ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-4/W7-2025
9th International Conference on Smart Data and Smart Cities (SDSC), 2–5 September 2025, Kashiwa, Japan

Data-Driven Energy Simulations To Evaluate Positive Energy District Potential In Rotterdam

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Keywords: Urban Building Energy Modeling, Positive Energy Districts, SimStadt, Energy ADE, Heating and Cooling Demand

Abstract

As urbanization accelerates, accurately simulating the heating and cooling demand of buildings becomes increasingly vital for effective energy system planning. This study proposes an urban building energy modeling framework that prioritizes data quality enhancement through pre-processing (e.g., outlier detection and repair), integrates SimStadt-based simulations, and automates post-processing for 3D database storage and visualization, validated through case studies in Rotterdam's districts of Feijenoord and Prinsenland. The pre-processing framework targets geometric and attribute errors in municipal CityGML data by employing our proposed data repair workflow and correcting energy-critical parameters. A post-processing workflow automates the integration of simulation results into the Energy ADE-extended 3DCityDB and streamlines 3D visualization through a scalar value mapping strategy. Empirical analysis shows that the framework significantly improves the rationality and reproducibility of the heating and cooling demand results compared to those of a previous study commissioned by the municipality. This research provides a scalable technical pathway to support the evaluation of the potential of positive energy districts.

1. Introduction

Urban energy consumption is a critical challenge amid population growth, energy transitions, and climate risks. By 2050, 68% of the projected 9.7 billion global population (6.6 billion) will reside in cities, up from 55% (4.4 billion) in 2023 (UN, 2018), with urban per capita energy use projected by the IEA to increase 35% by 2043 relative to the level of 2023 (IEA, 2023). Decentralized renewables (IRENA, 2022) and urban heat island (UHI) effects (Santamouris, 2021) necessitate precise modeling to address supply-demand imbalances and resilience threats. Buildings account for 40% of the European Union's energy use (Ali et al., 2021) and 79% of residential heating/cooling demand (Eurostat, 2024), with refurbishment and smart technologies offering savings potential. Urban-scale optimization requires integrating microclimate impacts (Hong et al., 2020), occupant behavior (Yan et al., 2015), and UHI-driven loads to achieve positive energy districts (EC PEDs, 2022).

Urban building energy modeling (UBEM) uses top-down (aggregate trends) or bottom-up (granular simulations) approaches, with physics-based tools like EnergyPlus (Crawley et al., 2000) enabling spatial analysis but facing computational limits. Reduced-order tools such as SimStadt (Nouvel et al., 2015) balance efficiency and accuracy through standardized assumptions, facilitating district-level simulations. This research merges the computational advantages of SimStadt with physics-based rigor to address urban energy challenges.

Data quality critically affects UBEM effectiveness and the integration of geometric/non-geometric parameters with weather input (Johari et al., 2020). Inconsistent 3D models, oversimplified occupancy archetypes, and neglected microclimate variations hinder accuracy (Johari et al., 2020). Validation challenges arise from low-resolution municipal data and restricted utility access (Reinhart et al., 2016), with parameter errors (e.g., 15–25% cooling load variations from window-to-wall ratios (Chen et al., 2020)) that impact grid planning despite city-scale error cancellation (Shimoda et al., 2004).

These challenges are manifested in platforms like SimStadt, where data fidelity directly dictates simulation reliability. SimStadt exhibits sensitivity to data quality in urban building energy simulations: LoD1 models introduce 9.2% mean absolute percentage error (MAPE) for the energy reference area and 7.3% for the heating demand, while missing refurbishment status overestimates the heating demand by up to 180% (Nouvel et al., 2017). Such building-level discrepancies persist in peak loads, challenging, for example, grid resilience.

To address these limitations, we propose a systematic framework for robust simulation of building energy at the urban scale. We present a framework for the simulation of the cooling/heating demand of buildings using SimStadt. First, a CityGML (OGC, 2012) data repair method and an attribute integration mechanism are developed, replacing flawed parameters through CityGML generic attributes for broader applicability. Second, a post-processing pipeline parses CSV results into the 3D City Database (3DCityDB) (Yao et al., 2018), enabling visualization and comparative analysis. Empirical validation demonstrates better transparency and reproducibility of our method compared to the previous study commissioned by the Municipality of Rotterdam, which estimates the heating and cooling demand at the level of the building unit, however, not exploiting any spatial data coming from the semantic 3D city model of Rotterdam.

2. Related work

Urban Building Energy Modelling (UBEM) integrates multi-scale analysis of building performance and urban microclimate interactions to inform energy demand insights for urban design, policy, and operations, relying on datasets, simulations, and stakeholder-driven evaluation (Hong et al., 2020). Residential

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https://doi.org/10.5194/isprs-annals-X-4-W7-2025-25-2025

energy models use top-down approaches (macroscale econometric/technological) or bottom-up methods (high-resolution physics/data-driven), balancing scalability and granularity but facing trade-offs in adaptability and computational complexity (Ali et al., 2021). We focus on bottom-up methods for UBEM, emphasizing the critical role of diverse data types in enabling high-fidelity urban energy simulations.

2.1 Modelling approaches

Physics-based UBEM methods (Swan et al., 2009) use distribution-, sample-, or archetype-based strategies with tools like EnergyPlus (Crawley et al., 2001) for detailed thermal simulations. While distribution/sample methods aggregate spatial data (Nägeli et al., 2022), archetype models simplify inputs via standardized assumptions, limiting adaptability despite scalability (Swan et al., 2009). Data-driven approaches (statistical/AI) achieve up to 91% energy prediction accuracy (Ali et al., 2024) but require extensive datasets and struggle with complex occupant behavior (van den Brom, 2020). Innovations like Bayesian calibration (Yoon, 2020) enhance reliability, although generalized applicability remains challenging. Reduced-order models (e.g., SimStadt (Nouvel et al., 2015), CitySim (Walter et al., 2015)) align with standards such as ISO 52016 ISO 52016-1 (2017) to balance efficiency and physical parameter integration. Their reliance on standardized assumptions improves urban-scale scalability but may compromise precision compared to detailed physics-based tools (Rossknecht et al., 2020).

While existing UBEM methods address specific challenges, their computational inefficiency and non-standardized inputs necessitate adaptable frameworks. SimStadt advances the field by combining reduced-order models with automated semantic processing, enabling scalable energy assessments while maintaining interoperability with physics-based tools.

2.2 Data requirements

Semantic 3D city models (s3DCM) for UBEM require geospatial data that integrates geometric, topological, and semantic elements. If such data also follows a standardized open data model, such as CityGML (OGC, 2012), ideally extended with the Energy ADE (Agugiaro et al., 2018, 2025) for energy-specific objects and attributes, then some of the typically time-consuming data integration and harmonization steps can be reduced or simplified. Multi-LoD (Level of Detail) frameworks balance granularity and scalability, enabling adaptive resolution from block models (LoD1) to detailed interiors (LoD4) (Biljecki et al., 2016). Building physics data are critical for demand prediction, but are challenged by heterogeneous building stocks. Archetype classifications (e.g., TABULA (EPISCOPE, 2017)) harmonize data by age/type, although standardized models remain incomplete (Agentschap NL, 2011). Occupancy schedules, stochastic archetypes, and agent-based models capture behavioral dynamics (Doma et al., 2023) but risk oversimplification, while weather inputs (TMY datasets, microclimate parameters) struggle to reconcile static assumptions with urban climate variability (Deng et al., 2023).

UBEM uncertainties arise from input inaccuracies—including geometrical and attribute errors—and scale-related trade-offs, necessitating frameworks that address data standardization gaps and interoperability challenges (Kong et al., 2023). This study introduces a CityGML repair pipeline to enhance SimStadt-based simulations by resolving these errors, improving data fidelity for cooling/heating demand prediction.

3. Methodology

Accurate prediction of urban heating and cooling demand requires robust integration of multi-source data (geometric, meteorological, and typological) and scalable simulation tools. To address this need, we developed a four-stage framework. First, input data such as CityGML 3D building models, weather data, and building typology/function are gathered. Second, pre-processing via data repair and integration is carried out. Third, energy simulation for heating and cooling demand calculations is performed using SimStadt. Finally, post-processing includes database storage and visualisation.

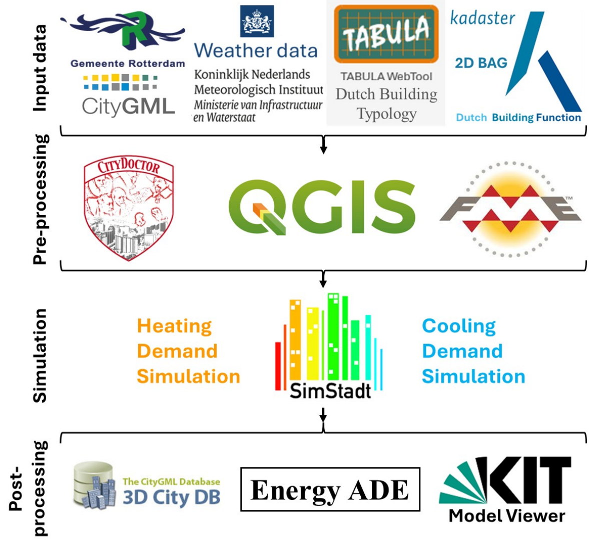


Figure 1. Overview of the proposed workflow of urban energy simulation. A four-step framework: (1) Input data (CityGML 3D building models, weather data, building typology/function); (2) Pre-processing (data repair and integration); (3) Energy simulation (heating and cooling demand calculations); (4) Post-processing (database storage and visualisation).

3.1 Input data

Our objective is to simulate the cooling and heating demand of the buildings in the study area based on weather data and 3D building models, providing a foundation to support the creation of positive energy districts. We focus on the Feijenoord (8.5 km^2, population estimated at 80,000) and Prinsenland (1.8 km^2, population estimated at 10,000) districts in Rotterdam (see Fig. 2), which together encompass 25,681 buildings—14,915 of which have active energy consumption profiles. The building stock is dominated by terraced houses (85.2%), with smaller shares of apartment blocks (4.3%), commercial properties (9.1%), and single-family houses (1.4%), spanning mixed functions including residential, commercial, industrial, and cultural uses. Feijenoord's building year distribution includes pre-WWII and newly built structures, while Prinsenland is mostly composed of new constructions. These areas were prioritized by the Municipality of Rotterdam due to their heterogeneous building typologies and high energy intervention potential. As shown in Fig. 1, the input comprises:

- 3D building models: Sourced from Rotterdam3D in CityGML format, the Level of Detail 2 (LoD2) models provide (Rotterdam, 2018): *Thematic surfaces*: roofs, walls, and ground surfaces for geometric energy reference area/volume calculations; *Generic attributes:* construction year and height to infer thermal parameters (e.g., U-values via TABULA typology-year mappings) for SimStadt inputs; *Spatial context*: adjacent building positions (distance, height, orientation) for microclimate effects like shading/ventilation on heating/cooling demand.

- Weather data: Derived from the Royal Netherlands Meteorological Institute (KNMI (2024)), hourly meteorological averages (1954–2023) in EPW format were converted to TMY3, including irradiance, ambient temperature, wind speed, pressure, precipitation, and diffuse radiation. These data influence building energy demand simulations under local climatic conditions. Ambient temperature and solar radiation from weather data directly drive conduction losses and solar gains in the heat balance equation for heating demand, while for cooling demand, high temperatures and solar radiation increase conduction gains and solar heat influx. Consequently, inaccuracies (e.g., from suburban station measurements) propagate to both heating and cooling demand uncertainties (see Limitations).
- Building typology: Based on TABULA (EPISCOPE, 2017), covering construction periods from pre-1964 to post-2015. Building types include *Single Family House*, *Terraced House*, *Multi Family House*, *Apartment Block*, *Commercial*, *Big Multi Family House*, and *High Tower*. This database predefines envelope parameters (e.g., U-values, thermal capacity, airtightness) for different building types, enabling rapid parameter assignment via CityGML semantic mapping to minimize manual errors.
- Building functions: Obtained from the Dutch Cadastral 2D BAG dataset (Kadaster, 2025), including building functions (residential, commercial, industrial). These attributes allow to associate internal loads and operational profiles (occupancy, heating/cooling schedules, domestic hot water usage) to the building.

Local datasets often exhibit incompleteness, inconsistencies, and mismatches, necessitating pre-processing for integration into energy simulations.

Figure 2. Study areas in Rotterdam. The Feijenoord and Prinsenland districts are outlined in the red polygons.

3.2 Pre-processing

We aim to repair and integrate data to meet simulation input requirements, ensuring reliable results. National-level datasets (e.g., weather data and building functions) generally have fewer errors, whereas municipal-level data (e.g., CityGML (OGC, 2012)) often require extensive corrections. Additionally, building typologies and functions must be integrated into CityGML for SimStadt compatibility, though these attributes are rarely preconfigured, which are typically designed for visualization; thus, energy-specific attribute extensions are essential.

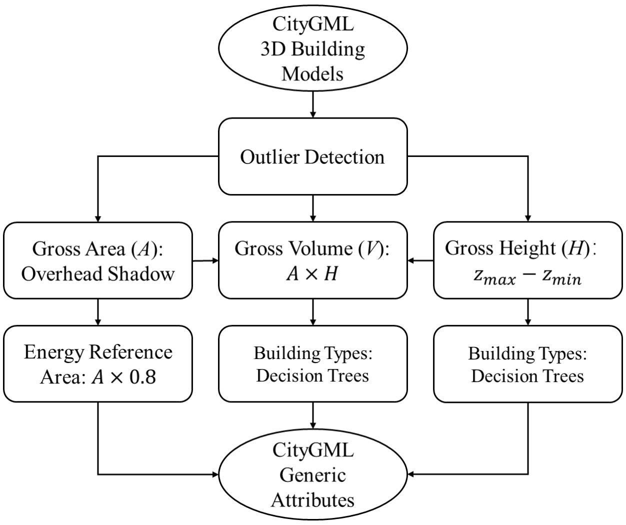


Figure 3. Schematic overview of the data repair workflow.

Data repair: We address two issues in CityGML data, including: (1) Geometric errors, such as holes, non-manifold geometries, incorrect normals, and self-intersections, often caused by modeling quality issues or format conversions. Conventional mesh repair tools -designed for non-semantic 3D models- often risk semantic data loss. We employed CityDoctor2 (e.g., Genetic algorithm) (HFT, 2021) and FME (GeometryValidator module) (FME, 2025) to preserve semantics while repairing geometric errors; (2) Attribute errors, such as outliers, missing values, and inconsistencies in the units of measure directly impact critical energy simulation parameters, including energy reference area, volume, and building type. After the repair by CityDoctor2, we still detected 389 (out of 25681 total) buildings with geometric or attribute outliers in the study area, and these outliers were estimated through the method we proposed. These errors may arise from data entry errors during model creation or irreparable geometric errors that propagate to attribute inconsistencies. The energy reference area depends, among the rest, on the building footprint, while volume calculations rely on a watertight model, and building types are mapped using height, construction year, and TABULA classifications (EPISCOPE, 2017). To address outliers (e.g., null, zero, missing, infinite, or negative entries) in area and height, we implemented alternative methods (see Fig. 3): area was estimated via 2D planar projections of overhead shadows, and height was interpolated from bounding box z-axis values ($z_{max}-z_{min}$), and for models with invalid solid geometries (e.g., with holes), the volume was approximated using these new area/height values. Both *Building* and *Building Part* entities were processed independently. Corrected values for area, volume, energy reference area, and building type were stored in the CityGML file as generic attributes, enabling direct input into SimStadt and overriding its internal computations and classification algorithms, which are restricted to valid geometries and would otherwise skip simulating buildings with invalid geometries.

Data integration: The energy simulation tool (SimStadt) uses the ALKIS code system (AdV, 2015), a German cadastral standard. To align Dutch building functions (from 2D BAG (Kadaster, 2025)) with ALKIS codes, we manually mapped local functional categories to the closest ALKIS equivalents using QGIS and FME. Challenges arose in mixed-use buildings (e.g., residential-commercial combinations), where dominant functions were determined via street-view image validation. For the study area, 104 functional combinations were identified and mapped to ALKIS codes, stored in the 'citygml_function' attribute.

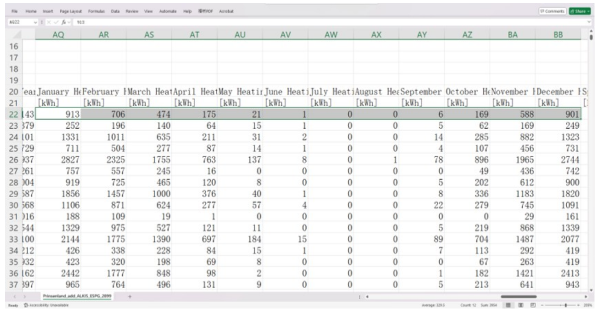
3.3 Energy simulation

Our objective is to simulate the energy demand of buildings within the study area. The input data consists of the repaired CityGML dataset and the weather data, processed through the *Heat Demand Analysis* workflow in SimStadt2 (Nouvel et al., 2015), which outputs files in CSV format containing both heating and cooling demand values. To efficiently handle large-scale data, the CityGML files are partitioned into administrative sub-regions, each containing hundreds to thousands of buildings. The simulation workflow integrates multiple computational modules: the *Geometric Preprocessor* (handling building geometry metrics such as height and volume, and identifying neighboring buildings), the *Geometric Estimator* (deriving energy-related parameters like heated areas), the *Physics Preprocessor* (classifying building types), the *Usage Preprocessor* (defining occupancy zones), the *Weather Processor*, the *Irradiance Processor* (leveraging INSEL HAY (INSEL, 2025) for solar calculations), and the *Monthly Energy Balance* module (applying DIN V 18599-2 standards (DIN, 2018) for energy balance calculations and IWU_NUTZUNG-based (Hörner et al., 2022) consumer behavior modeling). Notably, precomputed attributes stored as generic attributes in the input CityGML—such as area, volume, and building type—are directly utilized by the *Geometric Preprocessor*, *Geometric Estimator*, and *Physics Preprocessor* to streamline calculations. The final CSV output files undergo post-processing to enable database integration and visualization on 3D building models, ensuring compatibility with downstream applications.

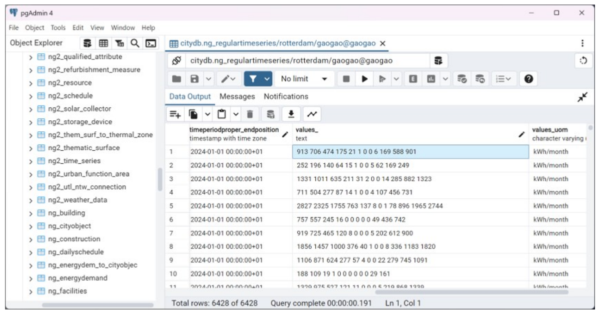
3.4 Post-processing

The purpose of post-processing is to transform the simulation output into storable, visualizable, and comparable data formats. Specifically, storage and visualization are achieved by integrating simulation results into CityGML.

To database: To integrate energy simulation outputs from SimStadt into the 3DCityDB (extended with EnergyADE (Agugiaro et al., 2018)), a Python-based script was developed to address interoperability gaps in urban digital twin workflows. It connects to a remote PostgreSQL database via SSH, parses SimStadt's CSV outputs (e.g., monthly cooling/heating demand) and maps them to Energy ADE entities through batch SQL operations (see Fig. 4). The main steps are: (1) Automated CSV-to-Energy ADE mapping, which structures CSV entries into Energy ADE entities. For each simulated building, several EnergyDemand objects, each one containing a RegularTimeSeries object (either with monthly or hourly values), are created and stored in the respective tables in the 3DCityDB. During the process, additional attributes are generated (e.g., unique gmlids via UUID functions); (2) Transactional batch insertion, leveraging the pandas library for data transformation and SQLAlchemy for efficient bulk operations to insert heating/cooling demand data; and (3) Atomic transaction management, which ensures data consistency through rollback mechanisms. This solution successfully writes all simulation results into Energy ADE tables. It provides a scalable ETL solution to easily enrich the 3DCityDB with simulation results and allow for further analyses.



(a) SimStadt outputs (CSV files)



(b) 3DCityDB visualisation via pgAdmin.

Figure 4. An example of SimStadt results to 3DCityDB

For visualization: Due to limited native 3D rendering support for Energy ADE results, a method was developed to visualize energy simulation outcomes in 3D by converting the energy demand values per-building into scalar values stored in CityGML's generic attributes. Using KITModelViewer (KIT, 2024), CityGML data is imported, and color mapping is applied by selecting rendering categories (e.g., yearly heating demand) under *Color → Property Value → Type Independent*. This approach also supports converting CityGML into other 3D formats (e.g., OBJ, PLY) by embedding scalar values into data attributes, enabling visualization in 3D tools. Additionally, to enable comparative analysis, energy simulation results from Rotterdam's previous study were similarly integrated into CityGML for consistent rendering and evaluation.

4. Evaluation

Our analysis quantifies the heating and cooling demand per building by calculating the specific space energy demand (based on energy reference area) and annualizing monthly profiles, with results compared against Rotterdam Municipality's data.

4.1 Results

Analysis of the study area revealed distinct historical patterns in the age distribution of buildings (see Fig. 5 left). The majority of buildings were constructed in two primary periods: the late 19th century to the 1940s (peaking around 1920) and post-1980s (around 2000), with relatively fewer buildings built between 1940 and 1980. The spatial distribution of the specific heating demand (Fig. 5 middle) further highlighted

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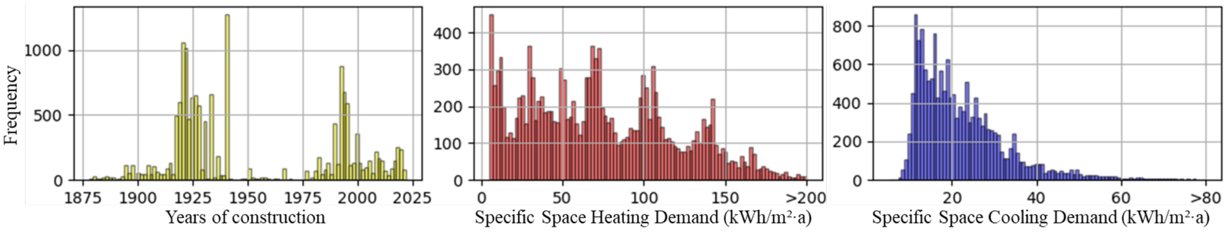

Figure 5. Building year of construction, distribution, and simulated energy demand. Left: Year of construction in the study area; Middle and right: SimStadt results for specific heating/cooling demand, expressed in kWh/($m^2 \cdot a$).

Dimension	Values provided by Municipality of Rotterdam	Our simulated values (from SimStadt)
Input Data	Relies on archival data (Rc/Uw values, ventilation types) and field measurements (e.g., airtightness).	CityGML models with 3D geometry; requires material properties and user behavior profiles.
Simulation Method	Static model (NTA 8800 and TOjuli) for annual heat demand and summer overheating risk.	Hourly simulation (DIN V 18599) with weather data and thermal inertia analysis.
Building Typology	Classified by residential type (apartment / terraced / detached) and construction era (pre-/post-1945).	Classified by functional use (terraced house / apartment block) with energy demand profiles.
Building Function	Focuses on residential refurbishment; no explicit commercial/industrial analysis.	Supports multi-functional buildings (e.g., offices, schools) with distinct load patterns.
Output Objective	Prioritizes policy compliance (energy labels) and cost-effective retrofit packages.	Optimizes city-scale energy systems (grid interaction, renewables integration).

Table 1. Main differences between values provided by the Municipality of Rotterdam and our SimStadt input/output values

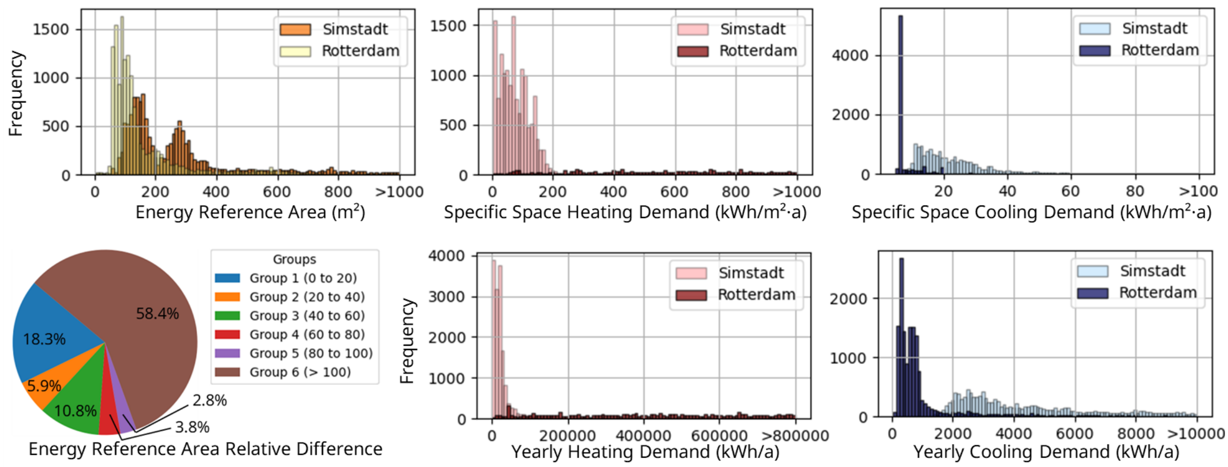

Figure 6. Quantitative comparison between values provided by the Municipality of Rotterdam and our SimStadt input/output values. From left to right, it shows the energy reference area (absolute/relative differences), space heating and cooling demand (both for specific and absolute values).

that approximately 15% of the high-consumption buildings (>175 kWh/($m^2 \cdot a$)) were pre-1945 residential structures, most likely with poor thermal insulation, while post-1980 buildings exhibited lower demand (50–100 kWh/($m^2 \cdot a$)), aligning with more recent and improved insulation standards. The cooling demand (Fig. 5 right) remained below 30 kWh/($m^2 \cdot a$) for most buildings, consistent with Rotterdam's temperate maritime climate (Rotterdam Partners, 2025). However, modern glass-facade commercial buildings showed elevated cooling demand values (>60 kWh/($m^2 \cdot a$)), underscoring the need for optimized shading and natural ventilation. These findings corroborate the urgency of refurbishing older buildings while balancing passive design strategies in new constructions.

4.2 Comparative analysis

Due to fundamental differences in the data granularity and geometric approximation between the two methods, results from Rotterdam's previous study and SimStadt should be compared with caution, especially given the high prevalence of outliers in the former's data at the building unit level. Values of heating and cooling demand from Rotterdam's previous studyNieman (2023) are computed using the Dutch NTA8800 (2024) standard. For each building unit, averaged or estimated input data such as area, orientation, compactness, envelope thermal properties (Rc/Uw values for walls, roofs, windows), ventilation airtightness (infiltration rates, system types), and construction periods (pre-1945 vs. post-1945) are used. Its semi-static model calculates the heating demand via NTA8800 (in kWh/($m^2 \cdot a$)) and cooling demand using the TOjuli index (RVO, 2025) to assess the risk of overheating in summer. Buildings are categorized by type (apartments, row houses, detached) and age, with pre-1945 buildings prioritized for upgrades like HR++ glazing (AA Glas, 2025) and internal insulation, while post-1945 buildings focus on comprehensive insulation. Functional distinctions (e.g., apartments vs. detached homes) influence heating demand, as shared structures in apartments reduce per-unit consumption. Unlike SimStadt, which emphasizes city-scale dynamic energy system optimization, Rotterdam's previous study prioritizes compliance with single-building refurbishment policies (see Table 1).

Energy reference area comparison. The two approaches diverge significantly in energy reference area (ERA) modeling. Rotterdam's method, operating at the building unit level with aggregated results for whole buildings, relies on simplified geometric approximations (e.g., averaged dimensions and generic thermal properties), which introduce uncertainties—especially evident in the high frequency of zero or near-zero ERA values (see Fig. 6, left). In contrast, SimStadt leverages validated 3D building models with corrected geometries and outlier-adjusted parameters, yielding a right-skewed ERA distribution (peaking at 50–400 m^2) that better reflects the actual diversity in building size. Relative difference analyses reveal polarization: 18.3% of buildings show $<$20% deviation (Group 1), while 58.4% exhibit $>$100% deviation (Group 6), likely driven by unresolved data gaps or input errors in the previous study's approximations at the building unit level. These discrepancies underscore the need for rigorous data cleaning—such as the geometric repairs and attribute corrections applied in SimStadt—before meaningful cross-method comparisons can be conducted.

Heating demand analysis. Significant differences exist between SimStadt and Rotterdam's values in heating demand simulations (see Fig. 6 middle, and Fig. 7 top). For specific space heating demand, SimStadt's results cluster within 0–200 kWh/($m^2 \cdot a$), consistent with Rotterdam's typical insulation performance, whereas the values from Rotterdam exhibit scattered values, including values exceeding 1000 kWh/($m^2 \cdot a$), probably due to data anomalies or area calculation errors. In the yearly heating demand, SimStadt's distribution ($\leq$60,000 kWh/a) corresponds to small-to-medium buildings, while Rotterdam's method includes implausible records ($>$1,000,000 kWh/a), possibly reflecting unsegmented industrial complexes or parameter errors. SimStadt's reliance on our (corrected) 3D model appears to ensure higher physical consistency, whereas Rotterdam's results require further validation or additional checks on data quality, consistency, and accuracy.

Cooling demand analysis. As shown in Fig. 6 (right) and Fig. 7 (bottom), cooling demand simulations diverge markedly between the two models. SimStadt's specific cooling demand peaks at 20–40 kWh/($m^2 \cdot a$), reflecting Rotterdam's climate-driven passive cooling potential. Rotterdam's values, however, show polarization: 88.3% of buildings fall below 20 kWh/($m^2 \cdot a$), yet some exhibit high values ($>$100 kWh/($m^2 \cdot a$)), possibly due to input errors or oversimplified assumptions. Yearly cooling demand distributions further highlight differences: SimStadt spans 0–10,000 kWh/a, capturing diverse building scales and functions, while Rotterdam's values are concentrated (0–2000 kWh/a), suggesting systemic underestimation or exclusion of non-residential spaces (e.g., glass-facade commercial buildings). Again, it seems that SimStadt and (corrected) 3D models ensure a better reliability, whereas anomalies in Rotterdam's values necessitate further checks.

5. Summary

This study describes how semantic 3D city models, if properly checked for data inconsistencies and geometrical errors, can be used as a source of integrated spatial and non-spatial information to perform energy analyses at the urban scale. In particular, our work focuses on the simulation of the heating and cooling demand of buildings for two test areas in the municipality of Rotterdam, in the Netherlands. The simulation tool using the s3DCM as input is SimStadt. We defined pre- and post-processing procedures to enhance input data quality (improving simulations) while automating result integration and visualization. Empirical validation in Rotterdam shows that the repaired CityGML models effectively mitigate geometric errors, reducing average discrepancies in energy reference area and heating demand calculations. Refined mapping of building functions and types minimizes parameter assumption biases. Comparative analysis with results obtained from a previous study commissioned by the municipality of Rotterdam highlights the advantages of our method in terms of characterization of spatial heterogeneity and prediction of peak loads, offering a reliable tool that can support urban energy system planning.

Limitations and future work. This work has limitations: microclimate influences (vegetation shading, urban infrastructure) are neglected, potentially underestimating cooling loads; LoD2 models lack detailed architectural features (openings, sunshades) affecting energy balance; meteorological data rely solely on suburban station records without urban canopy validation; and TABULA's coarse building classes combined with German DIN standards may introduce local applicability biases. Future work should prioritize integrating urban microclimate measurements and refining typologies with local parameters, while exploring LoD3 models and vegetation coupling to address these constraints.

Acknowledgements

The work presented in this paper has been developed within the European project DigiTwins4PEDs (Utilisation of urban digital twins to co-create flexible positive energy systems for districts). The project is funded by the European Commission under the Horizon Europe Partnership scheme (Funding Indicator: 03EN3081A). The DUT Call 2022 also contributes to the Urban Transition Mission of Mission Innovation as part of the MICall 2022 initiative.

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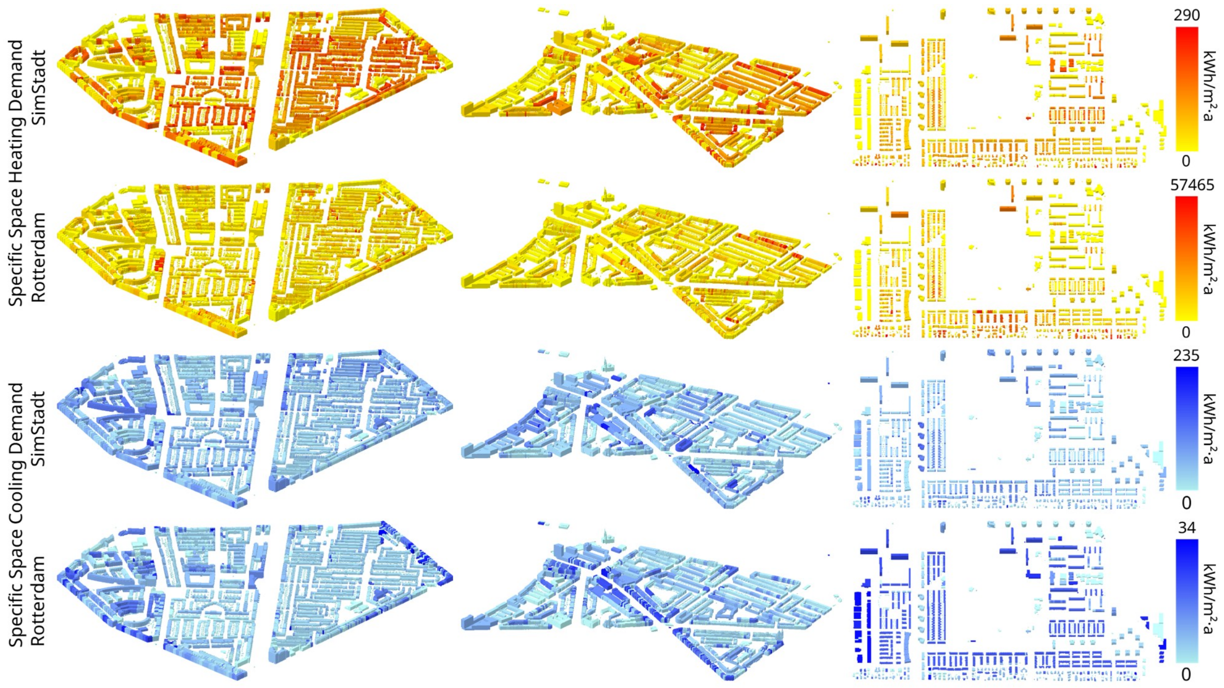

Figure 7. Example of qualitative comparison between values provided by the Municipality of Rotterdam and our SimStadt output values. Top rows: Specific space heating demand (SimStadt [top], Rotterdam [bottom]); Bottom rows: Specific space cooling demand (SimStadt [top], Rotterdam [bottom]).

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