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Empirical Validation of UBEM: An Assessment of Bias in Urban Building Energy Modeling for Chicago

Ankur Garg
BlocPower

Santiago Correa, Ph.D.
BlocPower

Fengqi Li, Ph.D.
ASHRAE Member

Shovan Chowdhury
ASHRAE Member

Joshua R. New, Ph.D.
ASHRAE Member

Kevin Bacabac
BlocPower

Christian Kunkel
BlocPower

Donnel Baird
BlocPower

ABSTRACT HEADING

Residential and commercial buildings currently account for 30% of total global final energy consumption. Urban-scale building energy modeling (UBEM) can enable scalable investments and unlock building improvements by quantifying energy, demand, emissions, and cost reductions of specific measures or packages for building-specific technologies in large geographic regions. While the sophistication of UBEM data sources and technologies have increased dramatically in the past decade, there remains a knowledge gap for empirical validation and sources of bias between building-specific energy models and measured data at varying geographic scales.

As UBEM continues to develop, systemic analysis of accuracy, bias, and limitations of the resulting models is necessary to inform best practices and move toward standardization. These are characterized for the Automatic Building Energy Modeling (AutoBEM) software suite with an initial case study involving metered electricity consumption data from 247,188 buildings in Chicago, Illinois, USA - averaged across years 2019-2021 - compared to the following datasets: (1) the AutoBEM-generated nation-scale Model America version 2 (MAv2) data for 596,064 buildings, (2) tax assessor data for 579,829 buildings, (3) tax assessor data filled with MAv2, and (4) 102 representative dynamic archetypes. Accuracy is reported for every building type and vintage combination, along with multiple sources of bias for unique building descriptors. The AutoBEM simulation workflow produced energy consumption estimates that closely match aggregated metered electricity consumption data for different types of buildings constructed during various time periods at the city scale - with initial normalized mean bias error of 10.9% and 1.1% after removing outliers. The contribution of statistically significant factors, including building type, land use, age, and size, to variance in UBEM bias is quantified.

INTRODUCTION

The Paris Agreement aims to limit global warming to 1.5°C with 196 Parties acting to limit a greenhouse gas emissions peak before 2025 and decline 43% by 2030 (Falkner 2016). In 2022, the U.S. combined end-use energy consumption by the residential and commercial sectors was 22 quadrillion British thermal units (Btu), about 30% of total end-use energy consumption. Approximately 42% and 48% of this energy consumption comes from residential and commercial electricity use, respectively ("Annual Energy Outlook 2023 - U.S. Energy Information Administration

Ankur Garg is a Director of Data and Analytics at BlocPower, New York, NY. **Santiago Correa, Ph.D.** is a Data Scientist at BlocPower, New York, NY. **Fengqi Li, Ph.D.** is a research fellow at Oak Ridge National Laboratory, Oak Ridge, TN. **Shovan Chowdhury** is a Ph.D. student at the University of Tennessee, Knoxville, TN. **Joshua R. New, Ph.D.** is a Distinguished R&D Staff Member at Oak Ridge National Laboratory, , Oak Ridge, TN. **Kevin Bacabac** is a Data Engineer at BlocPower, New York, NY. **Christian Kunkel** is a Director of Data Acquisition and Partnerships at BlocPower, New York, NY. **Donnel Baird** is the CEO of BlocPower, New York, NY.

(EIA)" n.d.). This gap between the electricity and the total end-use energy consumption presents a significant opportunity to achieve the goal of net-zero emissions by transitioning buildings away from fossil fuel-based energy sources, such as natural gas or oil, and relying on electricity as the primary energy source.

Urban building energy modeling (UBEM) (Reinhart and Cerezo Davila 2016) plays a key role in many use cases (Ang, Berzolla, and Reinhart 2020), including designing and quantitatively assessing pathways toward achieving energy conservation goals. UBEMs help urban planners identify the impacts of urban morphology on energy performance, enabling them to design more sustainable communities. This application combines geospatial information with UBEM outputs to understand trade-offs between shading, daylighting, and community forms on peak energy use and performance (Yu et al. 2021; Pisello et al. 2012). For carbon reduction strategies at the building and stock level, UBEMs can estimate impacts on the building greenhouse gas (GHG) emissions footprints and facilitate studies that lead to better estimates for cost-effective sustainability programs (Chen, Hong, and Piette 2017).

To create an accurate energy model for applications that require it, such as building-level carbon reduction strategies, it is necessary to have representative building characterizations. This includes information such as the building type, location, age, construction materials, usage patterns, occupancy levels, cooling and heating fuel and system type. Traditional bottom-up, physics-based building energy models rely on building simulation tools such as EnergyPlus ("EnergyPlus" n.d.), Dymola (Fuchs et al. 2016), and IDA ICE (Nageler et al. 2017). These simulation tools use thermal, hydrothermal, and physical models that can account for over 4,000 variables, ensuring a detailed temporal and spatial resolution of energy profiles. However, this level of complexity requires significant computing power to analyze and calibrate energy signatures at a high granularity for city-wide scales. Data-driven building energy models, on the other hand, use mathematical representations of general building characteristics and historical measurement data to estimate building-level energy usage. These types of black-box models can estimate energy profiles without relying on the underlying physical properties of the building. However, they struggle to evaluate the impact of energy conservation measures or building retrofits on energy demand since they depend on the availability of training data for each upgrade measure (Chen, Hong, and Piette 2017).

Many UBEM methods leverage the growing accessibility of public building data (e.g., tax assessor records), Geographic Information System (GIS) data, satellite imagery, lidar data, or other remote sensing data to generate either building-specific models or representative archetypes for a region of interest. Both can employ environmental factors with heating/cooling loads to produce building energy profiles on a larger scale (Li et al. 2015). Archetypal approaches run the risk of oversimplifying the representation of an entire building stock. This has led to an increased need for empirical validation in existing literature to identify sources of bias and to evolve best approaches that improve the fidelity of models.

AutoBEM

Models in this study were generated and simulated using the Automatic Building Energy Modeling (AutoBEM) software suite applied to the Model America version 2.0 (MAv2) dataset. AutoBEM utilizes OpenStudio ("OpenStudio" n.d.) to generate building energy models and EnergyPlus ("EnergyPlus" n.d.) to simulate the models.

A previous version of U.S. building energy models was made publicly available for 122,930,327 US buildings as the Model America dataset (New, Adams, et al. 2021), constituting approximately 98% of the nation's building stock in 2015. AutoBEM has been used for city, county, utility, and nation-scale building energy modeling analyses considering electricity-saving technologies, peak-demand reduction techniques, climate projections, and other uses (Bass, New, and Berres 2021; Bass and New 2020; Bass, New, and Copeland 2021).

There is a lack of empirical validation for UBEM in existing literature, which is necessary for productively moving the technology forward. UBEM suffers from a cacophony of data sources (esp. non-scalable ones such as tax assessors data (New et al. 2020)) and methods, with most UBEM projects involving fewer than 100 buildings and with error rates ranging from 1—1000% for individual buildings (Oraiopoulos and Howard 2022). While further review of UBEM empirical validation is beyond the scope of this paper, AutoBEM-specific validation efforts are provided.

There has been a validation of specific MAv1 data fields against data from individual cities (New, Bass, et al. 2021). Height and building type were the primary foci of efforts for MAv2 which achieves sub-1-meter vertical resolution in height for most US buildings, along with better characterization of mixed-use buildings. This study extends (Bass et al. 2022) to focus on validation of building energy models against reported annual electricity consumption of buildings in Chicago, Illinois, USA. Empirical validation is presented covering more than 200,000 buildings with Analysis of Variance (ANOVA) assessing the effects of building characteristics on accurately representing energy signatures. This study examines the limitations of metered and publicly available building characteristics that can lead to bias in model estimates and presents a processing workflow to improve representation of a region's building stock while showcasing initial results for Chicago.

MATERIALS AND METHODS

Datasets

Simulated Building Energy Profiles. While most UBEM techniques leverage tax assessor or other local sources of data, AutoBEM used only scalable data, algorithms, and compute infrastructure to allow nation-scale building energy modeling - synthesizing data and simulating every building in a country. To do this, a 7-step process was employed: 1) identifying which building descriptors are most important via a sensitivity analysis for every building type, vintage, and climate zone combination and fractional factorial design for up to 4,700 variables of each building to identify the plus/minus 30% impact of each variable on energy (kWh) and peak demand (kW); 2) scaling up generation and simulation on supercomputers for annual performance of 1,068,813 buildings in one hour (Berres et al. 2021) 3) survey of over 40 data sources that map to building simulation inputs with comparison matrices for characteristics such as spatio-temporal resolution, geographic extent, cost, legal considerations for derivative intellectual property, or rate limits to application programming interfaces (API) calls; 4) establishing partnership agreements with organizations in the business of collecting, cleaning, or processing relevant data; 5) extending algorithms to work at the scale required; 6) estimating important unknown parameters such as building type (Bass et al. 2021); and 7) identifying sufficiently large data hosting (New, Adams, et al. 2021) or intuitive visualization platforms ("CesiumJS" 2023; "Virtual EPB" n.d.) for making the data, models, and analysis available.

Measured Electricity Data. Building energy consumption from building-specific reported energy use in Chicago, IL, is used to assess bias. This dataset contains aggregated annual electricity consumption from 2019 to 2022 for over 579,000 meters (about 359.77 mi). This analysis aims to avoid periods impacted by the COVID-19 pandemic to sublimate the impact of unusual consumption patterns. We combined measured consumption with tax assessor data to obtain building characteristics such as building type, vintage, and area. Due to the many-to-many matching between premises and meters, some readings showed unrealistic values, which we filtered out to assess the bias better. Meter data presents additional challenges when mapping meter numbers and locations to addresses. The meter location description often does not directly correlate to the address, for example, in a multi-building complex with a garage across the street or a multifamily building with all meters centrally located in the basement. Similarly, tax assessor data suffers from incompleteness, and some building characteristics were unavailable.

Data Cleaning and Preprocessing

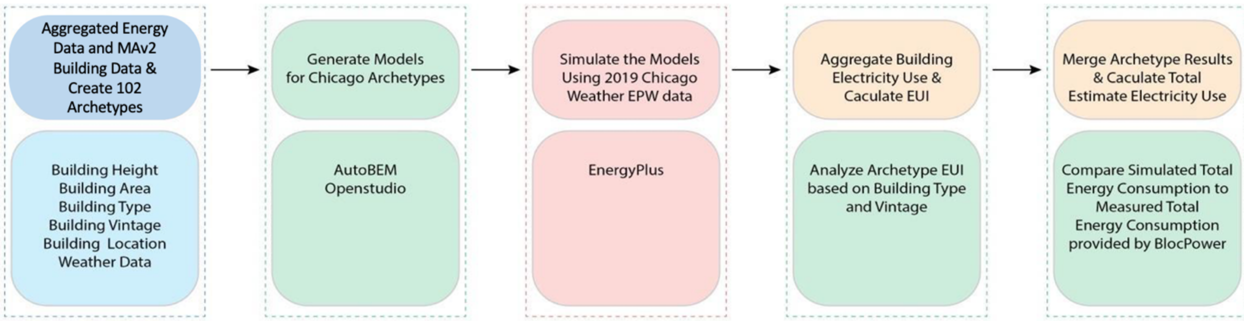

Figure 1. AutoBEM workflow for Chicago archetypes simulation

To ensure accurate analysis and comparison between modeled data and ground truth metered data at the individual building level, a data cleaning and preprocessing workflow was implemented. To calculate the error at the individual building level, the modeled data needed to be matched with the corresponding ground truth metered data. This matching process involved creating a data processing workflow to ensure alignment between the datasets. The workflow is outlined in figure 1 and the corresponding buildings count at each step are noted in figure 3. Unreliable buildings with null or zero energy consumption in the ground truth data were removed to maintain analysis integrity. Building subtypes based on land use allowed for more detailed categorization. These subtypes were used to create distinct building types within the dataset. To match MAv2 buildings with ground truth data, various factors were considered, including geographic coordinates, floor area, building type, and construction year. Relying solely on geographic coordinates presented challenges due to the mismatch between the tax assessor and building roof-centered coordinates, as illustrated in Figure 2. Accuracy was improved by incorporating additional factors such as floor area and building type to establish a reliable correspondence between modeled and ground truth data.

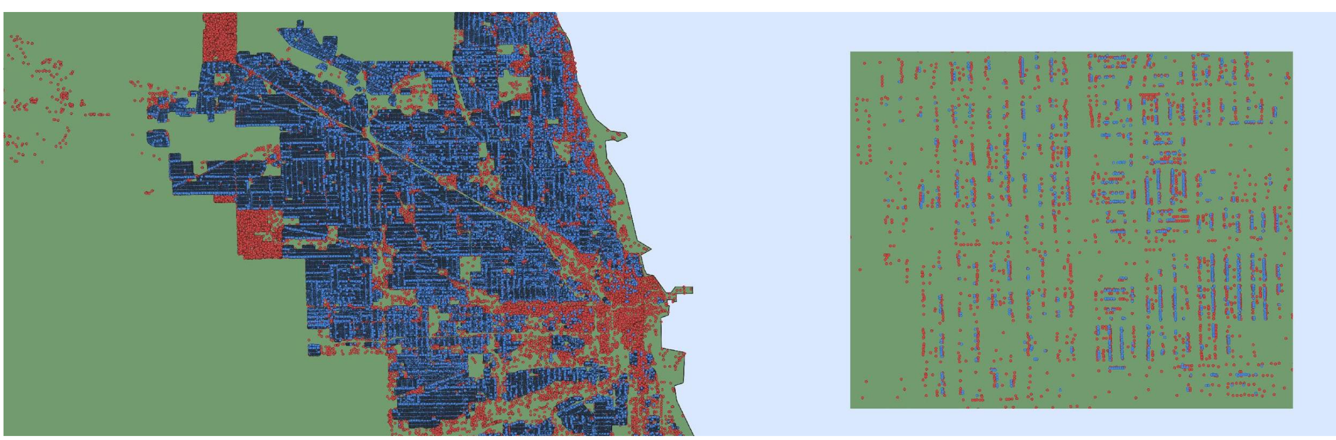

Figure 2. Spatial Relationship between MAv2 (Red Dots) and tax assessor Data (Blue Dots).

Buildings with extremely low annual energy consumption, as determined by a threshold (less than 5150.1 kWh per year), were identified as outliers. In this study, we found that the average energy consumption of a typical U.S. household amounts to approximately 11,000 kilowatt-hours (kWh) per year. It is important to note that electricity usage in residential properties differs significantly across different regions within the United States, as well as across various housing types ("Electricity Use in Homes - U.S. Energy Information Administration (EIA)" 2015). As a result, we employed the standard deviation value (5150.1 kWh) of the energy consumption data column as a reference point to determine the outliers for the specific building dataset we selected. These outliers were then removed from the dataset to minimize their impact on the analysis and ensure the robustness of the results. This approach ensured inclusion of reliable and relevant data points for further analysis.

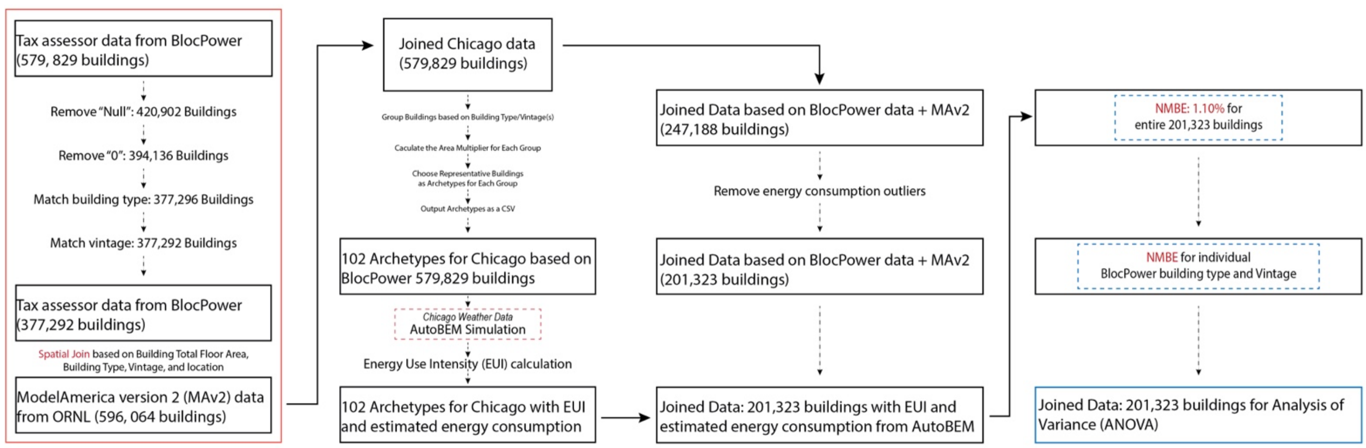

Figure 3. Detailed processing workflow for calculating the Normalized Mean Bias Error (NMBE) for combined Chicago data.

Quantification of the Source of Bias

To assess the accuracy and bias of UBEM, we employed two commonly used performance metrics: Normalized Mean Bias Error (NMBE) and Coefficient of Variation of Root Mean Squared Error (CVRMSE). There could be various factors that contribute towards bias in the modelled electricity consumption. We identified four factors that represent the age of the building, the size of the building and the usage of the building. As shown in figure 4, specifically, we looked at building standard, building type, building subtype, and building size. Building standard is derived from the age of a building, building type and sub-type are derived from the way a building is used and building size is derived based on the total area of a building.

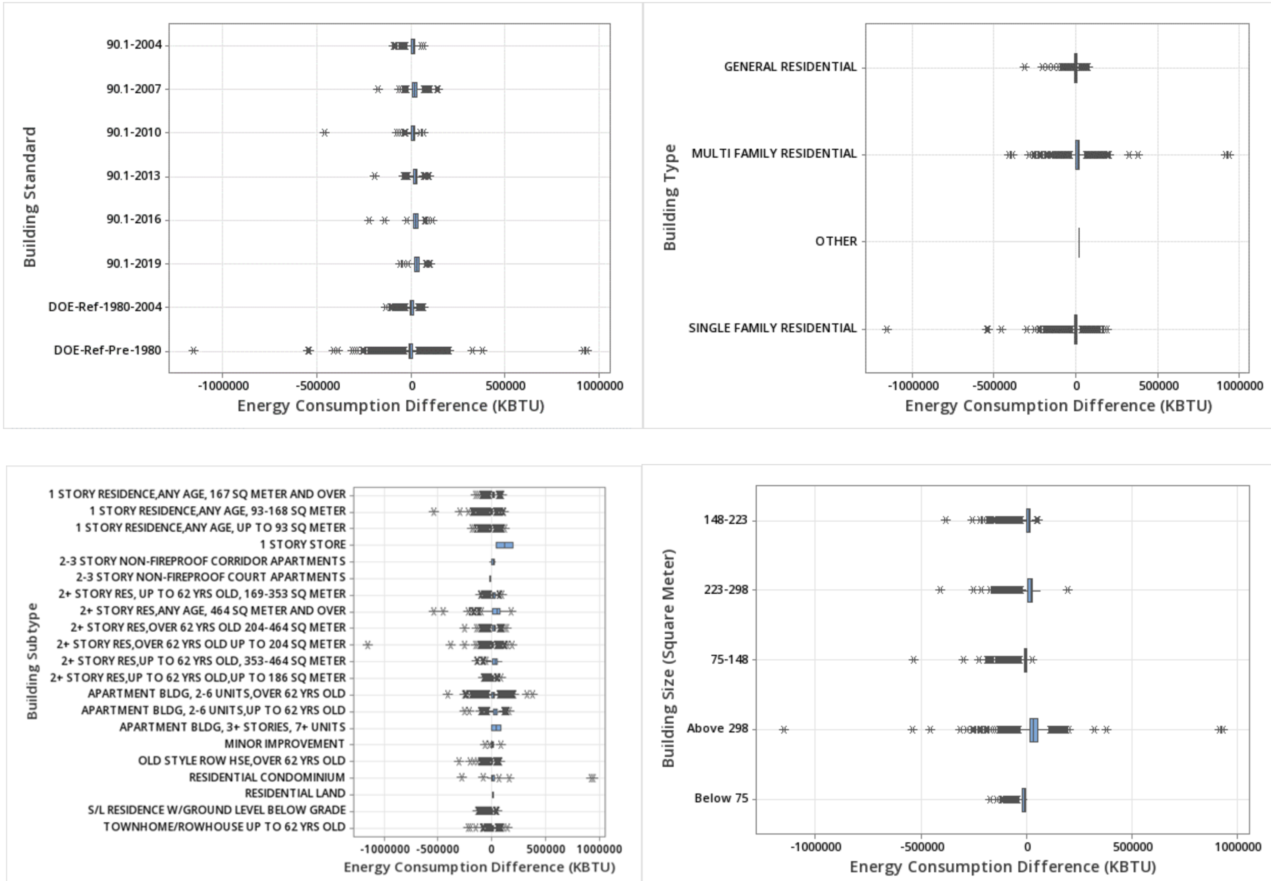

Figure 4. Boxplots illustrating the distribution and variability of energy consumption differences across building standards (top left), building types (top right), building subtypes (bottom left), and building sizes (bottom right).

To assess the contribution of different factors on the bias in modeled electricity consumption, a two-step analysis approach was employed. First, a One-way Analysis of Variance (ANOVA) was conducted to determine the individual influence of the four factors. Subsequently, a multivariate regression analysis was performed to examine the combined effect of these factors.

One-way Analysis of Variance (ANOVA). One-way ANOVA was conducted to evaluate the influence of each factor on the bias in modeled electricity consumption. We compared the means of the bias across different levels or categories of each factor. The mean bias in modeled electricity consumption was calculated for each level of buildings standard, building type, building subtype, and building size. The ANOVA test then determined whether there were significant differences in the means between the levels of each factor, indicating their individual impact on the bias. In each ANOVA, the null hypothesis stated that all means are equal, while the alternative hypothesis argued otherwise. A significance level of $\alpha = 0.05$ was set, and equal variances were assumed for all analyses.

Multivariate Regression Analysis. A multivariate regression analysis was performed to examine the combined effect of the four factors on the bias in modeled electricity consumption. This analysis aimed to identify the extent to which each factor contributes to the overall bias when considered together. The regression model included the four factors as independent variables and the bias in modeled electricity consumption as the dependent variable. The coefficients of the regression model indicated the magnitude and direction of the effect of each factor on the bias, accounting for the influence of other factors. Multivariate regression also allows for the identification and management of collinearity among independent variables. We used Variance Inflation Factor (VIF) to determine multicollinearity. VIF values greater than 10 suffer from severe multicollinearity (Chowdhury et al. 2021).

RESULTS AND DISCUSSION

The overall NMBE was calculated to be 1.1% after removing outliers (initially 10.9%), indicating good accuracy in estimating aggregated energy consumption at the city scale. The CVRMSE was relatively high (51%). This suggests that while the model accurately estimates aggregated energy consumption, there is considerable variability at the individual building level. Based on the ANOVA results in table 1, it is evident that building type significantly influences energy consumption, contributing 5.22% of the variance.

The interpretation of the figure 4 reveals substantial insights about the factors influencing energy consumption differences. Figure 4 (b) illustrates that the 'Single Family Residential' type has a negative mean value, indicating that the observed energy consumption is generally less than the estimated consumption for this type. In figure 4(c) building subtype categories such as '1 STORY RESIDENCE, ANY AGE, UP TO 999 SQ FT' and 'S/L RESIDENCE W/GROUND LEVEL BELOW GRADE', have negative mean values, suggesting that the observed energy consumption tends to be less than the estimated amount. In figure 4(d) the areas above 298 square meter and single-family houses demonstrate pronounced discrepancies in energy consumption. An elongated distribution is apparent in the case of single-family houses, implying an extensive range of energy consumption values within this category. In Figure 4 (a) the 'DOE-REF-PRE-1980' standard within building standards also shows an expanded range in energy consumption differences, reflected by a wide box in the boxplot. This hints at higher variability and potentially, a skewed distribution, for buildings adhering to this standard. In the building Subtype category (figure 4 (c)), an increased number of outliers are observed for '2+ STORY RES, OVER 62 YRS OLD UP TO 204 SQ METER' and 'Residential Condominium'. This is indicated by points that lie significantly away from the box, suggesting potential extreme values in energy consumption for this category. Taken together, these findings from the boxplots highlight the potential biases and variability across different building standards, types, subtypes, and sizes.

Table 1 provides a summary of the contributions and significance of variables in predicting the energy consumption difference when considering all variables together. The results show that the regression model was highly significant ($F = 2142.95$, $p < 0.001$) and accounted for 26.58% of the total variance in energy consumption difference. Individually, the variables made significant contributions to the model. Building Standard showed a significant contribution ($F = 196.40$, $p < 0.001$) with a contribution value of 2.13%. Building Type also had a significant contribution ($F = 168.28$, $p < 0.001$) accounting for 5.22% of the variance. Building Subtype contributed significantly ($F = 287.05$, $p < 0.001$) and explained 12.21% of the variance. Building Size made a significant contribution ($F = 4807.65$, $p < 0.001$) with a contribution of 7.01%. Out of all the 4 factors, building type shows very high VIF values for the "MULTI FAMILY RESIDENTIAL" level (VIF = 824.80) and the "SINGLE FAMILY RESIDENTIAL" level (VIF = 895.17), indicating strong multicollinearity for these categories. This could be due to significant cross-classification between these building types based on the building subtypes.

Currently, our analysis has focused solely on Chicago, Illinois, USA as an initial case study to establish the foundation of our primary methodology for investigating bias conditions between the simulation results of MAv2 and the measured energy consumption data. However, in the future steps of our research, we intend to expand our study to include multiple cities across different climate zones. By doing so, we aim to develop a more comprehensive understanding from the bias assessment process. This expansion will enable us to establish a robust approach for bias correction in energy consumption analysis across various regions within the United States, thus contributing to the development of a general methodology for bias correction for building energy simulations.

Table 1. Contributions and Significance of Variables on Energy Consumption Difference when Considering All Variables Simultaneously

Source	DF	Contributions	Adj SS	Adj MS	F-Value	P-Value
Regression	34	26.58%	1.80928×10^{13}	5.32140×10^{11}	2142.95	0.000
Building Standard	7	2.13%	3.41391×10^{11}	4.87702×10^{10}	196.40	0.000
Building Type	3	5.22%	1.25363×10^{11}	4.17875×10^{10}	168.28	0.000
Building Subtype	20	12.21%	1.42560×10^{12}	7.12799×10^{10}	287.05	0.000
Building Size	4	7.01%	4.77538×10^{12}	1.19384×10^{12}	4807.65	0.000
Error	201288	73.42%	4.99842×10^{13}	2.48322×10^{5}		
Lack-of-Fit	208	1.57%	1.07101×10^{12}	5.14910×10^{6}	21.17	0.000
Pure Error	201080	71.85%	4.89132×10^{13}	2.43252×10^{5}		
Total	201322	100.00%	6.80769×10^{13}			

Note: "Adj SS" = Adjusted Sum of Squares, and "Adj MS" = Adjusted Mean Square

CONCLUSIONS

This work presents a comprehensive analysis of accuracy, bias, and limitations in urban building energy modeling (UBEM), focusing on evaluating the Automatic Building Energy Modeling (AutoBEM) software suite. The study utilizes a case study of metered electricity consumption data from a large sample of buildings in Chicago, Illinois, USA. It compares it to various datasets, including the AutoBEM-generated Model America version 2 (MAv2) data, tax assessor data, and representative dynamic archetypes. The findings reveal that the AutoBEM simulation workflow produces energy consumption estimates that closely align with the aggregated metered electricity consumption data at the city scale. The initial normalized mean bias error (NMBE) of 10.9% indicates a slight bias in the modeled data. However, after removing outliers from the analysis, the NMBE significantly improves to 1.1%, indicating a prominent level of accuracy in estimating energy consumption.

Furthermore, the study quantifies the contribution of significant factors such as building type, land use, age, and size to the variance in UBEM bias. This analysis provides valuable insights into the factors influencing the accuracy of the modeling results, contributing to the understanding of building energy performance at various levels of granularity. The research highlights the importance of systemic analysis in evaluating the accuracy, bias, and limitations of UBEM models. By examining various datasets and considering multiple factors, this study informs best practices and moves towards standardization in building energy modeling. The results demonstrate the potential of the AutoBEM software suite in accurately estimating energy consumption across different building types and vintages, offering valuable insights for policymakers, energy professionals, and researchers involved in energy efficiency and sustainability initiatives.

As we gather more accurate and comprehensive data, our plans involve broadening the scope of our analysis to cover various regions within the US. This expansion will allow us to quantitatively assess biases across multiple climate zones and building characteristics. Ultimately, this assessment will improve our understanding of the generalization capabilities of UBEMs and enable us to explore and develop potential techniques for mitigating the inherent biases present in these models.

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