat Planning and Decarbonization of Heating Networks Act, which was passed on 17 November 2023. This law obliges cities and municipalities to draw up municipal heating plans to accelerate the transition to the use of renewable energies and improve energy efficiency in the heating sector. The aim is to achieve a climate-neutral building stock by 2045 (Federal Ministry for Housing and Construction, 2024).

The energy efficiency in the building sector is crucial in the context of the current energy crisis, as this sector represents about 30%-40% of the total energy consumption worldwide (Invidiata et al., 2018). Almost a third of the total greenhouse gas emissions come from building use, which emphasizes the need to promote sustainable building practices (Danish et al., 2019; Hafez et al., 2023).

1.1 Digital Twins

Digitalization is a cross-industry trend that is often associated with concepts such as the Internet of Things, cyber-physical systems, and the digital twin (Newrzella et al., 2021). In recent years, the digital twin has become increasingly important in industry and science and is being used increasingly (Tao et al., 2019). A digital twin is generally understood as a virtual replica of physical objects or systems (do Amaral et al., 2023).

The adoption of digital technologies, particularly Digital Energy Twins, presents a promising solution for optimizing energy use in buildings and minimizing environmental impacts. Digital Energy Twins enable precise monitoring and management of energy flows, offering substantial potential for CO2 reduc-

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tion and cost savings (do Amaral et al., 2023).

Amaral et al.do Amaral et al. (2023) argue that using digital energy twins offers numerous advantages for energy management. A digital energy twin enables the monitoring and control of energy systems in (near) real time. This allows performance to be optimized, downtimes to be reduced, and operating costs to be lowered.

Digital twins of energy generation and consumption can provide invaluable insights from simulations. In addition, they improve the efficiency of operations while minimizing environmental impact. Through these capabilities, smart city applications can address urban energy challenges with substantial potential for sustainable urban development.

1.2 Smart City

In recent years, the smart city concept has attracted significant interest from governments, companies, and research institutions. The primary goal of a smart city is to enhance the efficiency, sustainability, and livability of cities. This is achieved by implementing modern digital twin technologies alongside information and communication technologies (ICT) (Yin et al., 2015).

Implementing digital twins offers a powerful way to improve efficiency and quality of life in smart cities (Farsi et al., 2023). By accurately modeling and monitoring urban systems, these virtual replicas enable better decision-making, which, then applied in focused environments such as university campuses, showcase their benefits in controlled, research-based settings.

1.3 Smart Campus

A campus consists of several buildings with different years of construction, energy sources, and energy consumers. By optimizing the energy system on campus, goals such as reducing the carbon footprint and minimizing energy costs can be achieved (Lesnyak et al., 2023).

As stated by Alghamdi et al. (Alghamdi et al., 2020), they claim that controlling and managing energy along with the resource flows is a core function of a smart campus. With the help of sensors and the use of IoT technologies, energy and water consumption alongside carbon emissions can be tracked in real time. Such data allows the efficient monitoring and management of resource flows hence resulting in reduction of emissions and consumption (Afram and Janabi-Sharifi, 2014).

To conclude, enhancing and incorporating intelligent parts for the digital energy twin deployed on campus is viewed as one of the ways of improving environmental performance and creating operational efficiencies. This research will delve into how these technologies can be adapted for the Computer Science and Mathematics faculty building at OTH Regensburg, leveraging the digital twin concept to optimize energy management on campus.

1.4 Smart City Project of OTH Regensburg

The Smart City project at OTH Regensburg focuses on developing a digital energy twin for the mid-sized city in Germany. The project's central goal is to create a web-based platform that visualizes various energy data in an interactive 3D map. This platform is intended to help the city administration, homeowners, tenants, and other stakeholders by providing transparency in energy consumption and the potential for energy savings (Thelen et al., 2023). The platform will be referred to as the Cesium platform.

The Cesium platform integrates various data sources including electricity, hot water, heating consumption, and solar data (Thelen et al., 2023).

Figure 1 shows a screenshot of the platform with an exemplary selection of diagrams. The buildings and districts are colored based on energy consumption, using a color spectrum from red (high consumption) to green (low consumption).

The platform's user interface is designed to be customizable and expandable to many users with different requirements (Thelen et al., 2023). Thanks to this foundation and its adaptability, this platform represents the basis for integrating the idea of a Smart Campus at OTH Regensburg into this Smart City project.

1.5 Objective of the Work

This work aims to design and analyze smart components for a digital energy twin, using the campus building as a case study. Initially, the work involves analyzing current energy consumption, including data collection and evaluation, and examining relevant factors such as weather and building usage.

From this analysis, specific requirements for the digital energy twin's smart components will be identified and tailored to meet the needs of different user groups. In addition to technical aspects, the work will focus on the user interaction with the digital twin and its integration within the university's overall system.

Figure 1: Cesium Web Platform (Thelen et al., 2023).

Core to this work is developing a predictive algorithm for forecasting future energy use. The system's architecture will be designed to support real-time data access, enabling enhanced energy management.

Ultimately, this analysis and design process will contribute to the ongoing development of the Digital Energy Twin, supporting sustainable energy analysis and optimization efforts at the campus.

2 ANALYSIS

This section presents the main results of the data set analysis, focusing on identifying and understanding notable patterns and trends in energy consumption. The analysis begins with evaluating key metrics, followed by a detailed quarterly and annual examination. All analyses are based on data gathered from sensors installed in the buildings and the main building distribution system, considering various temporal and device-specific aspects.

2.1 Key Metrics

Table 1 lists the key parameters of the main building distribution system from 2019 to 2022. In Table 2, the data for the years 2023 and 2024 are shown. The first thing that stands out is the total annual energy consumption in megawatt hours (MWh). The year 2020, in particular, shows a significant deviation, which is attributable to the coronavirus pandemic and is therefore considered in further analysis.

Table 1: Key Figures (2019-2022).

Year	2019	2020	2021	2022
$\sum E$ (MWh)	548	480	519	531
AVG I (A)	51.83	45.60	46.35	48.61
AVG P (kW)	62.60	54.61	59.27	60.64
AVG S (kVA)	70.77	62.67	67.05	68.88
AVG cos φ	0.877	0.872	0.887	0.884

Table 2: Key Figures (2023-2024).

Year	2023	2024
$\sum E$ (MWh)	552	>275
AVG I (A)	53.95	55.57
AVG P (kW)	63.06	64.42
AVG S (kVA)	71.63	73.73
AVG cos φ	0.889	0.882

From 2021 onward, however, an upward trend will reach and exceed the 2019 level by 2023. The difference between apparent power and active power has remained relatively constant, except for 2024. As this year was not yet complete at the time of the analysis, this could still change over the year.

Finally, the average power factor cos(phi) is analyzed. Here, there is only a noticeable change of 0.015 between 2020 and 2021, indicating that electrical energy has been used more efficiently since then.

However, some general conditions must be considered when evaluating these figures. The steady increase in values is due to the expansion of the faculty and not because of inefficient energy use. As a technical faculty, which has numerous computer rooms, server rooms, and a quantum computer project (Regensburg, 2024), larger base loads can occur. These facilities are not only in operation during regular opening hours but also during quiet periods, which increases the energy demand accordingly.

2.2 Quarterly-Level Analysis

In this section, the differences in energy consumption by quarter were analyzed. The year 2024 was not included as it is incomplete and could, therefore, distort the percentage shares. Firstly, the percentage share of each quarter in total consumption is analyzed, as shown in Figure 2. The fourth quarter has the highest share, followed by the first quarter. This shows that the winter semester consumes more electricity than the summer semester

Figure 3 visualizes the monthly consumption in comparison. The months of October to March ac-

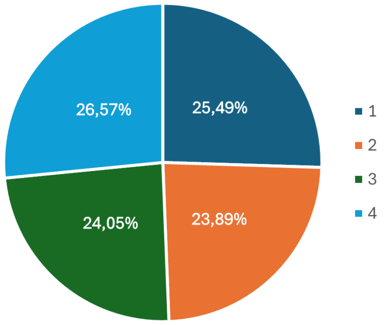

Figure 2: Quarterly Percentage of Total Consumption.

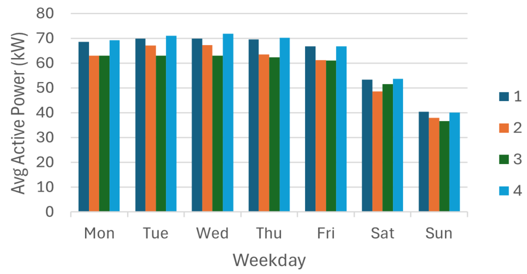

Figure 4: Quarterly Average Daily Active Power.

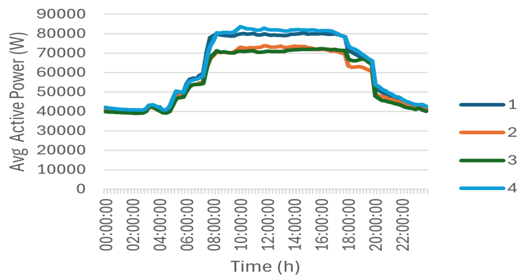

Figure 5: Yearly Avg. Daily Active Power.

count for 52.06% of total consumption, while April to September account for 47.94%. The higher consumption in winter can be explained by shorter lecture-free periods. October and January have the largest shares, which coincide with the start of the semester and the examination phase of the winter semester.

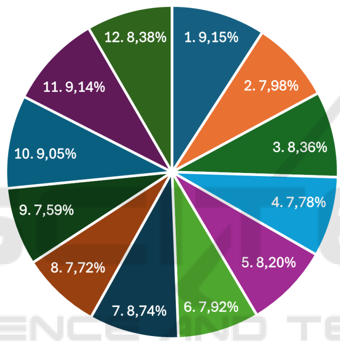

Figure 3: Monthly Consumption Percentage.

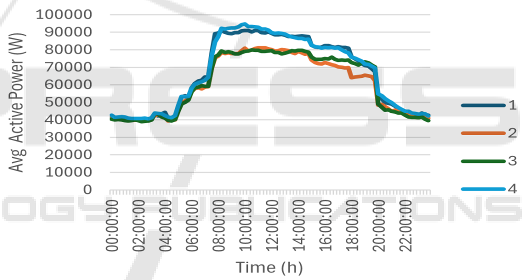

Figure 6: Seasonal Friday Variations.

Figure 4 shows the average daily active power by quarter. A comparison with the daily view shows that the active power is particularly high in the first and last quarters, indicating increased energy utilization in winter. A slight curve can be seen from Monday to Friday, with Wednesday as the peak. Saturdays show lower values in the second quarter, while an unusual increase can be observed in the third quarter, which could indicate an increase in events and courses on Saturdays. Sundays show a similar distribution to the other weekdays, suggesting a higher base load during the first and fourth quarters.

An analysis of the daily curves for the individual quarters, as shown in Figure 5, makes it even clearer that the first and fourth quarters have a higher average effective capacity. As these quarters comprise the winter semester, it could be argued that the winter semester is generally more heavily attended.

As the daily analysis revealed Friday to be particularly conspicuous, Figure 6 looks at Friday in detail. This figure shows even more clearly than Figure 5 that the values in the third quarter rise in the evening to the level of the first and fourth quarters.

2.3 Annual-Level Analysis

This analysis at the annual level included not only the years but also the months and their trends.

The monthly differences in energy consumption over the years are shown in Figure 7. The dotted trend line shows a steady increase in electricity consumption, which can be attributed to the growing number of students and the expansion of the technical infrastructure. October and November are particularly energy-intensive months, while July and January also show peak values. Overall, the winter semester shows higher energy consumption than the summer semester. The year 2020, characterised by the coronavirus pandemic, differs significantly from the others. The start of the semester in March is also noticeable but not as pronounced as in October.

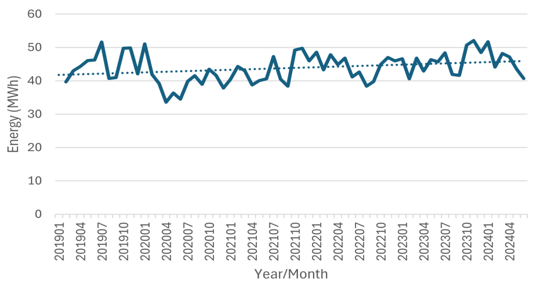

Figure 7: Annual Monthly Energy Differences (MWh).

Figure 8 shows the development of daily energy consumption over the years. The Christmas holidays are clearly recognisable, while the months of August and September show a gradual decrease in consumption without abrupt drops. Sundays are clearly identifiable. In March, daily consumption in the second half of the month is lower than in winter, especially compared to December and January.

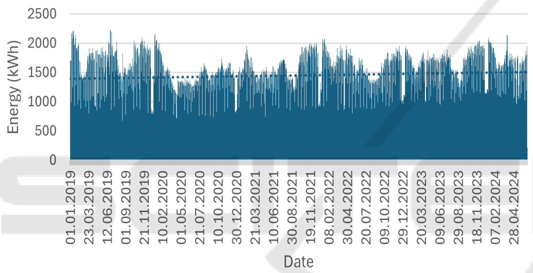

Figure 8: Yearly Daily Energy Consumption.

An interesting comparison of monthly energy consumption over the years can be seen in Figure 9. The year 2020 again stands out in particular due to the coronavirus pandemic. In contrast, 2023 shows consistently higher consumption values than the previous years. The year 2022 shows unusual fluctuations, with higher and lower consumption values than the other years. Particularly in the examination phases in January and July and at the beginning of the winter semester in October and November, clear consumption peaks can be seen.

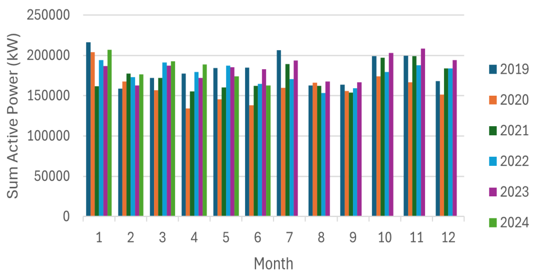

Figure 9: Annual Monthly Energy Comparison.

2.4 Conclusions

The analysis of energy consumption at different observation levels and on an appliance basis has provided several interesting findings.

The quarterly analysis showed that the fourth quarter had the highest energy consumption, followed by the first quarter. This indicates that the winter semester requires more energy than the summer semester due to the shorter lecture-free periods and more intensive use. The higher consumption during the winter was also confirmed at an annual level, with a steady increase in total consumption.

The power factor (cos (phi)) varied considerably over the course of the day and, in some cases, followed the operating times of the appliances. Noticeable peaks and fluctuations in the cos (phi) value, especially in the early morning, suggest that further research would be useful to identify optimization opportunities for air conditioning or ventilation systems.

Overall, the analysis provides valuable insights into the temporal distribution of energy consumption. The results can be used as a basis for future measures to optimize energy use and improve energy efficiency.

3 FORECAST OF FUTURE ELECTRICITY CONSUMPTION VALUES

Predicting future electricity consumption is crucial for energy and resource management, especially in large institutions like universities. A precise forecast makes it possible to take measures to optimize energy use in order to both reduce costs and promote sustainability (Khan et al., 2023). Different prediction methods can be applied based on historical consumption data collected over several years. These include both classical statistical methods and machine learning (ML) approaches.

3.1 Model Selection

The choice of model for energy forecasting depends largely on the type of data available and the required forecast accuracy. Appropriate approaches include statistical models such as linear regression (LR) and ARIMA models and the application of ML algorithms. The LR is a simple statistical model that describes a linear relationship between historical consumption data and time. It assumes that electricity consumption depends on time in a linear manner. It is particularly effective when the data to be forecast follows a clear linear trend but is less suitable for more complex or non-linear patterns and for data with seasonal fluctuations (Kim et al., 2020).

A common model for forecasting time series is the ARIMA model. It combines autoregressive (AR) components, which use past values for forecasting, with moving average components based on past forecast errors. Differentiation removes long-term trends or seasonal patterns to make the data stationary, a basic requirement of the model. This model has proven itself in numerous use cases for forecasting energy consumption data, especially when considering seasonal and recurring patterns (Mahia et al., 2019).

In this work, a time series model, specifically an ARIMA model, was used as a basis because it is particularly well suited to detect seasonal and recurring patterns in the energy data. Due to the historical data being distorted by the Corona pandemic, the use of ML is less advantageous as model's ability to generalize and identify reliable patterns is compromised. Accordingly, the ARIMA model is the better choice for making precise and reliable forecasts.

3.2 ARIMA Model

The ARIMA model is a popular method for time series forecasting, consisting of three main components: autoregressive (AR), integrated (I), and moving average (MA). These elements form the basis for the analysis and forecasting of time series data. The AR component describes the relationship between the current data point and several of its previous values, assuming that past values influence future values. This makes the AR model particularly useful when a clear trend can be seen in historical data (Shumway and Stoffer, 2017).

The I component ensures the differentiation of the time series to achieve stationarity. Stationary data have constant means and variances over time, which is a prerequisite for many time series models. Differentiation eliminates long-term trends and seasonal effects, making the data easier to analyze (Hirschle, 2021).

The MA component uses the prediction errors of previous models to correct future values. By analyzing the differences between actual and predicted values, this component increases the accuracy of predictions by smoothing out unforeseen fluctuations (Shumway and Stoffer, 2017).

The Seasonal ARIMA (SARIMA) model extends the classic ARIMA model to include seasonal patterns. While ARIMA covers linear trends and short-term fluctuations, SARIMA includes periodic patterns like those seen in energy consumption. The model considers seasonal autoregressive, differentiated and moving average components to enable more precise forecasts. SARIMA is particularly useful for data that show recurring patterns over the years (Hirschle, 2021).

Overall, the SARIMA model provides a solid basis for predicting time series with pronounced seasonal patterns, as occur in energy consumption.

3.3 Application of the SARIMA Model

The SARIMA model was used in this work to forecast energy consumption. The process was divided into several steps. Several Python libraries were utilized for the analysis and evaluation. For data manipulation and analysis, pandas NumPy, and matplotlib.pyplot were used. Time series analysis was performed using the SARIMAX model from the statsmodels library. The Augmented Dickey-Fuller (ADF) test was conducted to check stationarity. The influxdb_client library was used to retrieve data from the InfluxDB database. The sklearn.metrics functions mean_absolute_error and mean_squared_error evaluated model performance.

The raw data was retrieved from the InfluxDB. Due to significant fluctuations in daily data, which can be caused by factors such as holidays or operational variations, weekly aggregation was chosen. This approach smooths peaks and captures seasonal patterns without focussing short-term volatility.

The autocorrelation function (ACF) measures the correlation between a time series value and its previous values over different lags, while the partial autocorrelation function (PACF) measures direct correlations adjusted for shorter lags McKinney et al. (2011).

Figure 10 and Figure 11 show the ACF and PACF values of the daily and weekly aggregated data. The ACF plot of the daily data shows periodic peaks indicate a seasonal dependence. In contrast, weekly aggregated values show a clear final peak at the 2nd interval, making them especially useful for forecasting.

The PACF plot of weekly data shows a clear final peak at 2nd interval, indicating a strong two-week dependency. Weekly aggregation captures seasonal fluctuations more precisely than monthly data.

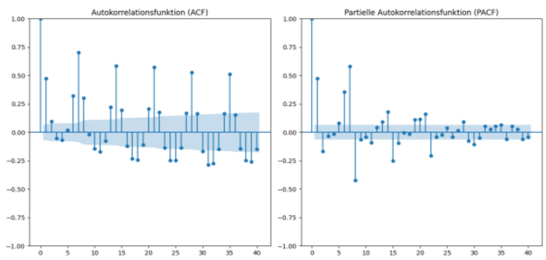

Figure 10: ACF and PACF Plots for Daily Aggregates.

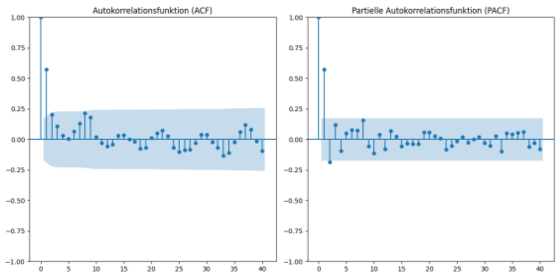

Figure 11: ACF and PACF Plots for Weekly Aggregates.

After aggregation, stationarity tests such as the ADF test was performed to check the need for differentiation (Shumway and Stoffer, 2017). These results indicate no need for additional differentiation The results of the ADF test for the weekly aggregated data were as follows:

- ADF statistics: -4,682
- p-value: 9.08e-05

Exogenous variables such as holidays and university vacation periods, that affect energy consumption, were aggregated weekly to match the time series data.

To reflect realistic fluctuations, time-varying scaling of noise was implemented, with noise scaled more strongly in the last third of the period.

Figure 12 shows historical data and forecasted values for the next year with a 95% confidence interval. This forecast starts from January 2, 2022.

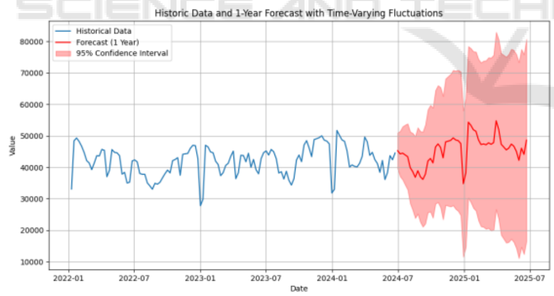

Figure 12: Energy Consumption Forecast.

The SARIMA model combined with weekly aggregation and exogenous variables provides a robust method for forecasting energy consumption. Seasonal patterns and careful tuning allowed accurate predictions. Future improvements will refine the model based on new data.

3.4 Validation of the Forecast

To evaluate the accuracy of the forecast, various validation methods were applied. While the previous section focused on the visual representation of the model, this section provides a detailed performance evaluation using specific metrics.

- **Log-Likelihood:** This metric measures the model's goodness of fit to the data, with higher (less negative) values indicating a better fit Burnham and Anderson (2004). In this case, the Log-Likelihood value is -2103.813, suggesting that the model moderately describes the data.
- **Akaike Information Criterion (AIC):** The AIC assesses model quality by balancing goodness of fit against model complexity. It is calculated as
$$\text{AIC} = -2 \cdot \text{Log-Likelihood} + 2 \cdot k$$
where k is the number of estimated parameters, a lower AIC value indicates a better model (Burnham and Anderson, 2004). The AIC value of 4213.626 given here can serve as a basis to compare it with other models.
- **Bayesian Information Criterion (BIC):** Similar to the AIC, the BIC considers model complexity, but with a stronger penalty term for the number of parameters. It is calculated as
$$\text{BIC} = -2 \cdot \text{Log-Likelihood} + \log(n) \cdot k$$
where n is the number of observations, a lower BIC value indicates a better model (Burnham and Anderson, 2004). The BIC value of 4222.182 is higher than the AIC value, suggesting that the model may be too complex and should perhaps be reduced to achieve a better balance between model complexity and fit.
- **Hannan-Quinn Information Criterion (HQIC):** The HQIC takes into account both the number of parameters and the number of data points and is calculated as
$$\text{HQIC} = -2 \cdot \text{Log-Likelihood} + 2 \cdot \log(\log(n)) \cdot k$$
The HQIC value of 4217.102 is between the AIC and BIC values, indicating that the model has a balanced level of complexity and fit (Ding et al., 2018).

The performance of the model was additionally evaluated using the following metrics:

- **Mean Absolute Error (MAE):** The MAE measures the average absolute difference between the actual and the forecast values. It is calculated as:
$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t|$$
where y_t represents the actual values, and $\hat{y}_t$ represents the forecasted values. In this case, the MAE

is 3877.523, meaning that the average absolute deviation between the actual and forecasted values is approximately 3877.523 kW.

- **Mean Squared Error (MSE):** The MSE calculates the mean square difference between the actual and the forecast values. The MSE is 22,333,269.584. This high MSE value indicates that larger errors have a significant impact on the model evaluation.
- **Root Mean Squared Error (RMSE):** The RMSE is the square root of the MSE and indicates the average size of the errors in the units of the data. The RMSE is 4725,809 units. This indicates the average size of the errors in the same units as the data.

The validation of the model's forecasting performance shows mixed results. The Log-Likelihood of -2103.813 and the calculated information criteria (AIC of 4213.626, BIC of 4222.182, and HQIC of 4217.102) indicate that the model needs to be evaluated in terms of its complexity and fit. The significant parameters such as ma.L1 and ma.S.L52 confirm the relevance of seasonal and moving average effects. The error metrics (MAE of 3877.523, MSE of 22,333,269.584, and RMSE of 4725.809) show that the model gives acceptable predictions but has high error dispersion. These results suggest that the model could be improved with more data and optimization.

4 VISUALIZATION

The implementation of the web interface for visualizing energy consumption requires careful attention to design principles and graphic standards to ensure a clear, understandable and interactive presentation of the data. In addition, the workflow from the database to the web interface must be explained.

4.1 Design Principles

Figure 13 shows the current view of the electricity data forecast and heat estimate. The colour scheme is consistent with existing elements. A close button allows easy return, and closing is also possible by clicking outside the window. The graphs can be zoomed, and the individual lines can be shown or hidden.

A key principle in visualizing energy data is clarity. Visualizations must highlight the most important information and allow for quick interpretation. This includes presenting the data clearly and understandably without creating excessive complexity.

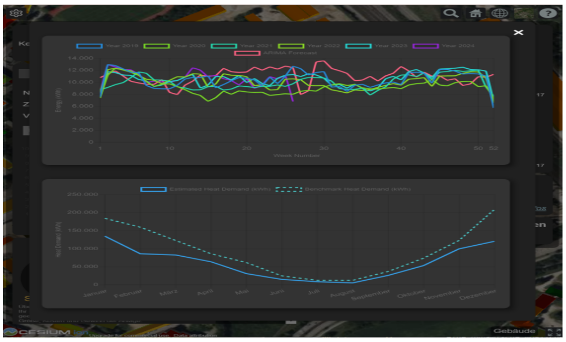

Figure 13: Cesium Platform: Forecasting and Estimation.

Consistency is also very important. Uniform colors and symbols should consistently represent similar data types and categories. This increases usability and simplifies data interpretation. The design is based on the existing platform to ensure consistency. To improve clarity, an overlay screen takes up most of the screen and allows complete insight at a glance.

Interactive elements play a crucial role in visualizing energy data. Features like hiding/showing data and zooming allow users to gain deeper insights into the data and query specific information, promoting detailed analysis and a better understanding.

To improve the user experience, the data display has been linked to a button in the navigation bar. This simplifies the search for the building on the map and enables faster access to the desired data.

When graphically displaying energy data, certain standards must be observed. Uniform scales for axes facilitate comparisons between different diagrams. Clear and understandable labels for axes, legends and data points are essential to enable precise interpretation of the data presented. The choice of colors also plays an important role: colors should be aesthetically pleasing and easily distinguishable for all users, including those with color vision deficiency.

4.2 Workflow

The workflow from data source to visualization on the web interface starts with storing and managing the data in an InfluxDB database. Next, the InfluxDB is integrated with the backend service, which is written in Python. This backend service connects to the InfluxDB via its API to perform data queries and process, retrieve, and prepare the necessary information.

Once processed, the data is sent to the frontend. The frontend uses ChartJs to display the data visually. It handles receiving data from the backend, formatting it appropriately for ChartJs, and rendering interactive and informative visualizations on the web interface. ChartJs presents the data in clear appealing charts, giving users with clear insights into energy data.

This workflow enables efficient data collection, processing, and visualization, offering users a seamless and user-friendly experience for analyzing and interpreting energy data.

5 CONCLUSION

This work focused on implementing and analyzing smart components within a digital energy twin for the Computer Scince and Mathematics faculty building at OTH Regensburg, aiming to support the development of the digital twin and facilitate sustainable energy analysis and optimization possibilities. The comprehensive investigation into the building's current energy consumption yielded valuable insights into energy flows and highlighted areas for potential improvement. While the analysis revealed intriguing trends and statistics, many anomalies were only speculative, as several underlying factors remain unexamined. The analysis covered various levels, though a more in-depth exploration of specific aspects is still required. Two main requirements emerged from the analysis and were further explored:

Forecasting Future Energy Consumption: This requirement aims to predict future energy usage to anticipate peak loads and take preventive actions. The SARIMA algorithm was selected for this task, proving the available data was suitable for forecasting. While the model showed promising initial results, the limited historical data suggests that more time is needed to establish a robust predictive foundation.

Visualization of Forecast and Estimation Results: The integration of forecast and estimation visualizations into the Cesium platform's frontend was successfully implemented. Although the backend was tested locally, it requires further adaptation for deployment in a live environment.

In conclusion, this work has significantly contributed to the development of the digital energy twin, providing practical insights to enhance energy efficiency and supporting smart campus's vision of becoming a model for sustainable practices. The project has laid a strong foundation for future research and delivered initial functionalities that can be expanded and refined in subsequent initiatives.

ACKNOWLEDGEMENTS

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