

# Scalable energy retrofitting: A comparison between static and dynamic UBEM methods

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## ABSTRACT

The urgency of meeting 2030 climate goals has encouraged housing companies in Sweden, as one of the energy and carbon intensive sectors, to seek effective methods for analyzing and taking action on building retrofits. A key challenge in this process is the need for reliable and efficient tools to estimate the impact of energy conservation measures (ECMs), which are essential for informed renovation planning. Although various tools exist, many rely on simplified models, and there is a lack of expertise in their use. Dynamic simulation tools suffer from limited adaptability to large scale applications. These challenges have made it difficult for housing companies to implement ECMs effectively. This study benchmarks a simple template-based model used by Svenska Bostäder (SvB), \_\_publicly owned rental buildings in Stockholm, Sweden\_\_ against a detailed dynamic simulation called massive area Urban Building Energy Simulation (MUBES) by comparing their Thermal Energy Demand Intensity (TEDI) savings and simulation performance from applying three classical ECMs, namely triple-glazed window insulation, façade insulation, and heat recovery (HR). The results demonstrate that, although the static tool enables very fast estimations, it systematically overestimates energy savings across all ECMs, whereas the calibrated and validated dynamic simulations provide more consistent and moderate estimates of retrofit impacts. The calibration of MUBES was conducted manually and then validated against another dynamic simulation tool called City Energy Analyst (CEA).

**Keywords:** Urban Building Energy Modeling, Building Energy Retrofitting, Static Model, Dynamic thermal simulation, Stockholm

## 1. INTRODUCTION

To achieve the fit for 55 goals by 2030 defined by the European Green Deal, new legislation and policies across diverse sectors have been introduced. In the building

sector and more specifically residential types, all must undergo major renovation to reduce greenhouse gas (GHG) emissions and energy consumption. These are to achieve at least energy performance class E by 2030, and D by 2033 as indicated in the revision of Energy Performance of Buildings Directive (EPBD) in 2021. Also new buildings need to be zero-emission from 2028 and equipped with solar technologies by 2028. However, focusing on new buildings—which represent [1] only 5% of the building stock annually—is insufficient to achieve climate goals compared to retrofitting existing buildings. In Sweden, this need for retrofitting is particularly evident for the large number of inefficient buildings constructed between 1965 and 1974 under the public housing initiative known as the Million Program (Miljonprogrammet).

Public housing in Sweden accounts for almost 20 percent of Sweden's housing stock – half the rental sector and falls under the authority of municipalities, but the buildings are managed by a range of smaller municipal housing companies. In Stockholm, for example, these include Svenska Bostäder, Familjebostäder, and Stockholmshem. These companies are responsible for implementing policies and directives issued by the National Board of Housing, Building and Urban Development (Boverket) or the European Union. To effectively retrofit the buildings under their management, they require tools that can assess the impact and outcomes of applying various retrofitting strategies—commonly referred to as Energy Conservation Measures (ECMs).

### 1.1 Urban Building Energy Modeling

With the advancement in ICT the volume of information and rate of information sharing have increased exponentially with an ever-decreasing cost in all sectors of society has interrupted conventional building energy simulation [2]. Over the past decade Urban Building Energy Modeling has gained significant attention as a technique for assessing energy dynamics

or retrofitting scenarios for building portfolio managers, energy policy makers and researchers thanks to its inclusiveness feature such as inter building effects

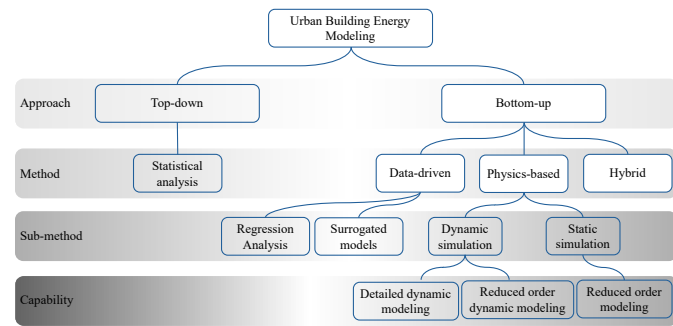


Fig. 1 Small diagram

compared to Building Energy Modeling (BEM) that focus on a single or few numbers of buildings [3].

In general classification UBE has top-down and bottom-up approaches as illustrated in figure 1. For statistical analysis the former approach is used using aggregated data and the latter one which usually requires more detailed data of the buildings, builds up models at individual level and scales it up to the whole district [4]. Both approaches are associated with pros and cons while top-down approach is fast and less detail oriented, it usually suffers from lower degree of accuracy. Bottom-up approach is usually data extensive but should offer a better level of accuracy. However, the results from both approaches could always be compromised because of data uncertainty or poor calibration [5].

In the bottom-up approach, the physics-based ones are the most popular according to the number of publications in this topic. They enable the possibility of integration of inter building effects, microclimate impact, co-simulation, etc. all contribute to the level of model complexity [6]. These models are data extensive and require geometric and non-geometric information of the buildings which have great impact on the results. In large scale simulation of course the data uncertainty is inevitable, However, when working with many buildings data requirements become less rigid, and a lower degree of accuracy is often tolerated [7].

Dynamic tools often face challenges related to high computational time and slower performance, as they rely on building-by-building simulations. To mitigate this, some studies have proposed dynamic reduced-order models, such as resistor-capacitor (RC) networks, to avoid intensive calculations. For instance, CitySim [8] adopts this approach by simplifying buildings into thermal RC circuits, enabling efficient simulation of district energy performance under various retrofit

scenarios. Similarly, TEASER [9] and OpenIDEAS [10] are reduced-order RC models developed in Modelica.

TEASER is designed to support efficient multi-building simulations for retrofitting and includes a data enrichment module, while OpenIDEAS enables the simultaneous modeling of multiple buildings connected to district energy systems. Some studies combine reduced-order models with archotyping to limit the number of simulations. For instance, CEA uses archetypes, GIS, and energy system data to assess retrofit options and optimize district energy systems [11]. Despite these advances, key challenges persist, notably balancing model scalability with detail, addressing the substantial calibration requirements, accurately incorporating occupant behavior and schedules, and effectively simulating complex retrofit dynamics [12]. Moreover, enhancing model generalizability across varying urban contexts and systematically quantifying uncertainties remain critical areas for further research.

Any simplification aimed at increasing speed—whether through reduced-order models (e.g., shoe-boxing), simplified heat transfer principles (such as ignoring inter-building effects or shading), uncertainties in data (like occupancy patterns or facade materials), imputed missing data, or reduced computation time through archotyping and neglecting calibration—can compromise the accuracy of the results [1]. Therefore, it is important to be objective and efficient to make balance between model complexity, accuracy, and scalability [13].

## 1.2 Aim and Scope

This study forms part of a PhD project focused on developing an automated, scalable retrofitting tool based on physics-based dynamic simulation. The paper compares preliminary results from the proposed tool with those of an existing static simulation tool to ultimately assess its performance over the static tool. The static simulation tool is a spreadsheet used by SvB for rapidly estimating the impact of various retrofitting measures.

The dynamic thermal simulation was carried out using MUBES developed by [14], which incorporates EnergyPlus as its thermal engine. The key questions addressed include how to automate the retrofitting process within MUBES and how template-based models perform when compared with dynamic simulations for a sample of buildings. The dataset provided by SvB initially contains 857 address points; however, as this dataset includes small auxiliary buildings that are not part of the

heated building area, these entries were excluded from the analysis. After filtering, 643 address points remained, from which 10 buildings were selected for further study. In addition, a second dataset provided by the City of Stockholm was used, which includes buildings from SvB.

Instead, the calibration variables were infiltration, and the U-values of the roof and floor, as well as the window solar gains. The process was carried out in two stages.

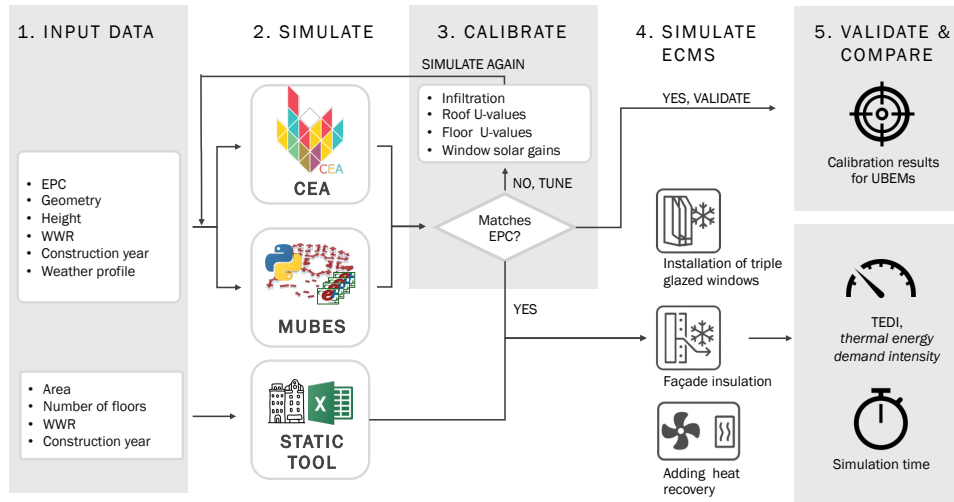


Fig. 2 Simulation workflow

## 2. MATERIAL AND METHODS

Figure 2 illustrates the workflow used to compare a spreadsheet-based static retrofitting tool currently employed by SvB with MUBES. Building input data are first collected and processed through a shared data-adaptation module that standardizes datasets for use in dynamic simulations, while the static tool relies on aggregated inputs and steady-state heating balance equations (Appendix 1). Due to limited information on individual building heights, all buildings are modeled at LOD 1. For the dynamic simulations, MUBES was extended internally with a retrofit module to enable automated retrofitting analyses while preserving default simulation settings. To assess the reliability of MUBES results, an additional dynamic simulation tool, CEA, is employed as an independent reference for validation. Model calibration is performed by tuning key parameters to match EPC values, after which energy conservation measures are applied. The tools are then compared in terms of calibration performance, TEDI, and simulation time.

## 3. CALIBRATION

To ensure that the results were comparable, a calibration step was necessary. Because the number of buildings was limited, the calibration was performed manually. The U-values of the windows and walls—which strongly influence the results—were kept unchanged and were directly taken from [7].

These variables were first adjusted in CEA to match TEDI in EPC. Once suitable values were identified, the infiltration rate was fixed. In the second step, the infiltration rate was kept fixed when moving to MUBES, because infiltration strongly influences the building’s space-heating demand, and in our setup this demand is tightly coupled to the HVAC system. Keeping infiltration constant ensured consistency between the two modelling environments. With infiltration locked, the remaining parameters—roof and floor U-values, as well as window solar gains—were adjusted within MUBES to reproduce the same TEDI obtained in CEA. This approach allowed us to align the thermal performance across tools while respecting the physical role of each parameter in the energy balance.

## 4. RESULTS

Figure 3 presents the first calibration step, where the simulated Base TEDI values from each tool are compared against the measured EPC data to ensure that the baseline models accurately represent the existing building performance.

The figure indicates that the dynamic tools perform comparably in calibration, with minor differences in stability. Both dynamic tools, MUBES and CEA, achieve calibration errors close to zero, indicating that they can be reasonably aligned with EPC values. MUBES shows a slightly smaller spread of errors, meaning its calibration results are more consistent across buildings, while CEA exhibits a wider variation. The SvB static tool shows zero

calibration error, as its results are directly based on EPC-related assumptions rather than a calibration process.

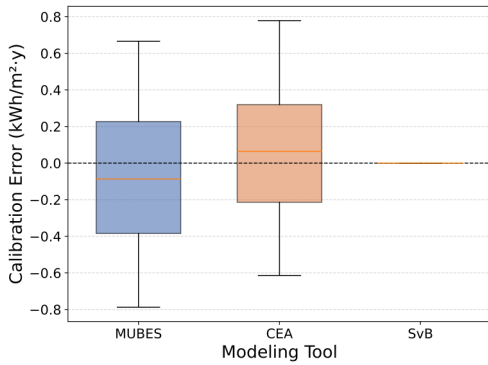


Fig. 3 Baseline Calibration Against EPC Data

Figure 4 shows the cross-validation between MUBES and CEA for all retrofit scenarios. The points align closely with the 1:1 line, indicating that MUBES reproduces CEA’s TEDI results with high accuracy. Small variations appear mainly in the wall and window insulation cases, but no systematic bias is observed. Overall, the results confirm that MUBES is well-validated against CEA and can reliably represent dynamic retrofit impacts, providing a basis for comparison with the static SvB method.

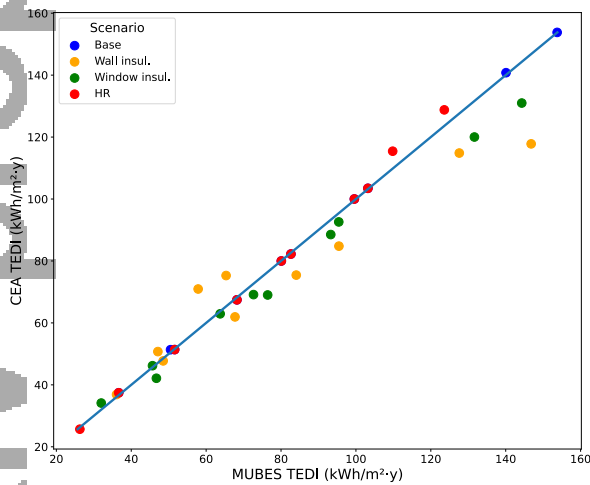


Fig. 4 Cross-validation of MUBES against CEA

The TEDI results obtained from the three modelling tools for the three ECMs are presented in Figure 5. Each group of boxplots shows the distribution of simulated TEDI values across all buildings for a given ECM. Across all ECMs, MUBES and CEA exhibit similar median values and interquartile ranges, indicating strong consistency between the two dynamic models. This observation supports the earlier validation results, confirming that MUBES closely reproduces the dynamic behavior captured by CEA. In contrast, SvB shows a larger spread and greater variability, reflecting the limitations of the static calculation approach in capturing retrofit impacts

with the same sensitivity as the dynamic tools. For wall and window insulation, SvB generally displays lower median TEDI values compared to the dynamic models, implying higher predicted energy savings and suggesting that the static method may overestimate the effectiveness of envelope retrofits. For heat recovery, SvB exhibits noticeably wider variability, highlighting differences in how ventilation and heat recovery effects are represented in static framework.

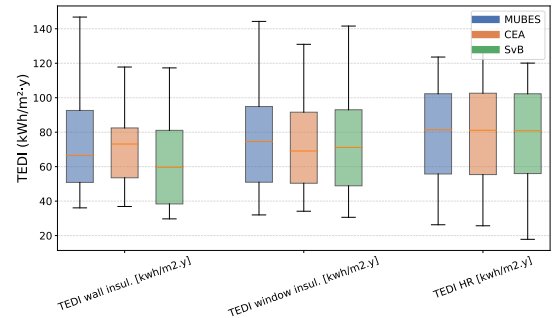


Fig. 5 Comparison of TEDI outcomes across retrofit scenarios for all tools

Figure 6 compares TEDI Savings from Different ECMs across modeling Tools. The figure shows that, across all buildings, the static SvB tool consistently predicts higher energy savings than the two dynamic tools for all three ECMs, with the largest differences appearing for wall insulation and heat recovery. MUBES and CEA follow very similar patterns, both in magnitude and in how savings vary from building to building, indicating strong agreement between the dynamic models. Savings from envelope measures (wall and window insulation) are generally larger for older buildings, reflecting their poorer initial thermal performance, while newer buildings show more limited potential. For heat recovery, savings are more uniform across buildings, but SvB still shows systematically higher values. Overall, the figure highlights that dynamic tools produce more consistent and moderate savings estimates, whereas the static approach tends to overestimate retrofit impacts.

From a computational performance perspective, the simulation time differs substantially across the three modelling approaches. The spreadsheet-based static tool is computationally lightweight, requiring less than 5 seconds per building and thus enabling rapid screening and early-stage retrofit assessments. In contrast, the dynamic simulation tools involve time-resolved thermal calculations and consequently require longer runtimes, with simulation times of approximately 29 and 38 seconds for 10 buildings for MUBES and CEA, respectively. While this additional computational cost reflects the higher level of detail and modelling fidelity, both dynamic tools remain practical for district-scale

applications, highlighting the trade-off between computational efficiency and analytical depth in large-scale retrofitting studies.

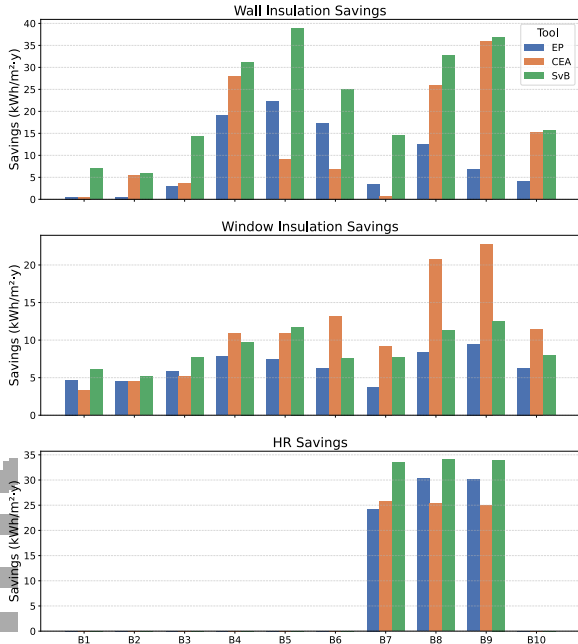


Fig. 6 Comparison of Predicted TEDI Savings from Different ECMs Across Modeling Tools

## 5. CONCLUSIONS

This study compared a spreadsheet-based static retrofitting assessment tool currently used by a municipal housing company in Sweden called Svenska Bostäder (SvB) with a physics-based dynamic UBEM approach called MUBES, focusing on their ability to estimate the impact of selected energy conservation measures. By validating MUBES's results against CEA, the study demonstrated that the two dynamic tools produce closely aligned results in terms of TEDI, confirming the robustness of the proposed dynamic workflow. At the same time, the comparison highlighted the inherent challenge of aligning different modeling tools, as each relies on distinct assumptions, data structures, default settings, and system configurations, making it difficult to operate them under fully identical conditions. Despite careful data adaptation and calibration, some discrepancies are therefore unavoidable and reflect structural differences rather than modeling errors. In contrast, the static tool consistently predicted higher energy savings—particularly for envelope insulation and heat recovery—illustrating the limitations of steady-state methods and simplified heat-balance formulations. While static models remain useful for rapid screening and early-stage decision-making, the results emphasize the added value of calibrated dynamic simulations for

producing more realistic retrofit assessments. Future work will focus on scaling the automated MUBES framework to larger districts, strengthening calibration strategies, and incorporating uncertainty analysis to better support municipal retrofit planning.

## 6. APPENDIX

Window and facade insulation and adding heat recovery are considered as the primary ECMs in this study. The corresponding TEDI savings of static tool for each ECM in buildings with characteristics shown in Table 1, are calculated using the following equations:

### 6.1 Façade Insulation

The thermal behavior of a building is typically described by equations governing heat and mass transfer within the building, through its envelope, and between the envelope and the external environment. Most thermal models rely on surface heat balance equations at interior and exterior surfaces, along with heat flux calculations through the envelope.

In general, and across all major building simulation tools, the net heat loss through walls between interior and exterior air is modeled as:

$$\Delta E_{\text{facade}} = \Delta U \cdot A_{\text{facade}} \cdot (T_{\text{amb}} - T_{\text{in}}) \cdot t \quad (2)$$

$$\Delta U = \frac{1}{\left(\frac{1}{U_0} + \frac{i}{\lambda}\right)} - U_0 \quad (3)$$

where  $\Delta E_{\text{facade}}$  denotes energy saving by insulation of the facade,  $(T_{\text{amb}} - T_{\text{in}}) \cdot t$  indicates the degree hour per year,  $A_{\text{facade}}$  facade area of the building,  $U_0$  is the U-value of the building facade extracted from [7]. that presents building classifications by construction year to determine wall and window U-values in addition to window to wall ratio.  $i$  and  $\lambda$  represent thickness and conductivity, respectively.

### 6.2 Window Insulation with Triple Glazed

The heat loss through the windows also follows the same logic as heat loss through the wall, so the loss through the window is modeled as:

$$\Delta E_{\text{window}} = \Delta U \cdot A_{\text{window}} \cdot (T_{\text{amb}} - T_{\text{in}}) \cdot t \quad (4)$$

where  $A_{\text{window}}$  denotes the area of the window and  $\Delta U$  represents the U-value of window after adding triple glazed.

### 6.3 Window Insulation with Triple Glazed

Ventilation losses through the building are estimated using Equation (6).

$$\Delta E_{\text{ventilation}} = Q \cdot t \cdot (1 - \epsilon) \quad (5)$$

$$Q = q \cdot A_{floor} \cdot \rho_a \cdot c_p \cdot (T_{in} - T_{out}) \quad (6)$$

Table 1. The characteristics of ten sample buildings for dynamic and static simulations.

Building	Built year	A <sub>temp</sub> (m <sup>2</sup> )	A <sub>facade</sub> (m <sup>2</sup> )	A <sub>window</sub> (m <sup>2</sup> )	Height	No. floors
B1	2008	11048	3405	1135	18	6
B2	2006	9018	3114	1038	24	8
B3	1984	6004	2589	863	18	6
B4	1968	5886	2668	470	21	7
B5	1967	1587	812	143	12	4
B6	1954	1034	732	129	9	3
B7	1952	1356	846	149	9	3
B8	1936	2086	1189	209	18	6
B9	1912	1353	977	172	15	5
B10	1894	3311	1534	270	12	4

where  $Q$  denotes the ventilation heat demand (considered as heat loss in the absence of heat recovery or internal/solar gains, under the assumption of perfect mixing),  $q$  is the specific airflow rate (in the Swedish context, it is assumed as 0.00035 m<sup>3</sup>/s.m<sup>2</sup>), and  $\rho_a$  and  $c_p$  are the air density (typically 1.2 kg/m<sup>3</sup>) and the specific heat capacity of air (approximately 1005 J/kg.K), respectively. This estimates the thermal energy (kWh) required to offset heat loss from cold outdoor air entering through ventilation.

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