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Bias Correction in Urban Building Energy Modeling for Chicago using Machine Learning

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***Abstract*—Urban-scale building energy modeling (UBEM) holds promise for optimizing energy usage across extensive geographic regions. However, there is a recognized bias between simulated energy consumption and actual measured data. This study, based on building data from Chicago, delved into bias correction techniques for enhancing the accuracy of UBEM energy consumption estimates. Initially, the AutoBEM simulation yielded a normalized mean bias error (NMBE) of 1.1% and 51% of Coefficient of the Variation of the Root Mean Square Error (CVRMSE) after outlier exclusion. To address this, three bias correction methods were deployed: Average Mean Bias Error based bias correction, Quantile mapping bias correction, and Machine learning-based bias correction using Linear Regression and Random Forest models. Post-correction results exhibited marked improvement. The NMBE values were diminished to 0 for Average MBE-based, 0.36 for Quantile Mapping, and 0 for Machine Learning-based corrections. Concurrently, the CVRMSE values registered reductions from an original 51 to 50.8 for Quantile Mapping, and 38.56 for Machine Learning-based corrections, pointing towards the effectiveness of specific bias correction methods in refining the precision of UBEM energy predictions. Such accurate estimations are paramount for informed energy planning and urban policy-making.**

***Index Terms*—Urban-scale building e nergy modeling, Bias Correction, Machine Learning, Random Forest, Quantile Mapping**

I. Introduction

Urban Building Energy Modelling (UBEM) plays a crucial role in shaping energy conservation strategies, designing urban neighborhoods, integrating buildings with the grid, and determining building-level carbon reduction strategies [1]–[3]. UBEM facilitates impact estimations for energy conservation measures, thus empowering decision-makers to devise and implement sustainable strategies. However, the accurate representation of building attributes, including function, location, age, usage patterns, and others, is critical for building effective energy models [4].

Traditional physics-based models rely on detailed simulations to create high-resolution energy profiles but are computationally expensive for city-scale applications. On the other hand, data-driven models estimate building-level energy usage using general building characteristics but are less efficient at evaluating the impacts of energy conservation measures [4]. Recent advancements in UBEM involve the use of public building data, Geographic Information System (GIS) data, and remote sensing data to create building-specific models or representative archetypes for a specified region [5]. However, despite the technological advances, there remains an urgent need to correct biases to further improve energy predictions.

This study uses the Automatic Building Energy Modeling (AutoBEM) [6] suite with the Model America version 2.0 (MAv2) dataset to generate and simulate energy models. AutoBEM utilizes OpenStudio [7] to generate building energy models and EnergyPlus [8] to simulate the models. AutoBEM has been developed and validated using diverse data sources and was compared to the measured data for 178,368 buildings in Chattanooga, Tennessee [9], [10]. However, there exists a gap in empirical validation of UBEM, especially in terms of bias correction, still warrants further exploration [11].

AutoBEM and MAv2 have undergone validation at multiple locations with data from the Electric Power Board of

Chattanooga, Tennessee, and aggregated building utility data from five different cities, among others [12], [13]. Also, specific data fields from MAv1, an earlier version of the Model America dataset, have been validated against city-specific data, such as building heights in Las Vegas [14]. These studies identified potential sources of error, leading to improvements in estimating height and function of buildings in MAv2.

Chen et al. (2017) stress the significance of ensuring accuracy in UBEM, noting that even minor deviations in attributes like building type or age can substantially skew predicted energy consumptions [4]. This precision becomes even more imperative when one considers the dichotomy between the granular depth of physics-based models and the scalable breadth of data-driven methodologies.

Data, particularly when sourced from Geographic Information Systems (GIS), is another potential pitfall. Reinhart and Cerezo Davila (2016) elucidate that while GIS offers rich geographical datasets, the translation of such data into energy metrics often introduces biases [15]. Temporal resolutions, especially in regions with diverse climates, can be another major source of variance in UBEM, as outlined by Amasyali et al. (2018) [16].

Machine learning, with its adaptive and heuristic nature, has been a transformative element in the bias correction field. Its efficacy has been evident across different sectors, such as wind power forecasts and real-time energy consumption predictions [17]. For instance, Wang et al. (2016) highlighted the benefits of deep learning techniques in real-time energy predictions, emphasizing its capabilities in discerning and rectifying nuanced biases [18].

The introduction of machine learning in UBEM, while promising, comes with its own set of challenges. As highlighted by Hong et al. (2016), the predictive capabilities of machine learning can be undermined if the foundational datasets are not robust and representative [19] [20]. Furthermore, Ascione et al. (2016) warn that without the right granularity in integrating weather data, UBEM can grossly misestimate energy consumption [21]. That is why refining computational predictions through bias correction has emerged as a pivotal component in energy modeling.

Notably, quantile mapping, a statistical downscaling method, has garnered substantial attention, particularly in climate modeling [22]. It has been employed to correct biases in climate model outputs by comparing the distribution of simulated values to observed data. Themeßl et al. (2011) affirmed the robustness of quantile mapping in ensuring that future climate projections adhere closely to historical observations, making it a widely adopted method in climate studies [23].

These bias correction techniques have been applied across different disciplines. Quantile mapping has been a technique used to bias correct weather forcasts [24]. Machine learning bias correction techniques have been applied to Aerosel Optical Depth [25] and chemical transport [26]. The broad uses of bias correction make urban building energy modeling an interesting case study.

TABLE I: Column Descriptors for City-based Building Archetypes

Column Name	**Description**
Building Type	Type of DOE prototype building
Vintage Year	Year of construction vintage
Num_build_per_zone	Number of buildings in the climate zone
Total_zone_area	Total floor area in the climate zone
Area_multiplier	Total_zone_area divided by median area value
MedianArea	Median floor area in the climate zone
MeanArea	Mean floor area in the climate zone
MinArea	Minimum floor area in the climate zone
MaxArea	Maximum floor area in the climate zone
SDArea	Standard deviation of floor area

In our study, we embrace a systematic approach by investigating three distinct bias correction methods. The general goal of this paper is to evaluate these techniques' efficacy in urban building energy modeling (UBEM) using the AutoBEM simulation data and measured tax accessor data for Chicago city.

II. METHODOLOGY

A. AutoBEM Simulated Data

To simulate building energy consumption, the city-based building archetypes are characterized by their building type (function) and vintage, and they have been generated from the Model America data. In addition to all the building features present in the MAv2t, each archetype dataset includes the information provided in Table-I for specific DOE prototype buildings and their corresponding vintage years.[Cite:https://zenodo.org/record/5798155]

The Annual Energy Use Intensity (EUI) for each archetype is calculated by dividing the Electricity consumption by the area of the representative archetype. This EUI is then assigned to all buildings in the city of the same type and vintage. Finally, to estimate total energy consumption, we multiply this EUI by the actual area of each building. Through the simulation of diverse building archetypes spanning various historical periods, and employing this methodology to compute Energy Use Intensity (EUI), we have generated estimations for the energy consumption of distinct buildings in Chicago.

B. Data Cleaning and Preprocessing

To ensure accurate analysis and comparison between the simulated data and the ground truth metered data at the individual building level, a rigorous data cleaning and preprocessing workflow was implemented.

The process of matching the MAv2 data with the corresponding ground truth metered data at the individual building level was a crucial step in the analysis. The workflow involved several steps to ensure alignment between the datasets and eliminate unreliable data points. Buildings with null or zero annual energy consumption in the ground truth data were removed from the dataset to maintain the integrity of the analysis and avoid potential biases.

In order to facilitate a more comprehensive classification of buildings, granular building sub-types were determined based

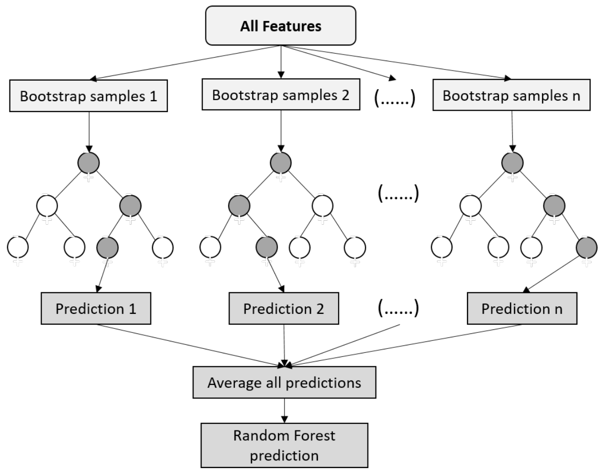


Fig. 1: Random Forest Regression Algorithm [27]

on land use description. These sub-types were then used to create distinct building types within the dataset. The MAv2 buildings, representing the modeled data, were then matched with the most suitable ground truth buildings based on multiple factors, including geographic location, building total floor area, building types, and year of construction.

During the spatial matching process, challenges arose due to differences in geographic coordinates obtained from different sources. To address this, additional factors such as building total floor area, building types, and year of construction were incorporated to enhance matching accuracy and establish a reliable correspondence between the modeled and ground truth data points.

Outliers, defined as buildings with extremely low annual energy consumption, were identified using a threshold value (less than 5150.1 kWh per year). To determine this threshold, we considered the average energy consumption of a typical U.S. household, which is approximately 11,000 kWh per year. Removing these outliers from the dataset ensured that their impact on the analysis was minimized, and the results remained robust.

C. Bias Assessment

In the pursuit of achieving a holistic assessment of the UBEM, we have anchored our evaluation on two primary performance indicators: the Normalized Mean Bias Error (NMBE) and the Coefficient of Variation of the Root Mean Squared Error (CVRMSE).

NMBE provides a glimpse into the average discrepancy or bias between the model-predicted energy consumption and the real-world observed values. It's calculated as:

$$NMBE = \frac{\sum(E - A)}{\sum A} \times 100 \tag{1}$$

Here, E represents the estimated energy consumption and A stands for the actual or observed energy consumption. An NMBE value gravitating towards zero is indicative of model efficiency. Positive or negative outcomes highlight over-predictions or under-predictions, respectively.

CVRMSE gauges the spread or dispersion of the model's errors relative to the mean of observed values. It is derived by:

$$CVRMSE = \frac{RMSE}{\bar{A}} \times 100 \tag{2}$$

Here, $RMSE$ is the root of the average of squared differences between the model's predictions and the observed values, and $\bar{A}$ is the mean of the observed values. Lower CVRMSE values are indicative of tighter error distributions, which, in turn, suggest a model that predicts more consistently in relation to the actual observations. In essence, while NMBE identifies systematic biases in predictions, CVRMSE provides a measure of the consistency or reliability of those predictions in relation to actual observations.

D. Bias Correction

1) Average MBE-based Bias Correction: The Average Mean Bias Error (MBE) is a simple bias correction method that involves calculating the average bias for each building type and applying the correction uniformly. The formula for the Average MBE-based bias correction is as follows:

$$E_c = E_s + MBE_{avg} \tag{3}$$

where:

- E_c is the corrected energy consumption after bias correction.
- E_s is the simulated energy consumption estimated by the building energy model.
- MBE_{avg} is the average Mean Bias Error for the specific building type.

2) Quantile Mapping Bias Correction: Quantile mapping is a non-parametric bias correction method that involves matching the quantiles of the simulated energy consumption distribution to the quantiles of the ground truth distribution. The formula for quantile mapping bias correction is given by:

$$E_c = F^{-1}_{\text{ground truth}}\left(F_{\text{simulated}}(E_s)\right) \tag{4}$$

where:

- E_c is the corrected energy consumption after bias correction.
- $F^{-1}_{\text{ground truth}}$ is the inverse cumulative distribution function of the ground truth energy consumption.
- $F_{\text{simulated}}(E_s)$ is the cumulative distribution function of the simulated energy consumption.

The process can be systematically divided into four major steps: filtering data for the specific building type under consideration, calculating cumulative distribution functions for both simulated and ground truth energy consumption, calculating correction factors by taking the ratio of the percentiles of ground truth consumption to the corresponding percentiles of simulated consumption, and finally, computing the corrected cumulative distribution functions after applying the quantile mapping correction.

E. Machine Learning-based Bias Correction

In the machine learning-based bias correction, we employ Linear Regression and Random Forest models to predict and correct the biases based on building characteristics. We selected Linear Regression as a representative of parametric models, which assumes a specific functional form for the relationship between variables. In contrast, we chose Random Forest Regression for its non-parametric nature, allowing it to capture complex, non-linear relationships without a predetermined form. The decision to utilize both models provides a comprehensive approach, catering to potential linear and non-linear patterns in the data. The formula for the machine learning-based bias correction using Linear Regression is given by:

$$E_c = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \tag{5}$$

where:

- E_c is the corrected energy consumption after bias correction.
- $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients obtained from the Linear Regression model.
- (x_1, x_2, $\ldots$, x_n) are the selected building characteristics used as features for bias correction.

Similarly, the formula for the machine learning-based bias correction using Random Forest is given by the ensemble of decision trees, and the prediction is made based on the average of the individual tree predictions (See figure 1).

The Random Forest Regression (RFR) is a powerful machine learning algorithm known for its ability to handle complex relationships between variables and make accurate predictions. For each building type in the dataset, the bias correction process using the RFR involved several key steps. First, the data was filtered to isolate the specific building type under consideration. To ensure the robustness of the analysis, building types with fewer than 1000 instances were excluded to avoid insufficient data for accurate training.

Next, a set of relevant features, including floor area, building height, Windows-Wall-Ratio, Number of floors, EUI from UBEM, building type, and standard (age), were selected as predictors, while the target variable was measured energy consumption (ground truth), representing the total building annual energy consumption.

To facilitate the machine learning process, categorical features such as "Building Type" and "Standard" columns were transformed into numerical data using one-hot encoding. The dataset was then split into training and testing sets, with 70% of the data used for training and 30% for testing.

The RFR model was trained on the training set, where the algorithm learned to map the predictor variables to the target variable. After training, the model was used to make predictions on the testing set to assess its performance.

To evaluate the effectiveness of the RFR for bias correction, key metrics such as Mean Squared Error (MSE) and R-squared (R^2) were calculated. The MSE quantifies the average squared difference between the predicted and actual values, while the R^2 provides an indication of how well the model captures the variance in the target variable.

III. Results and Discussion

A. Initial Results

We found that the aggregated NMBE for the modeled building stock was 1.1% after removing outlier. In terms of CVRMSE, we found that it was 51% after following the same pre-processing step. This relatively high CVRMSE suggests that while the model accurately estimates aggregated energy consumption, there is considerable variability at the individual building level.

Figure 5a and 5b presents the NMBE and CVRMSE values across various building types and standard vintage breakdowns. Notably, the breakdown related to construction prior to 1980 encompasses a substantial number of single and multi-family residential structures. The outcomes reveal that AutoBEM achieves a higher level of precision in estimating energy consumption for single-family buildings (NMBE of -5.39%) compared to multi-family residential buildings (NMBE of 23.5%). The negative NMBE in single-family buildings suggests a slight underestimation by AutoBEM, while for multi-family buildings, the model tends to overestimate consumption, resulting in a larger absolute disparity in contrast to single-family buildings.

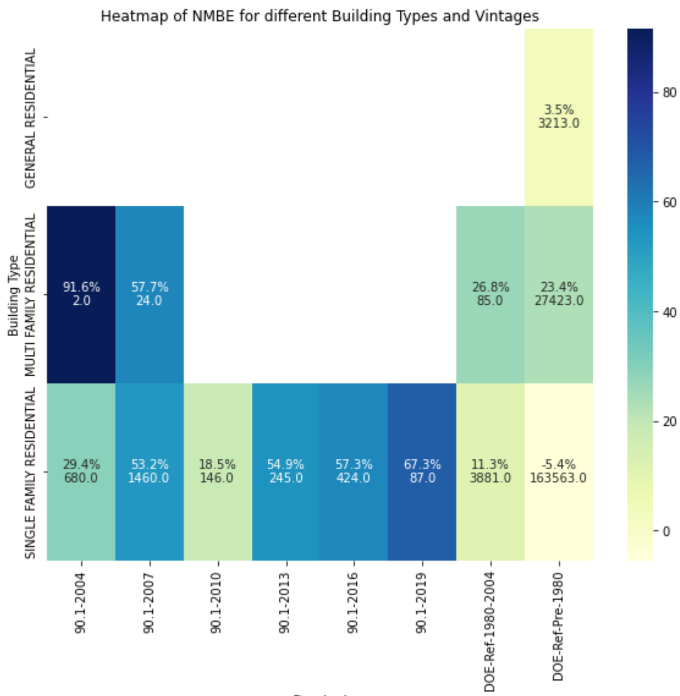
When comparing the slopes of the regression lines in Figure-3, it becomes evident that the R^2 values associated with each building type are notably low. This indicates that the predictor variables employed in the model explain only a limited portion of the observed variations in electricity consumption.

B. Bias Correction Results

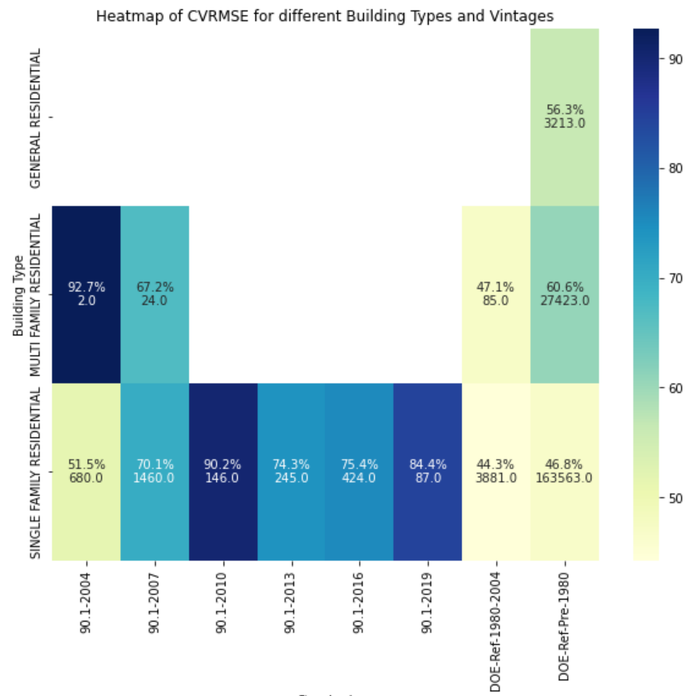
The bias correction analysis was conducted with a focus on building subtypes that were identified as contributing more to the bias through ANOVA analysis. Before bias correction, the original Normalized Mean Bias Error (NMBE) for Chicago was 1.1, indicating a positive bias in the modeled energy consumption as compared to the ground truth data. This suggested that the energy consumption estimates were generally overestimating the actual energy usage for the buildings in Chicago.

After applying the bias correction methods, the NMBE values were significantly reduced, indicating that the bias was successfully corrected for all methods. The Average MBE-based correction and Quantile Mapping correction reduced the NMBE to 0, eliminating the positive bias observed in the original results. The Machine Learning-based bias correction using Linear Regression achieved the lowest NMBE of 0.41, highlighting its effectiveness in accurately correcting bias.

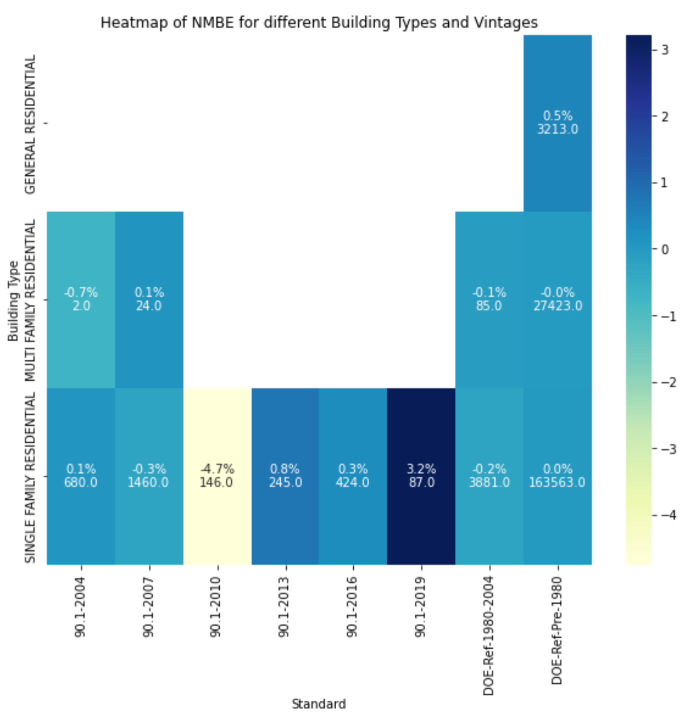
Additionally, the original Coefficient of Variation of Root Mean Squared Error (CVRMSE) for Chicago was 51%, representing the variability in the energy consumption estimates. After applying the bias correction methods, the CVRMSE values were reduced.



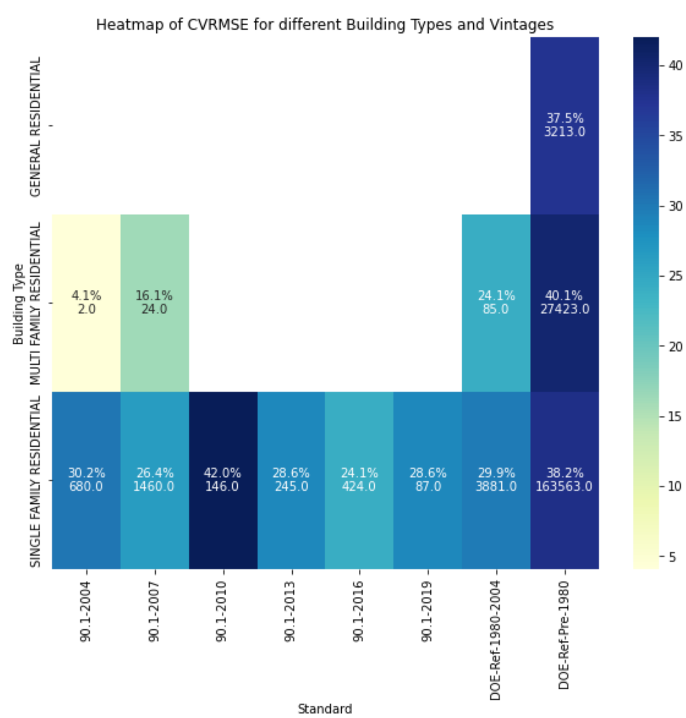
(a) NMBE before bias correction



(b) CVRMSE before bias correction



(c) NMBE after bias correction



(d) CVRMSE after bias correction

Fig. 2: NMBE and CVRMSE for building areas across different residential building types and vintages. Heatmap before and after bias correction showing significant improvement for both NMBE and CVRMSE. Number inside NMBE and CVRMSE showing the number of buildings for each category. After Bias correction, for the pre-1980 constructed buildings, the value of NMBE drops down from -5.4% to 0% for Single Family House and 23.4% to 0% for Multi Family House.

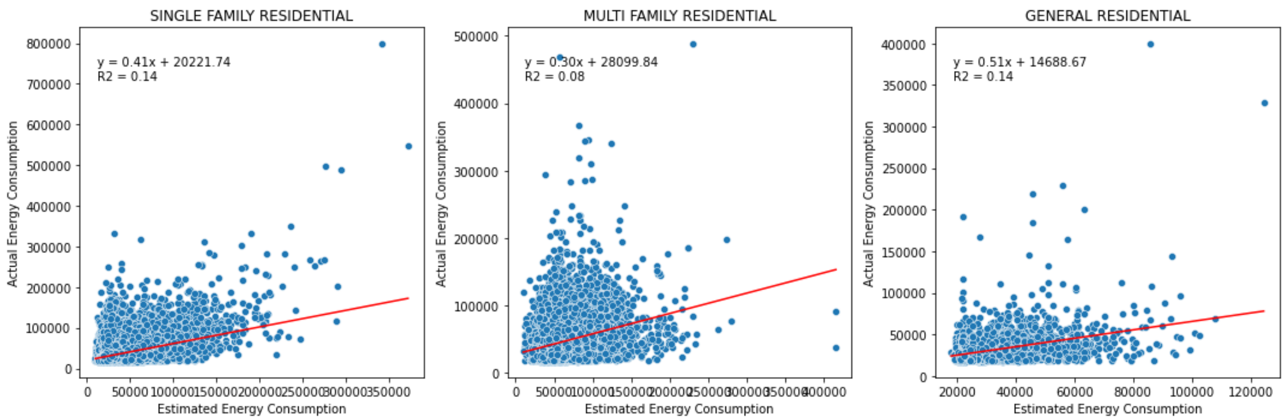


Fig. 3: Annual electricity consumption comparison among Multi-family, single-family residential, and General Residential buildings. Each of the building type is showing very low R^2 value before bias correction.

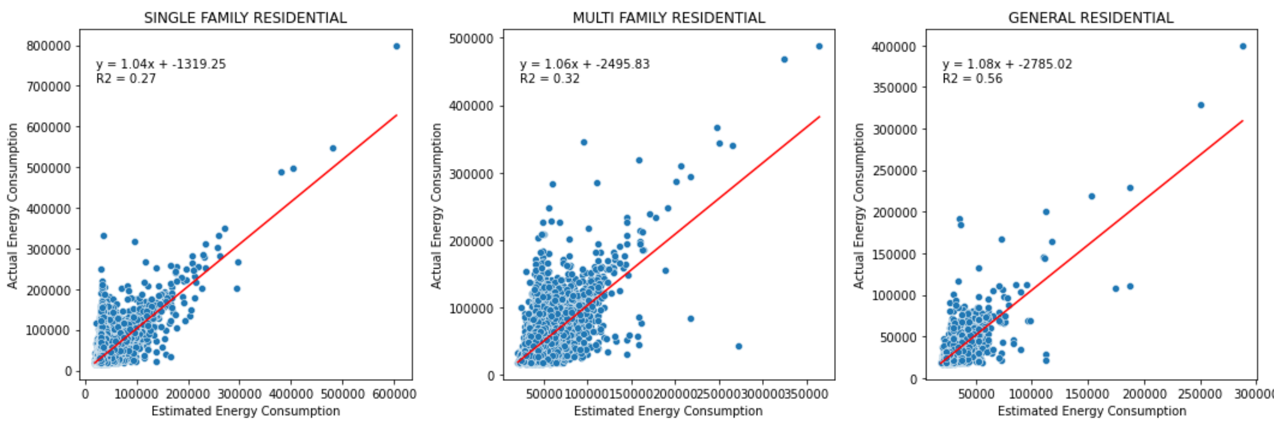


Fig. 4: R^2 value and correlation increased after bias correction for each of the building types. Significant improvement is noticeable for Multi Family Residential (from 0.08 to 0.32) and for General Residential Buildings (from 0.14 to 0.56)

TABLE II: Bias Correction Results comparison from different techniques. It is evident that machine learning model performed best in correcting bias.

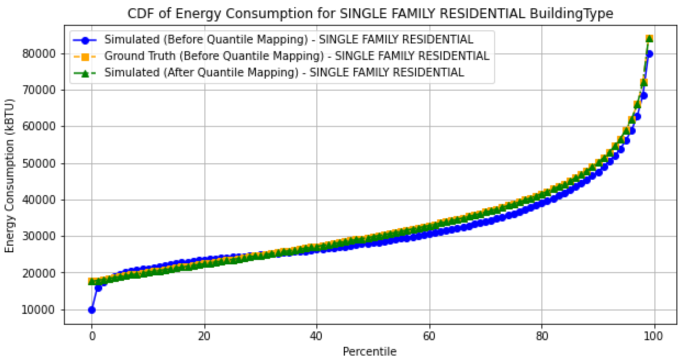
	Original	Avg-MBE-based Method	Quantile Mapping	Machine Learning
NMBE	1.1	0	0.36	0
CVRMSE	51	51	50.8	38.56

The Quantile Mapping method slightly reduced the CVRMSE to 50.8%, indicating a moderate improvement in the precision of energy consumption estimates. After applying the quantile mapping, cdf follows the same trend for both estimated and measured data (see figure- 5). The Machine Learning-based approach achieved the lowest CVRMSE of 38.56%, indicating that it not only corrected bias effectively but also improved the precision of energy consumption estimates, resulting in more accurate and consistent estimation. Figure 2 is the heatmap illustrating how NMBE and CVRMSE are improved for individual category.

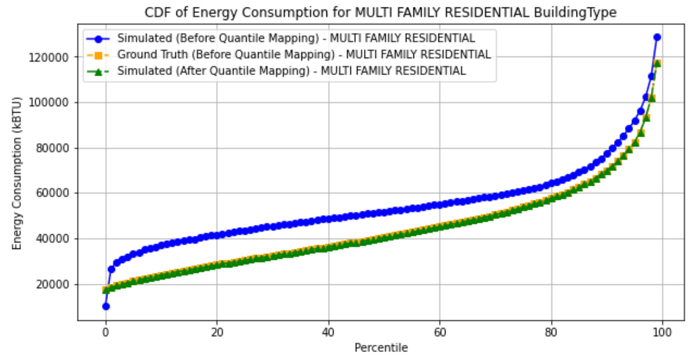
The insights derived from the machine learning analysis are noteworthy. When using Linear Regression, the model achieved training and testing accuracies of 19% and 18%, respectively, with an NMBE of 0.01 and a CVRMSE of 42.45%. On the other hand, the Random Forest algorithm showcased training and testing accuracies of 35% and 12%, respectively. This model returned an NMBE of 0.002 and a CVRMSE of 38.56%. The stark difference between the training and testing accuracies of the Random Forest model signals potential overfitting. As a next step, addressing this overfitting through hyperparameter tuning could be beneficial. Additionally, exploring alternative algorithms might also be a worthwhile endeavor.

IV. Discussion

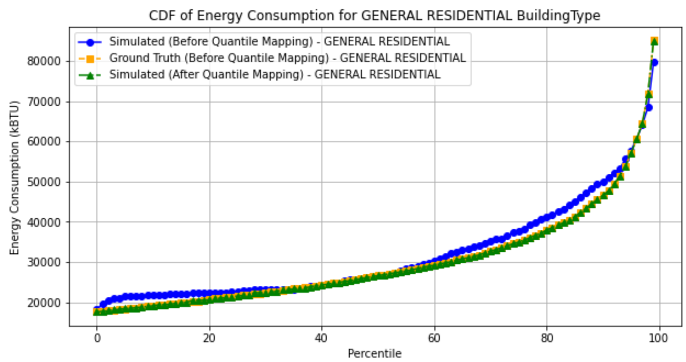
Despite employing multiple bias correction techniques, including Average MBE-based correction, Quantile Mapping, and various Machine Learning methods, the CVRMSE did not



(a) Single Family



(b) Multi Family



(c) General Residential

Fig. 5: After applying Bias Correction using Quantile Mapping, the Cumulative Distribution Function (CDF) of simulated data follows a similar trend as the ground truth data for each of the building type

TABLE III: Comparison of two Machine Learning bias correction techniques reveals that while Random Forest was successful in reducing the CVRMSE more significantly compared to Linear Regression, it exhibited signs of overfitting due to a huge difference between training and testing accuracy.

Algorithm	Training Accuracy (%)	Testing Accuracy (%)	NMBE	CVRMSE
Linear Regression	19	18	0.01	42.45
Random Forest	35	27	0.002	38.56

decrease to anticipated levels. This suggests a few possibilities. First, the underlying energy consumption data may possess inherent variability that isn't solely due to bias. External factors, such as anomalous weather patterns, unforeseen building occupancy, or equipment malfunction, might contribute to these deviations. Secondly, energy consumption is often influenced by multiple interacting parameters. While techniques like Quantile Mapping or linear regression attempt to tackle biases in a predominantly linear manner, the actual interrelations might be more convoluted, requiring more advanced correction methods or model adjustments.

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 also 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.

V. CONCLUSIONS

In this study, we addressed the critical issue of bias in urban-scale building energy modeling (UBEM) and implemented various bias correction methods to improve the accuracy of estimated energy consumption. We applied three different bias correction methods: Average MBE-based bias correction, Quantile mapping bias correction, and Machine learning-based bias correction using Linear Regression and Random Forest algorithms. The results revealed that the bias correction methods effectively improved the energy consumption estimation for Chicago city. The findings from this study emphasize the importance of addressing bias in urban-scale building energy modeling. By employing appropriate bias correction techniques, we can significantly improve the accuracy of energy consumption estimation, which is crucial for energy planning and policy-making at the level of a city.

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