Heat Demand Modelling for a Sustainable Urban Development Project: A Case Study of Kopparlunden in Västerås, Sweden.

Alaa Krayem[a], Mohammed Guezgouz [a,*], Fredrik Wallin [a]

Future Energy Center, Department of Energy, Building and Environment, Mälardalen University, Västerås, Sweden

mohammed.guezgouz@mdu.se

Abstract

As cities grow and develop, urban planners face an increasing challenge to create more sustainable and environment friendly communities. The Kopparlunden district in Västerås, Sweden, is no exception, with plans underway to transition the area to a more sustainable neighborhood. To assist this effort, this paper presents a simple grey box modeling approach to predict the heat demand of eight buildings in the area. As the city transforms from a historical industrial district to a mixed district with residential buildings, shops, and offices, the model will allow urban planners to predict their new heat demand. The model is calibrated using a genetic algorithm, then validated using real historical data. The results show a good accuracy of the model and highlight the importance of increasing the insulation efficiency of the walls in the modelled buildings. The model can be used to predict the heat demand variations, with minimum error of 2.49 kW and up to 16.6 kW for large buildings. The model highlights the importance of energy modeling for urban development projects and shows its significance as a tool to aid in decision-making towards sustainable and more efficient urban areas.

1. Introduction

With the increased growth of urban population and urban energy use, cities around the world are facing an increasing challenge to provide sustainable and energy efficient environment for their residents. The building sector is one of the major contributors of CO_2 emissions worldwide, and thus presents a great potential to reduce energy use and associated emissions. Urban planners and policymakers are to plan and implement large scale improvements of buildings' energy performance, which imposes significant challenges and issues related to the complexity and scale of the urban environment (Hong et al., 2020; Keirstead et al., 2012), policy and regulatory frameworks essential to adequately support and /or incentivize sustainable and energy efficient practices (Economidou et al., 2020; Strielkowski et al., 2019), funding and securing financial resources for projects implementation (Alam et al., 2019; Bertoldi et al., 2021; Sebi et al., 2019), data availability and accessibility for informed decision making, and long term planning and adaptation with consideration of future needs and changing circumstances. In this context, the European Commision recently revised the Energy Performance of Buildings Directive (EPBD) under the ”Fit for 55” package (Wilson, 2022), and introduced stricter regulations. The revised EPBD aims at accelerating the renovation rates, targets the 15% of EU buildings that perform the worst, and establishes high energy performance standards. Notably, every building should achieve at least a Class E on the revised A-G energy performance scale by 2030.

The Kopparlunden district in Västerås, Sweden, is no exception to this global and regional trend. As part of a larger effort to foster sustainability, plans are underway to transition the district into a more sustainable neighborhood.

Building Energy Modelling (BEM) became an indispensable tool for building professionals and energy policy makers to optimize the design, operation, and energy efficiency of buildings (Al-Homoud, 2001; Reinhart & Cerezo Davila, 2016). BEM can be performed at the individual building level, up to the urban level (Urban Building Energy Modelling – UBEM). Its approaches comprise three main categories: white-box models, black-box models and grey box models (Foucquier et al., 2013). The white-box models are based on physical equations that describe the underlying mechanisms of the building. They offer transparency and understanding of the physical phenomena involved, allowing for accurate predictions and optimization, as well interpretability of the results. However, there are drawbacks to consider, such as the complexity of dealing with complex systems, and the time-consuming nature of model development (Harish & Kumar, 2016). Black-box models on the other hand, are purely data driven models. They use actual data and perform statistical analysis to capture the correlation between the building energy use and operation data (Li & Wen, 2014). Grey-box models represent a hybrid approach that combines physical and empirical equations to achieve a close approximation of the underlying physical representation (Harb et al., 2016). They are utilized when there are partial information or incomplete data, allowing for flexibility and adaptation in handling discrepancies, and providing a more robust modeling framework (Zhao & Magoulès, 2012).

Discrepancies between a model's predictions and actual energy use are inevitable. To reduce the entailing mismatch, calibration is applied. It is a process of changing and fine-tuning the model's parameters and input assumptions to guarantee that the simulated energy performance matches the actual energy use of the building (Chong et al., 2021). It consists of comparing the model's predictions to measured data in the building and making modifications to increase the model's accuracy and credibility. The calibration of BEM can be either manual, where it relies on the modeler expertise, or automated, where an objective function is set to match the simulation results with the measured data (Coakley et al., 2014; Hou et al., 2021). Among the popular calibration techniques are optimization evolutionary algorithms, such as genetic algorithms (Lara et al., 2017).

In this paper, we present a study that focuses on the simulation of eight buildings in the Kopparlunden area of Västerås, Sweden. Our main objective is to develop a grey box model capable of predicting the hourly heat demand for each building under steady state conditions. Despite the simplicity of the model, we ensured its accuracy through a careful calibration process using a genetic algorithm. By incorporating this calibration technique, we fine-tune the model's parameters to improve its performance and align it with measured data. The resultant model achieves a good balance between simplicity and accuracy, making it a useful and effective tool for predicting heat demand in the investigated buildings. Our findings demonstrate the successful use of a basic yet calibrated grey box model, emphasizing its utility in giving vital insights for energy efficiency and decision-making in building energy management.

2. Methodology

2.1. Case study

Kopparlunden, an industrial area in Västerås dating back to 1898, holds historical significance. Situated in close proximity to the city center, as depicted in Figure 1 on the map, the majority of its buildings still retain their original character and were originally utilized for metal industry purposes. However, the evolving landscape has seen a shift in usage, with the buildings now serving as offices or stores, accommodating nearly 200 companies in the vicinity. Recognizing the potential for optimizing the local area, plans have been set in motion to revitalize Kopparlunden into a contemporary residential space, integrating modern housing, commercial establishments, and workspaces[1].

The municipality is dedicated to maximizing the energy efficiency of the area and has actively collaborated with various partners to oversee the implementation of the plan. The transformation of Kopparlunden is part of a multi-step strategy that the municipality and building companies have collectively committed to. While many aspects of the project, such as the size and functionality of the buildings, have been determined, finer details regarding the architectural design and specific shape are still under consideration. However, at this stage, it is possible to make preliminary assessments of certain parameters, such as the current heat demand, which is the primary focus of the current study.

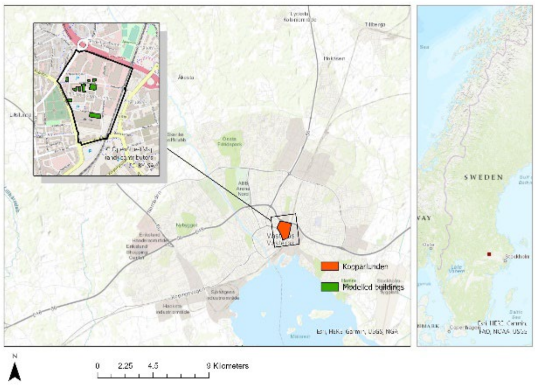

Figure 1: Kopparlunden district, in close proximity to Västerås center. The modelled buildings are shown in green.

2.2 Data Collection

The buildings simulated in this study are highlighted in Figure 2. Buildings data were obtained from the NRGYHUB dataset (Krayem et al., 2021). The data included buildings' perimeters, areas, and heights. The real heat demand data was obtained from Mälarenergi at hourly level for the year 2019. The outside temperature was downloaded from ERA5[2] for the same year at the hourly level.

[1] https://www.archus.se/kopparlunden-fran-ett-stangt-industriomrade-till-en-levandestadsdel/ (accessed 26/6/2023)

[2] https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form (accessed 26/6/2023)

2.3. Model and assumptions

It is assumed that the building heat balance is given using the following equation:

$$P_D + P_{people} = P_s \quad (1)$$

where P_s, power loss by transmission; P_D, generated heat power (only district heating and generated heat from the occupants). To simplify the model, losses by ventilation, unintended ventilation and air leakage were neglected.

For each element of the building, the transmission loss is calculated by the following equation:

$$P_s = U \,.\, A \,.\, (T_{in} - T_{out}) \quad (2)$$

where U, heat transfer coefficient in W/m^2.°C, A, area in m^2, T_{in}, indoor temperature in °C, and T_{out}, outdoor temperature in °C. The total transmission loss of the building is the sum of the individual transmission loss of each element.

The U_{value} of different elements of old buildings were assumed from the literature (Liu et al., 2014). The U_{value} of the floor was assumed 0.22W/m^2.°C and that of windows 1.3 W/m^2.°C. The walls assembly, with an overall thickness of 0.4m, were considered to be a composite structure comprising, in sequence, brick, concrete, wood, insulation material, wood, and a final concrete layer. The respective thicknesses of these materials are 0.09m for concrete, 0.06m for timber, and 0.1m for insulation. Corresponding thermal conductivity values for these materials are delineated in Table 1. The overall U_{total} of the walls is equal to the reciprocal of its total resistance R_{total}, which is calculated as follows:

$$R_{total} = \sum \frac{d_i}{U_i} \quad (3)$$

where d_i represents the thickness of layer i and U_i its corresponding thermal conductivity. The areas of the walls, floors and ceilings were estimated from the shapefiles. The area of the windows, which were assumed double glazed, was then calculated using the window to wall ratio from Table 1.

For T_{in} , it is assumed to be 21℃ to ensure indoor comfort.

The internal generated heat power is considered mainly generated from occupancy and is calculated using the following equation:

$$P_{people} = A_{floor}.n_{floors}.P_{ph}.r_p \quad (3)$$

where A_{floor}, a building's floor area, n_{floor}, number of floors, P_{ph}, heat generated per person, assumed to be 80W/person, and r_p, the person ratio in 1/m^2 and it is assumed to be one person per 35m2. The values are based on the Swedish National Board of Housing, Building, and Planning (BBR)[3].

Table 1: Range of values of inputs estimated with the genetic algorithm.

Variables	Range of variations
Window to wall ratio	0.1 – 0.65
Concrete heat conductivity	1.3 – 2
Wood heat conductivity	0.12 – 0.16
Insulation heat conductivity	0.06 – 0.1
Wall resistance indoor	0.1 – 0.16
Wall resistance outdoor	0.02 – 0.06

The walls of all buildings are assumed to be composed of double layers of concrete and wood with an insulation layer in between. Several key inputs related to the materials properties and buildings construction (shown in Table 1) remain indeterminate due to unavailable or ambiguous data. To address these uncertainties and ensure the reliability of the model, a calibration process was conducted using a genetic algorithm (Martínez et al., 2020). The objective of the calibration (cost function) was to minimize the Root Mean Square Error (RMSE) between the simulated heat demand and the observed heat demand data. This iterative process involved fine-tuning some of the model's parameters to achieve a higher level of accuracy in predicting the heat demand. During the calibration process, multiple design variables were considered, as outlined in Table 1. These inputs played a crucial role in optimizing the model's performance and aligning it with the actual heat demand patterns recorded in the Kopparlunden area. Careful selection and adjustment of these variables contributed to improving the model's capability to simulate the complex heat demand patterns observed in the buildings. The variations' range of the concrete heat conductivity was obtained from (Misri et al., 2018) and for wood from (Pásztory et al., 2020).

By iteratively adjusting and refining these design variables, the aim was to enhance the model's accuracy and its ability to capture the variation nature and seasonal patterns of the heat demand profiles of different buildings.

3. Results

Among the buildings studied, Building II exhibited the highest level of accuracy in terms of heat demand prediction, with an RMSE of approximately 2 kW, as shown in Table 2. Conversely, the first building demonstrated the largest deviation from the actual heat demand, resulting in an RMSE of 16 kW. This discrepancy can be attributed to several factors,

[3] Boverkets föreskrifter om ändring av verkets föreskrifter och allmänna råd (2016:12) om fastställande av byggnadens energianvändning vid normalt brukande och ett normalår, BFS 2017:6

Table 2: The estimated inputs of the model after calibration using the genetic algorithm.

Building number	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Window to wall ratio	0.10	0.14	0.10	0.10	0.10	0.10	0.10	0.10
U_{value} of window	0.85	1.28	0.85	0.85	0.92	0.85	0.85	0.85
Concrete heat conductivity	1.30	1.78	1.30	1.30	1.35	1.30	1.30	1.37
Wood heat conductivity	0.12	0.14	0.12	0.12	0.13	0.12	0.12	0.14
Insulation heat conductivity	0.06	0.07	0.06	0.06	0.07	0.06	0.06	0.08
Wall resistance indoor	0.16	0.16	0.16	0.16	0.12	0.16	0.16	0.15
Wall resistance outdoor	0.06	0.05	0.06	0.06	0.04	0.06	0.06	0.03
RMSE [kW]	16.60	2.49	5.62	10.92	14.71	4.93	8.51	4.97

including the lack of detailed information regarding the construction materials utilized in Building 1. Additionally, the accuracy of the geometry data employed in the model significantly influences the predictive performance.

Figure 2 (scatter plot) illustrates a comparison between the actual heat demand points and the corresponding predicted values. The closeness of the points to the diagonal red line indicates the degree of agreement between the actual and predicted values. A strong correlation is observed for most of the considered buildings, as signifies the tight clustering of points around the diagonal red line, while deviations suggest a divergence between the actual and predicted values.

The analysis reveals that buildings 1, 5, and 7 exhibit the highest discrepancies between predicted and actual values. Remarkably, these buildings are also the largest in the study, boasting significant annual heat demands of 153.52 MWh, 349.95 MWh, and 189.84 MWh, respectively. This highlights a notable limitation in the model's accuracy when estimating heat demand for sizable and complex buildings. Achieving more accurate results in these cases necessitates a more detailed approach that considers additional factors.

Figure 3 illustrates the distribution of losses among the buildings based on the optimal design variables obtained from the calibration process. It is evident that wall losses contribute the most significant proportion of total losses for all buildings, closely followed by losses through the ceiling. Conversely, losses through the windows are relatively low due to the smaller window-to-wall ratio considered and the utilization of effective insulation materials.

4. Summary and Discussions

The utilization of a grey-box model in this study provides a straightforward approach to estimate building heat demand. However, it is important to recognize that higher levels of accuracy may necessitate a substantial amount of data. A larger and more detailed dataset would have contributed to enhancing the precision of the model's predictions. While detailed data might be available for specific or individual projects, and it is possible to achieve detailed data collection, it might not always feasible for large scale modeling, such as in Urban Building Energy Modeling (Hao & Hong, 2021; Wong et al., 2021), given the vast heterogeneity in buildings and associated operational variables. Different modeling approaches are adopted, ranging from physics-based to statistical-based methods (Swan & Ugursal, 2009). Each comes with its own set of advantages and limitations, depending on the availability of data and the specific objectives of the analysis.

The heat losses shown in Figure 3 highlights the importance of insulation to reduce the wall heat losses for buildings. The findings suggest that improving the insulation and thermal characteristics of the walls could lead to substantial reductions in energy losses. Furthermore, using highly thermal resistant materials in the ceiling can also contribute to minimizing overall heat losses.

By focusing on these key areas of concern, such as wall and ceiling insulation, building operators and policymakers can effectively enhance energy efficiency and reduce heating demands. This understanding of the relative contributions of different building components to heat losses offers valuable insights for implementing targeted interventions and developing sustainable heating practices in the Kopparlunden area.

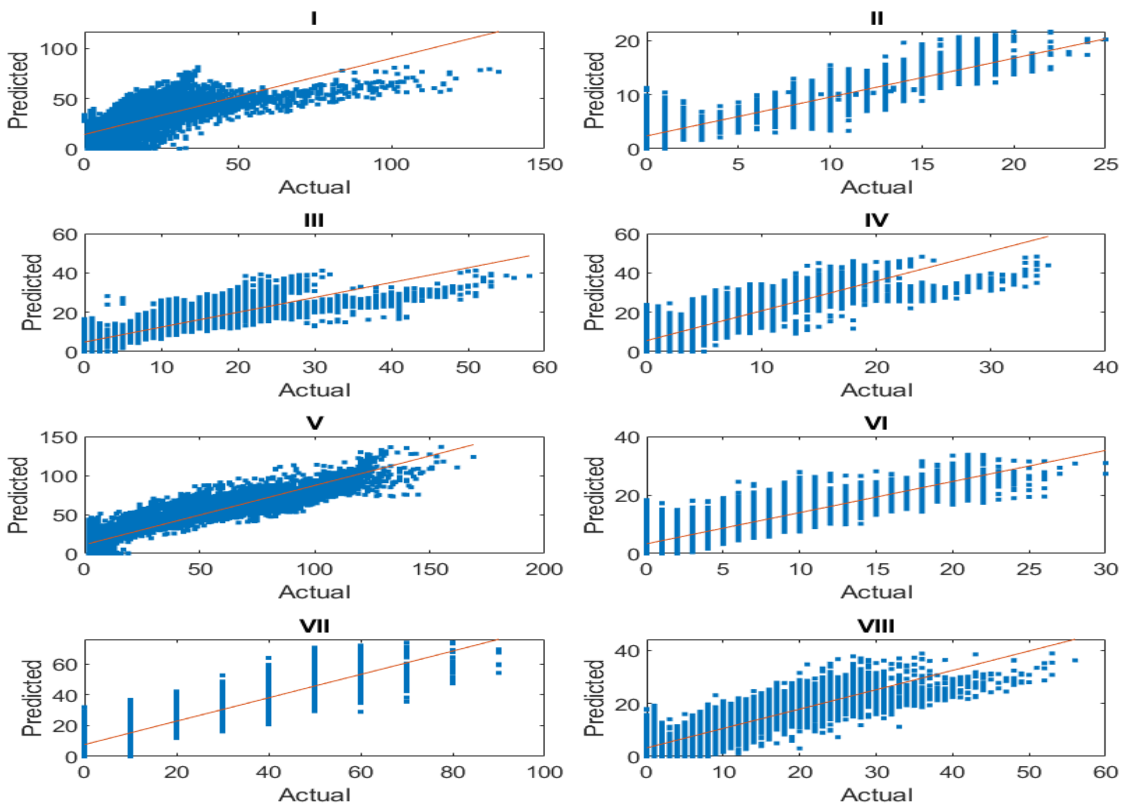

Figure 2: Comparison between the simulated and actual heat demand per building.

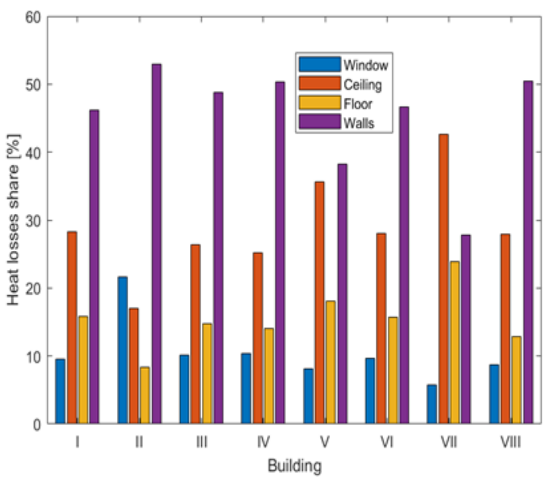

Figure 3: Estimated heat losses per building element, for the eight buildings modelled in this study.

While the results obtained from the model offer valuable insights into the fluctuations of heat demand in the studied buildings, it is crucial to realize the inherent limitations associated with this approach. Grey-box models may rely on simplified assumptions and estimated parameters and may not fully capture the intricate complexities of real-world systems. Nevertheless, this methodology serves as a valuable tool for providing initial estimations of heat demand and can serve as a starting point for further analysis and refinement.

By acknowledging both the strengths and limitations of the grey-box model and considering the availability and quality of data, researchers and practitioners can make informed decisions regarding energy management and optimization strategies. Future actions should concentrate on enhancing the model's accuracy through the incorporation of more detailed information, improved geometry data, and potential exploration of alternative modeling techniques to achieve even higher levels of predictive performance.

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