Developing a Multi-Building Scale Energy Model for a university campus using URBANopt

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Abstract

Building energy models are developed to describe energy performance. The energy performance of buildings is influenced by physical and human influenced factors. Therefore, to improve energy efficiency and renewable energy implementation in buildings on large scale, there is a need to analyze buildings on a large scale. In this study, URBANopt, a multi-building energy evaluation tool, was used to develop an accurate Multi building scale energy model for a university campus. This model will be useful in the future work to evaluate various available and emerging building-level and district-level technologies and retrofitting options to improve energy performance. URBANopt is a unique tool that leverages high-fidelity simulations of buildings, community-scale systems, distributed energy resources, and the associated interactions with local distribution electric infrastructure. A university campus in Norway was chosen as a case study. Results obtained from URBANopt were compared with a typical building energy simulation model in IDA-ICE for a representative building. This representative building was developed based on building characteristics, functionality, and geographic location, including indoor and outdoor climate conditions. Both models were validated by using measurement data. The results showed better simulation accuracy of the multi-building method of URBANopt with the measurement data, mainly due to the averaging of the characteristics of all buildings in the development of the representative building. Furthermore, the URBANopt allowed assigning a different scenario of technologies and retrofit options to each building in the evaluation process, which is impossible in the typical model due to its nature. However, it should be pointed out that the computational time of the model developed in URBANopt was higher and will increase more with the increased number of buildings.

1. Introduction

The rapid urbanization has led to an increasing demand for energy in urban areas. The building sector consumes a significant portion of the energy used in urban areas, accounting for 30-40% of global energy use (Li, Zhou et al. 2017). As a result, modeling building energy use at an urban scale has become a crucial task in achieving energy efficiency in urban areas. Urban building energy modeling (UBEM) refers to the process of predicting urban building energy use using computer simulations. UBEM is an essential tool for predicting energy use and evaluating energy efficiency strategies in urban policy (Wang, Ferrando et al. 2022).

In order to create a reliable building energy model of a new or existing neighborhood, the task can be broken into the following subtasks: simulation input organization (data input), thermal model generation and execution (thermal modeling) as well as result validation (validation) (Reinhart and Cerezo Davila 2016). The simulation input organization is concerned with the collection and integration of data from various sources, such as weather data, building design data, and energy use data, to create a comprehensive and accurate input dataset for the model (Wang, Ferrando et al. 2022). Once the input data has been collected and integrated, the thermal model generation and execution stage involves creating a mathematical model of the energy use of the buildings in the urban area, which can then be simulated and tested under various conditions (Wang, Ferrando et al. 2022).

Several different types of energy models have been proposed for modeling urban building energy use over the past few decades, each with their own strengths and weaknesses (Li, Zhou et al. 2017). Physics-based, bottom-up models are one of the most common types of models used for this purpose. These models rely on detailed physical data, such as the building's geometry, construction materials, and HVAC system, to generate a comprehensive model of the energy use of the building. These models are typically accurate but can be time-consuming to develop and require a lot of detailed data (Li, Zhou et al. 2017).

Another approach to modeling urban building energy use involves coupling bottom-up physics models with geographic information systems (GIS) techniques. This approach involves using GIS to integrate the physical data of the building with the spatial data of the urban area to create a more comprehensive model. One study that used this approach modeled urban building energy use and CO_2 emissions for Indianapolis-Marion County, IN by integrating their energy use model, eQUEST, with GIS techniques (Li, Zhou et al. 2017).

In addition to physics-based models, statistical models have also been used for modeling urban building energy use. These models rely on statistical analysis of data to generate a model of the energy use of the buildings in the urban area. While these models are typically faster and require less detailed data than physics-based models, they are also generally less accurate (Li, Zhou et al. 2017).

One important aspect of modeling building energy use at an urban scale is the development of archetype libraries. Archetype libraries are collections of building models that have been grouped into homogenous groups based on their characteristics, such as building type, size, and construction materials. These libraries can be used to streamline the modeling process by providing pre-existing models that can be easily adapted to new urban areas (Mohammadiziazi, Copeland et al. 2021).

The benefits of modeling building energy use at an urban scale are numerous. By accurately modeling the energy use of buildings in an urban area, policymakers and energy planners can identify areas of high energy use and develop targeted strategies for improving energy efficiency. This can lead to reduced energy use, lower energy costs, and reduced greenhouse gas emissions. In addition, modeling building energy use at an urban scale can also help to identify areas of the urban environment that are particularly vulnerable to heat waves and other extreme weather events and validate the performance of UBEMs. These validation techniques can range from comparing the simulated energy use with measured energy use data, to comparing the simulated thermal loads with real weather data (Li, Zhou et al. 2017).

One interesting application of UBEMs is the study of waste heat from buildings and its contribution to urban heat islands. A study conducted by the US Department of Energy found that during heat waves, waste heat from air conditioning can increase the amount of heat being dispersed from buildings to the urban environment by up to 20% (Luo, Vahmani et al. 2020). UBEMs can be used to simulate the impact of waste heat on urban temperatures, which can help policymakers develop strategies to reduce urban heat island effects.

Detailed building energy data and existing buildings that match prototypical building energy models (BEMs) are essential factors for the current UBEM development. There are several instances where building energy data are unavailable due to privacy concerns, lack of civic energy disclosure requirements, or properties that do not meet reporting threshold requirements. As highlighted by different studies (Holloway and Bunker 2006, Abrahamse and Steg 2009, Chen, Xu et al. 2017, Chen, Feng et al. 2022), establishing a correlation between energy usage and factors like socioeconomic status, climate, and building characteristics has been challenging. This may result in significant differences between a model based solely on prototype BEMs and a real community. This paper investigated the situation where energy data is only available at the aggregate district level, and current prototype BEMs do not account for actual energy usage in the community. This work aimed to establish a pathway for precise district-level building energy model creation with limited data.

Based on literature, UBEM, while valuable, has several limitations, three important ones are:

Data Availability: Gathering comprehensive and up-to-date data for large-scale urban models can be challenging. Limited data can lead to less accurate simulations.

Complexity: Urban environments are complex and dynamic, making it difficult to capture all factors affecting energy use accurately. This complexity can lead to simplified models that may not represent reality well.

Computational Intensity: Simulating energy use in large urban areas requires substantial computational resources, and it can be time-consuming. This limits the ability to perform real-time simulations or analyze numerous scenarios quickly.

The existing literature may be enriched by the present work, which illustrates how to create a reliable multi-building-scale energy model (MBSEM) for an untypical district when detailed energy data are unavailable. By highlighting essential datasets, tools, and partnerships, this addition establishes a roadmap for developing a model on a district scale. This contribution is accomplished through a university campus case study in Trondheim, Norway. The Urban scale energy simulation tool URBANopt (Polly, Chuck Kutscher et al. 2016, Kontar, Ben Polly et al. 2020) was used. The current effort is focused on describing the model development process.

2. Methodology

This section describes the case study, the URBANopt tool, and the MBSEM development.

2.1. Gløshaugen campus

The case study case in this paper is a university campus located in Trondheim, Norway. In the Gløshaugen campus, the system supplies heat to a total building area of 300,000 m², and the main functions of these buildings are education, offices, laboratories, and sports. The campus district heating (DH) system is connected to the city DH system by the main substation (MS). Apart from the heat supply from the city DH system, part of the annual heat supply comes from waste heat recovered from the university's data center (DC) (Li, Hou et al. 2021). According to the measurements from June 2017 to May 2018, the total heat supply for the campus DH system was 32.8 GWh. About 80% of the heat supply came from the central DH system through the MS. The other 20% came from the waste heat recovery from the DC (Li 2022). Map of the Gløshaugen campus is shown in Figure 2.

2.2. URBANopt tool

URBANopt is a physics-based energy modeling platform for districts and communities (Polly, Chuck Kutscher et al. 2016, Kontar, Ben Polly et al. 2020). URBANopt is a modular, open-source SDK, built on DOE tools such as EnergyPlus, OpenStudio, and Spawn of EnergyPlus. URBANopt includes capabilities and workflows that enable multi-building analysis at a neighborhood, district, or campus scale (generally 10 s to 100 s of buildings) and connections to other tools and engines that allow for the analysis of shared energy systems, distributed energy resources (DER), and the electric distribution systems, including interactions and impacts with building efficiency and demand flexibility strategies (Laboratory, 2022). Figure 1 (Fallahi, Sammy Houssainy et al. 2022) shows the structure of different tools in URBANOpt SDK.

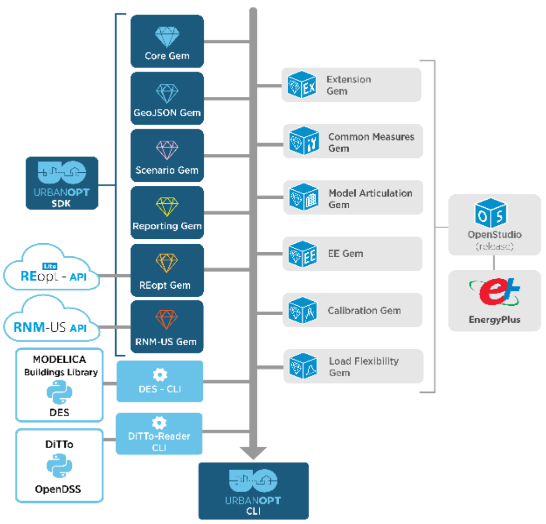

Figure 1. URBANopt SDK Gem structure

URBANopt helps manage geospatial information for modeling a community and automates the creation of detailed physics-based models for baseline scenarios (e.g., existing conditions) and advanced performance scenarios (e.g., retrofit upgrades). It exchanges data with other tools, manages simulations, and evaluates and compares scenarios. In this study one GeoJSON file describes Gløshaugen campus buildings, energy systems, and end uses, one CSV file tunes and implements scenarios, and another CSV file links building models to scenarios. URBANopt workflows for generating commercial building models were described in (Kontar, Ben Polly et al. 2020, Charan, Mackey et al. 2021).

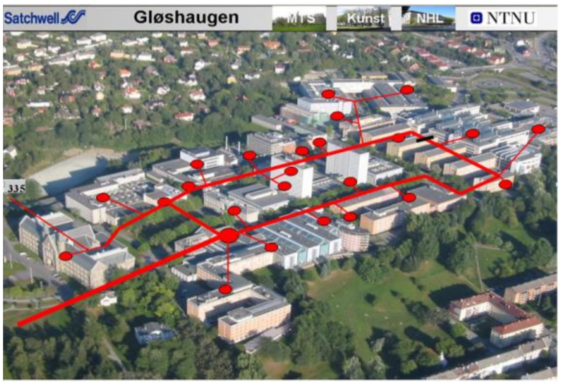

Figure 2. Aerial image and building cluster for the Gløshaugen campus.

2.3. Multi-building scale energy model development

This section describes the process of developing the Gløshaugen campus MBSEM, emphasizing critical datasets and resources. The objective of model development is to generate a precise and physics-based representation of energy use in the district. The first critical dataset is actual utility usage data for the district. There is a dataset for the campus DH demand for 2017, as shown in Figure 3.

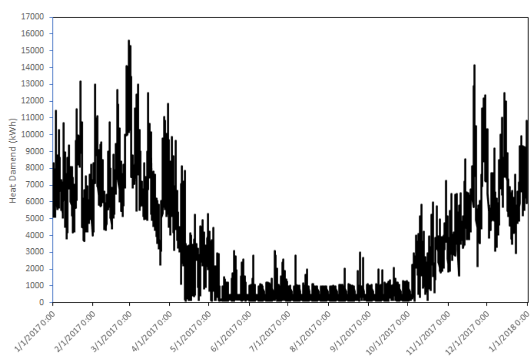

Figure 3. Hourly buildings heat demand for the year 2017

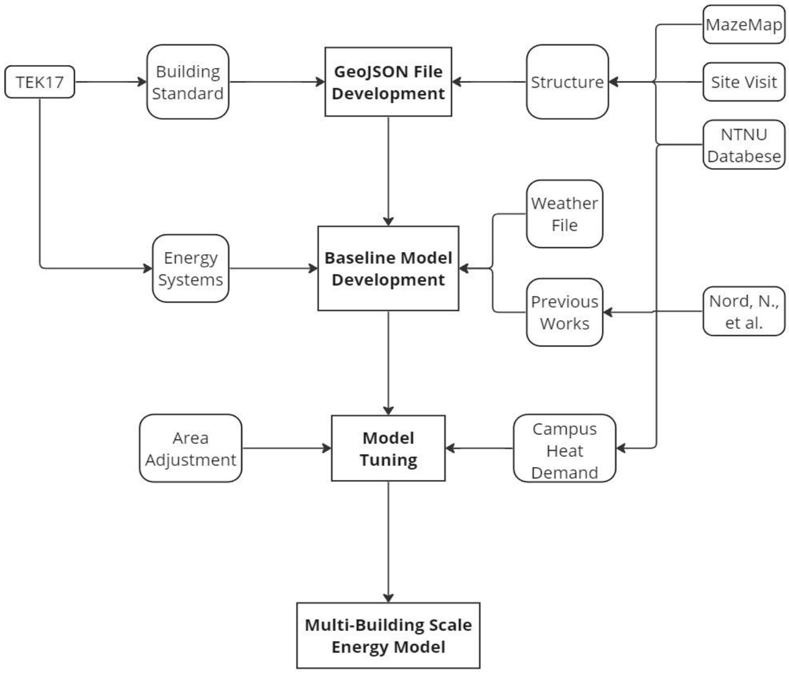

Figure 4. Summary of model development and tuning process, including data sources used to develop simulation result targets.

The assembly of the MBSEM was carried out in six steps. First, GeoJSON format was used to define building geometry, construction sets, and energy systems, which were then used for the URBANopt modeling platform. Second, OpenStudio measures were utilized to define building energy systems. Examples of these included HVAC, hydronic heating system types, and component efficiencies. Third step was the development of baseline predictions for building heat demand. In the fourth step, heat demands were adjusted for BEM end-users developed in step 3. The fifth step looked at BEM heat demands and compared to DH data shown in Figure 3. Finally, errors were found and the MBSEM was modified in the sixth step. This workflow is presented graphically in Figure 4, showing data sources and inputs. The different data used to develop the tuned MBSEM presented in this work can be broken down into three categories:

1. Building structure: Geometry (location, area, no. of stories etc.) and materials used in walls, windows, and building exterior.
2. Building energy systems: The performance characteristics of end use energy systems for heating, such as HVAC, domestic hot water (DHW), and all other devices/systems/appliances powered by district heating.
3. Aggregated building heat demand: Patterns that define how and when heat is needed on campus.

2.3.1. Building structure

Building geometries were developed using aerial images, Mazemap[1], and site visits. This information along with some building regulations, were used as input to develop the GeoJSON file as the first step of model development (Figure 4). The GeoJSON format was used to describe geometries. Building stories were determined using Mazemap and site visits. The campus buildings arrangement is displayed in Figure 5, modeled in GeoJSON format. The two assumptions were made for geometry development in buildings with mixed-use and asymmetric floor areas in some multi-story buildings. First, the current building workflow did not account for mixed-use buildings. In these instances, new uses were added to the library of the tool. For buildings with asymmetric floor areas by story, these buildings were split and modeled as separate buildings with symmetric floor areas.

Figure 5. Gløshaugen campus (GeoJSON format)

[1] MazeMap Indoor Navigation App. MazeMap Indoor Navigation. (n.d.). https://link.mazemap.com/fSPmwDL1

2.3.2. Building energy systems

Building energy systems address the properties of space conditioning and domestic hot water (DHW) systems. Trondheim, where the case study is located, has a Nordic climate, meaning space heating accounts for the majority of energy usage in these buildings. Therefore, the focus of this study was on heating demand and energy systems associated with it. Energy systems data, weather data, and other building information were used as inputs to create the baseline model of the campus from the pre-developed GeoJSON file, as shown in Figure 4.

2.3.3. Aggregated building heat demand

The entire campus's aggregated heat demand was utilized as input for model tuning and validation. Hourly space heating demand and DHW usage over one year make up this data.

2.3.4. Baseline load

Collected data on building structures and energy systems described in Sections 2.3.1 and 2.3.2 were converted to a GeoJSON format used by URBANopt to create a base model. Some key parameters defined in (Nord, Sandberg et al. 2019) were used for creating the base model. These input parameters included characterization of the building envelope, occupancy behavior, and building functionality. This initial model was used to create a baseline heat demand of the campus as an input in the tuning process of the model (3rd step in Figure 4).

2.3.5. Baseline tuning

OpenStudio measures were applied to tune URBANopt simulation results to match the baseline load described in Section 2.3.4 with aggregate heat demand described in Section 2.3.3. TMY3 weather data files for Trondheim, Norway, were used in this work.

Tuning occurred in two steps (model tuning part in Figure 4). First, total conditioned floor area was tuned to match heat demand values. After area tuning, the complete district-scale energy model was benchmarked against the measured data shown in Figure 3 by adjusting the model thermostat values.

For example, in one part of the tuning process, the initial thermostat set point for the model was a variable set point. 21°C for working hours and 15°C for non-working hours. The initial results showed a large difference between the simulation output and the measured data, especially in non-working hours. For this reason, each time, by increasing the temperature of the thermostat during non-working hours in the model with a step of one degree, the output of the model and the measured data were compared. Finally, the set point temperature of 19°C for non-working hours achieved the best adaptation in the results.

3. MBSEM simulation results

Results from the MBSEM are presented in two sections. In the first section, the accuracy of the simulation is measured by comparing the results with the actual heat demand data shown in Figure 3. The second section compares the heat demand produced in the MBSEM simulation against a typical building energy simulation model in the IDA-ICE tool, developed as a representative building for Gløshaugen campus (Nord, Sandberg et al. 2019). This representative building was developed based on building characteristics, functionality, and geographic location, including indoor and outdoor climate conditions.

3.1. Simulation accuracy

The evaluation of building energy models' accuracy is a necessary task, as it allows for the implementation and investigation of energy-saving strategies while maintaining human comfort. ASHRAE Guideline 14-2014, the International Performance Measurement and Verification Protocol (IPMVP), and the Federal Energy Management Program (FEMP) are the most widely recognized methodologies for evaluating the accuracy of these models (Ruiz and Bandera 2017). Normalized Mean Bias Error (NMBE), Coefficient of Variation of the Root Mean Square Error (CV(RMSE)), and coefficient of determination (R^2) are the principal accuracy indices used in these standards. This study used NMBE and CV(RMSE) as error indicators for our simulation results.

Table 1 shows the total annual heat demand based on measured data and simulation outputs. There is a 4 GWh underestimation in simulation results for the total heat demand on campus. Table 2 shows the accuracy indicators on an hourly and monthly basis. According to ASHRAE Guideline 14, the acceptance criteria for these indicators are +5% NMBE and 15% CV(RMSE) for hourly data and +10% NMBE and 30% CV(RMSE) for monthly data. Therefore, the simulation results could be acceptable, considering that the output is heat demand for a MBSEM instead of an individual BEM.

Table 1. Annual heat demand

	Heat Demand
Actual	32.8 GWh
Simulation	28.8 GWh

Table 2. Simulation error

Data type	MBE	CV (RMSE)
Hourly	8%	35%
Monthly	8%	12%

Figure 6 shows actual and simulation heat demand for a typical winter week starting from Saturday. The simulation provided an accurate forecast of hourly heat demand for both weekdays and weekends. The model's heat demand was at a minimum value during the night on working days, resulting in a significant difference. This also led to high peaks at the start of the working hours. Tuning process can reduce the difference by adjusting the thermostat of each building.

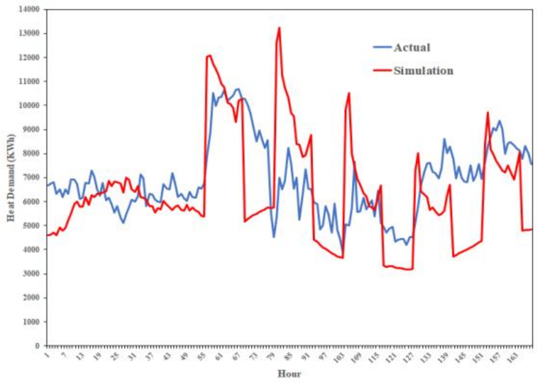

Figure 6. Heat demand for a typical winter week (starting from Saturday)

Figure 7 shows the monthly heat demand for both measured and simulation data. According to this, the underestimation in heat demand can also be seen in monthly data. The underestimation was more common in the cold season, when the demand for heat came mainly from space heating. However, during summer, when heat demand is solely for DHW, the developed model showed better prediction.as a result, an alternative approach may be necessary for adjusting thermostats despite sufficient input data for building energy systems.

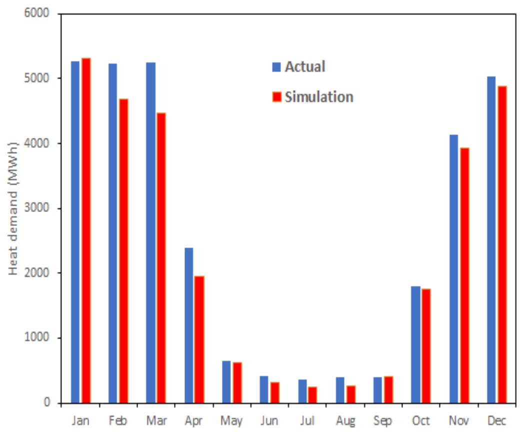

Figure 7. A comparison of actual monthly heat demand versus simulated data

3.2. MBSEM and IDA ICE typical building comparison

Using typical/reference buildings is another approach to deal with district-level building energy analysis. The most frequent building design in the examined area forms the foundation of the district's reference model. For the Gløshaugen campus, based on the average geometry, building envelope parameters, occupancy behavior, etc., a reference model was built in IDA-ICE simulation software (Nord, Sandberg et al. 2019).

To create the IDA-ICe model, information about the distribution of areas and rooms was provided by the Technical Management Section at NTNU.. It was found that the total area was divided by 140 rooms and 18 zones. Eventually, all zones have been combined to form the nine most representative: office, reading hall, lecture hall, laboratory, traffic area, technical room, workshop, cleaning and sanitary room and other. some zones with similar functionality were combined for creating the model and finally, the geometry and size have been selected for reference building. Table 3 summarizes key information of the Reference model building areas. The simulation model and the floor area distribution are shown in Figure 8.

Table 3. Reference model building areas

Building geometry	**Parameter**	**Reference model**
General	Total area [m²]	7220.00
	Heated are gross [m²]	7159.20
	Floor area [m²]	1805.00
	Number of floors	4
Total zone area/ per floor area	Office [m²]	1967.60 / 491.90
	Library [m²]	545.20 / 136.30
	Educational facilities [m²]	282.00 / 70.50
	Special room [m²]	2321.20 / 580.30
	Traffic area [m²]	2043.20 / 510.80

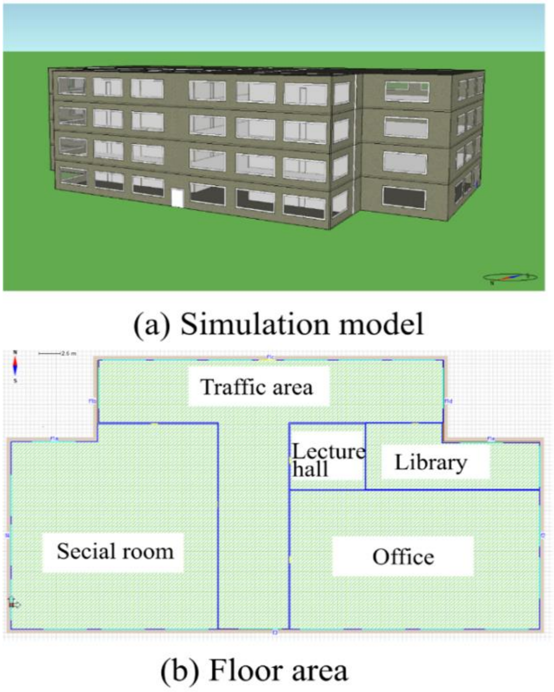

Figure 8. Simulation model developed in IDA-ICE

Based on the geometry and building envelope parameters, the model was built in IDA-ICE simulation software. Building envelope parameters and other important values were defined as weighted averages and shown in Table 4.

Table 4. building envelope parameters for IDA-ICE model

Category	Parameter	Reference model
U-value	External wall [W/m^{2}K]	0.57
	Internal wall [W/m^{2}K]	0.62
	External floor [W/m^{2}K]	0.19
	Internal floor [W/m^{2}K]	2.39
	Windows [W/m^{2}K]	2.19
	Doors [W/m^{2}K]	1.09
	Roof [W/m^{2}K]	0.48
General for façade	Normalized thermal bridge value [W/m^{2}K]	0.10
	Infiltration [l/h]	3.07
	Total windows area [%]	13.16

Since the conditioned floor area of this building is about 7 200 m², an area adjustment took place to calculate the total heat demand of the campus, based on this model. After this adjustment, the total annual heat demand of the Gløshaugen campus was 25.5 GWh (7.2 GWh less than the measured data). The monthly heat demand of the campus, based on IDA ICE, MBSEM, and measured data, is shown in Figure 9.

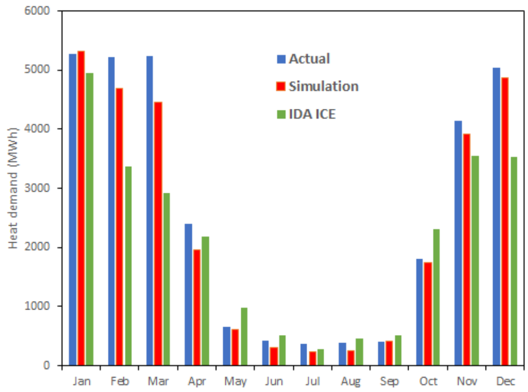

Figure 9. A comparison of actual monthly heat demand versus simulated data and IDA ICE results

Despite the MBSEM, the IDA ICE model overestimated the heat demand during the summer. During the cold season, especially in December, February, and March, there was a significant difference between IDA ICE results and measured data. The reason for this could be less heat loss through building envelope by aggregating all buildings in one typical building. This is something that should be considered in developing representative buildings.

This work aimed to demonstrate a replicable and scalable method for simulating multi-building scale energy models with minimum data available. Results from the URBANopt simulation tool showed good accuracy with measured heat demand. In general, the developed model underestimated the heat demand for campus (could be obtained from Table 1 and Figure 7). Adding more details of buildings' structure and energy systems and better adjustment in the tunning process could result in better accuracy of developed MBSEM. Furthermore, results obtained from the typical model showed even more underestimation of the heat demand of the Gløshaugen campus. This was mainly due to neglecting some properties of buildings in averaging process. However, it should be pointed out that the computational time of the model developed in URBANopt was higher and will increase more with the increased number of buildings, especially in the first stage, which is generating building energy models.

5. Summary and conclusions

This paper presents a process for developing a MBSEM for a university campus in Trondheim, Norway. The modeled district includes 24 educational, office, and laboratory buildings. The district-scale energy model includes individual BEM for all buildings. MBSEM tuning is accomplished through the matching heat demand values using local datasets. The developed model had acceptable accuracy on both monthly and hourly basis. MBSEM compared with a typical BEM developed for the same case study. The results showed better simulation accuracy of the MBSEM compared to typical BEM, mainly due to the averaging of the characteristics of all buildings in the development of this model. The approach facilitates detailed load construction to prepare for analyzing energy efficiency measures, electrification, onsite renewable energy conversion, and storage technologies.

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