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Narrowing Uncertainties in Forecasting Urban Building Energy Demand through an Optimal Archetyping Method

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Abstract:

This paper aims at indicating and certifying the implemented framework for forecasting buildings' energy demand of the city of Bologna, Italy. The method is developed through an automated calibration and is based on 7 known, physics-based building parameters and 6 unknown, and highly uncertain variables. The proposed method focuses on reducing computing time while keeping the accuracy of the output by narrowing the uncertainties in predicting unknown parameters. To accomplish this task, 11 archetypes are defined which are representatives of the buildings in a specific neighborhood in Bologna, Italy. For every defined archetype, the most informative unknown variables are recognized and the Gaussian Process (GP) is employed to emulate the variable-to-data map. A wide sampling of the GP outputs is then applied by No-U-Turn Sampler (NUTS). The methodology is validated for 1156 Italian urban buildings based on the city database. The level of evaluation metrics demonstrates no bias in the output of the long-term forecasting while it accelerated the prediction of building energy demand and calibration on the city scale. The method is flexible for application in other contexts and various available urban datasets.

Keywords: Urban building energy modeling, Energy demand forecasting, Bayesian calibration, Unknown parameter Estimation, Energy planning and management, Building archetypes, smart meter data analytics

Abbreviation:
Urban Building Energy Modeling (UBEM)
Gaussian Process (GP)
No-U-Turn Sampler (NUTS)
Hamiltonian Monte Carlo (HMC)
Latin Hypercube Sampling (LHS)

Highlights:

- This paper proposes an archetype coding method for simplifying buildings classification on large scales.
- The energy demand of 1156 buildings in the city of Bologna, Italy is forecasted by the Bayesian calibration method.
- The method prevents monotheism in applying retrofitting strategies for various types of buildings on large scales.
- The model has proven the accuracy in forecasting energy demand and also estimating unknown parameters in urban buildings.

1. Introduction

Attainment of reliable urban building energy measurements has appeared as one of the most challenging issues encountering societies that seek positive-environmental impact districts in highly complicated city structures [1]. This complexity has contributed to the recent boost in Urban Building Energy Modeling (UBEM) whereas lack of precise urban databases has cast doubts on the reliability of UBEM approaches [2]. In general, UBEM estimates the energy demand based on geometry, envelope fabric, equipment and appliances, climate characteristics, and indoor environment criteria. A common method to model a large number of buildings based on these parameters is to classify buildings in different archetypes according to their features. Archetyping benefits UBEM by time efficiency and data summarization. It has been employed in a wide range of urban energy forecasting methods [1]. Table 1 shows a list of these studies.

Table 1: Summary of studies for developed archetypes in UBEM, source: Gholami et al. [1]

Model developed by	The main aim of the model	Methodology	Studied location	Year
MacGregor et al. [3]	Creating an energy model for the residential area by 27 archetypes	Hourly analysis program (HAP)	Nova Scotia	1993
Kohler et al. [4]	Development of details and basic building elements from big databases for materials and operations	Energy, and monetary models	Germany	1999
Huang and Broderick [5]	Creating an engineering model for heating and cooling loads	Prototyping the multifamily and single-family houses in 16 various regions	US	2000
Snakin [6]	Creating a model to find the factors of conservation and alternatives for fuel	History databases and population and buildings features	Finland	2000
Shipley et al. [7]	Estimation of impacts of building envelope improvements	A monetary and energy emission model based on archetypes and ASHRAE	US	2002
Carlo et al. [8]	A model based on archetypes for commercial-buildings	Employing some initial parameters such as building energy regression equation to the roof area ratio, facade area ratio, and internal load density	Brazil	2003
Shimoda et al. [9]	A model for insulation levels in the city scale	A residential end-use energy consumption model based on archetypes	Osaka, Japan	2004
Wan and Yik [10]	define different window areas facing the sun	Archetypes for floor plans	Hong Kong	2004
Palmer et al. [11]	Introducing a model to calculate SH and DHW	Employing BREDEM-8 (Building Research Establishment Tool)	UK	2006
Nishio and Asano [12]	Recognizing distribution and housing variables	A tool for archetypes based on Monte-Carlo	Japan	2006
Petersdorf et al. [13]	Developing a European building stock by considering 5 standards and 8 insulation standards	Ecofys's BEAM for modeling heating demand in three different climate zones	EU	2006
Clarke et al. [14]	Development of a model to calculate the thermal energy demand	ESP-r in the Scottish building stock	UK	2009
Tornberg and Thuvander. [15]	estimating details such as building fabric, glazing, ventilation, water heating, space heating, and fuel costs	Energy and environmental model by archetyping and employing GIS	UK	2012
Ballarini et al. [16]	Analyzing cost-optimal aspects	A national building Typology for European building stock	Italy	2014
Cerezo et al. [17]	Vision creating as input data of a model	Formatting a standard input	US	2014
Yang et al. [18]	Energy performance forecasting	A clustering method to select representative buildings and a normative model to calculate energy parameters	China	2017

The energy performance of the buildings in an urban context is not exactly as software simulates it. Discrepancies between simulation results and the surveyed performance are unavoidably the consequences of inadequate input data, building users' behavior, and replication of simulation [19]. Calibration aims at creating a correlation between the quantity of a parameter in a specific methodology and the relative measurement of a declared value. Similarly, in UBEM, calibration is the process of tuning known and unknown parameters to reduce the discrepancies between the modeled and measured values [19]. Due to the complexity of various uncertainties sources on large scales, uncertainties of inputs in UBEM have raised a meaningful difference between predicted and measured values [20]. Indeed, without filling this gap, the UBEM approaches are not reliable in making retrofitting policies, operational promoting, or energy forecasting on the urban scale [21]. In a review in 2018, Tian and colleagues [19] have divided the calibration methodologies of building stock into two groups of forward and inverse models that the full description of this classification can be found there. However, in this paper, calibration methodologies are classified according to their approaches as user-driven or automated features. The main focus of the paper is on automated calibration methods.

1.1. Calibration methodologies for UBEM

Manual calibration is based on trial and error methods, which use the iterative manual tuning of input parameters without any systematic and automated procedure. The input data in manual calibration methods are highly dependent on users' experience and knowledge about the buildings. However, automated calibration methods are not user-driven and employ analytical and statistical methods. Among all automated approaches, calibrations with optimization algorithms and the Bayesian approach are the most employed methods in UBEM [22].

- **Bayesian formulation;** is a method for measuring uncertainties through probability dissemination. No matter if the input data is not accessible (epistemic uncertainty) or does not exist (aleatory uncertainty), bayesian calculates the uncertainty that is caused by inadequate input data and measurement errors [23–25]. Bayesian frameworks are well-adaptable in models with uncertain data inputs. Thus, it updates proposed probability dissemination based on model output data which makes it suitable for future predictions. The basic calibration model in building energy models is proposed by Kennedy and O'Hogan [26], later a guideline for the application of Bayesian calibration has published by Chong and Menberg [27]. Fernandez and colleagues in 2018 [28] have shown that the Bayesian method takes ten times more than an optimization method for individual buildings.
- **Optimization under uncertainty calibration;** is a technique that aims at minimization of the existed gap between modeled and real values to identify the best variable sets. It employs optimization algorithms to find the best data set of parameters for calibration. It finds a global minimum gap on a set by using global optimization approaches such as genetic algorithm, Particle Swarm Optimization, etc. Most of these methods are applied on individual building scales [29–35].

Although uncertainty methods on building scale do not differ from urban building energy calibration methods in the main steps, they alter to a certain extent. The reason is that there are some limitations on large scales that affect the efficiency of methodologies and their functionality. When the modeling process extends from one building to hundreds of buildings in a city, time, computation cost, and accessibility of supercomputers are among the limitations [17]. To reduce the costs, meta-models can be integrated into the models, meta modeling is resembling a complicated model to a simpler model through a mathematical model. Coefficients in these meta-models are defined based on bounded sets of input and output combinations [36]. It acts as a surrogate for the white box simulations. Thus, a Meta model benefits the original model with decreasing calculation time while it ensures the reliability of the model [37]. Among all the meta-models, the Gaussian Process (GP) is the most employed model because of the high level of accuracy and reliability in interpolations. This method is employed in some energy calibrations [37,38] A study by Lim and Zhai [39] has proved that GP models in building energy calibration are the most precise metamodel among others.

Some specific studies in recent years have led the urban energy building calibration to a more reliable status and sped it up. Booth and colleagues in 2012[40] introduced a UBEM based on clustering buildings and calibrated four unknown parameters through Bayesian calibration with 61 days of measured data. Later the model was improved by developing building archetypes based on the form and age of the buildings on city scales [25,41,42]. Kim and colleagues in 2015 [43] employed optimization for the estimation of five unknown parameters. In 2016, Zhao and colleagues [44] developed a method based on Bayesian calibration using a wide variety of variables for clustering buildings, later Evins et al. [45] investigated the impact of user behavioral factors and buildings' properties on a large scale. Sokol and colleagues in 2016 [21] continued this subject by classifying archetypes based on uncertain parameters through Bayesian calibration. In 2018, Nagpal and colleagues [46] modeled 3 buildings with different numbers of unknown parameters and iteration. They found out that when envelope parameters of the buildings are known, the model is more precise and fast. The latest model is trained with 6 years of measured data for heating demand by Wang and colleagues in 2020 [47]. They have simulated the model in CitySim. Building archetypes are classified based on the construction year and are calibrated by the Bayesian method.

1.1. Contribution of this work

As mentioned in the state of the art of this study, UBEM approaches have been significantly enhanced during the last decade. Yet, several unsolved issues exist in automated calibration approaches. UBEM calibration is still intensive in computation, the reason is that it is usually non-linear and multi-modal such that calibration methods easily fail to be accurately processed. Unknown parameters differ from building to building depends on the building's properties and human behavior. Common methods in individual building calibration are not enough responsive on urban scales. The reason is that there are several unknown parameters on city-scale such as outdoor air temperature or the last date of interior renovations. The challenge becomes more complicated when the number of unknown parameters in calibration increases. Furthermore, although meta-models are supposed to ease the calibration process, they become heavy in processing since the number of sampling and evaluation of variables combination affects the validity of outcomes.

Hence, to address the above-mentioned issues, a UBEM calibration technique has been proposed in this study that employs a coding method for classifying archetypes to cope with hundreds of buildings on the city scale. This approach is developed to ensure the distinction between informative and uninformative parameters and to reduce the computation time and cost for city governments while maintaining the robustness of calibration in UBEM calibrations. In this paper, the proposed technique will answer the main questions as follows:

- How to develop a long-term urban-scale tool for energy demand prediction considering informative parameters for cost-effective retrofitting strategies?
- How to integrate hundreds of buildings in one UBEM calibration while considering different unknown parameters for every building with computation efficiency and reliability?
- How to strengthen UBEM calibration considering the computational burden in large-scale UBEM calibration?

2. Materials and methodology:

Hence, to address all the above-mentioned factors, the methodology is proposed in 4 steps as shown in Fig 1. The methodology consists of 3 key features; first, coding urban archetypes to enhance the time efficiency of computation, second, sampling the data in an equal probability distribution to ensure the combination coherency in all dimensions, and lastly, the involvement of informative data to optimize the complexity of calibration and minimize the error in the evaluation process. The details of the important improvements in the proposed method will be discussed in the related subsections. The proposed methodology needs various modelings and coding engines. In the pre-process steps QGIS was employed to identify buildings on the map and link the geometrical features to the shapefile. The model was more developed in Rhinoceros 7 [48] and the energy models for every archetype were run by EnergyPlus [49] through the Grasshopper interface, automation and result collection were performed using Matlab codes [50]. R-programming was employed to code the main process of calibration and to export the outcomes and results.

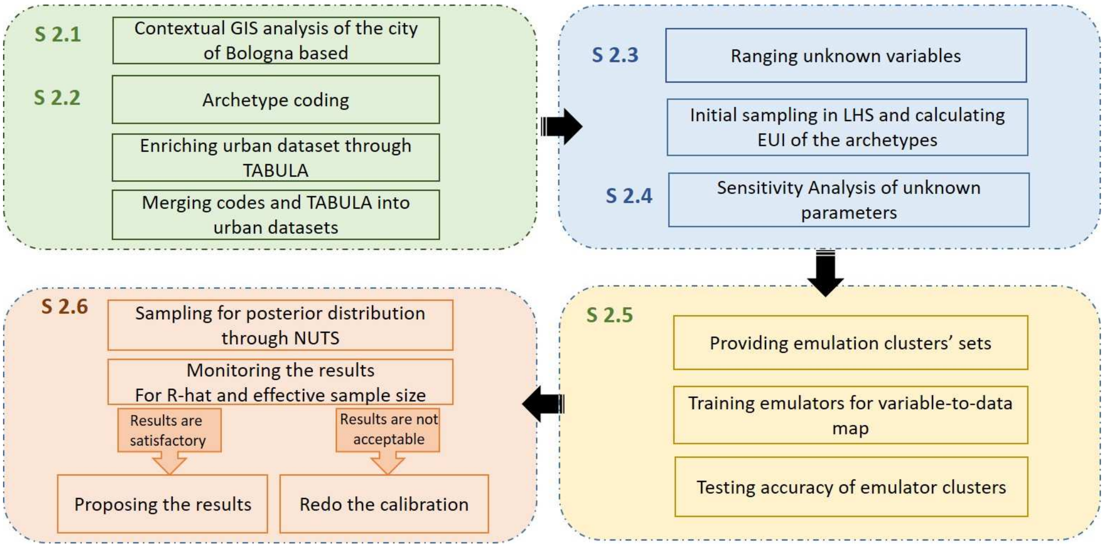


Figure 1: The proposed methodology in 4 steps

2.1. Developing a GIS database

The input database of the methodology relies upon the accessibility of data, but the contextual analysis of the urban area is based on the GIS database of the existing buildings. In this step, a GIS database is proposed where the buildings are characterized based on definite features consist of building construction period, building function, number of floors, net floor area, conditioned floor area, ceiling height, building surface area, and perimeter. These building properties are available in municipal urban datasets. The dataset was then enriched through TABULA which is a source for building archetypes available for several European countries. In this methodology, a specific TABULA [51] for the classification of Italian buildings is employed. TABULA classifies urban buildings based on their properties and energy systems. To consider the renovation conditions of the buildings, the official dataset of the municipality has been employed as a reliable and updated source. The GIS shapefile is then merged into this database and every parcel is associated with a building in the district. Fig 2 illustrates the 3 steps for developing GIS datasets. Then, six uncertain parameters were selected to be integrated into geo-referenced data. Table 2 shows these parameters.

Table 2:Uncertain parameters and their range for the initial calibration process

Num	parameter	Short Names	Prior Probability Distribution	Units
1	Infiltration	INF	0-1.5	ACH[1]
2	Occupant density	OCC	15-25	M^2 /PP [2]
3	Heat set point	HSP	15-25	°C
4	Cool set point	CSP	23-29	°C
5	Equipment power density	EPD	11-15	W/m^2
6	Domestic hot water flow	DHW	$(1\text{-}20) \times 10^{-8}$	$m^3/s/m^2$

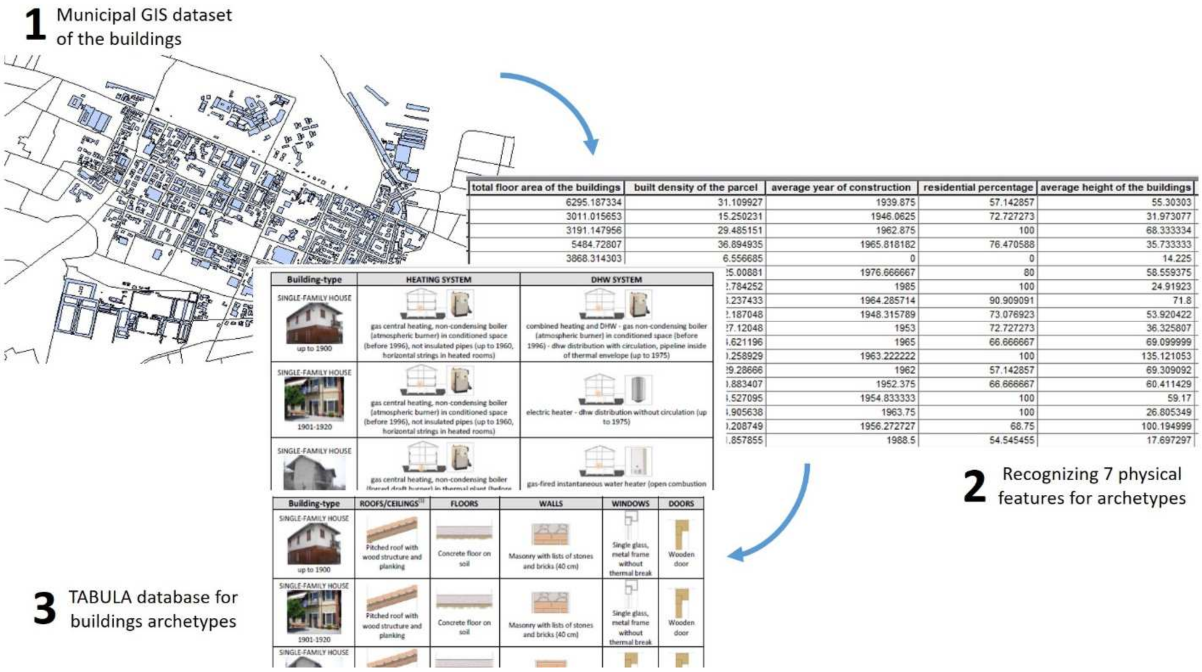


Figure 2: Developing GIS database in three steps; step 1: extracting Bologna municipal GIS database, step 2: defining building properties, step 3: enriching urban dataset by TABULA

2.2. **Archetype coding**

To define representative buildings in the neighborhood, a two-steps coding algorithm is designed to generate urban building archetypes. In the first step, each archetype will be classified by seven definite parameters such as function, age, orientation, construction type, window-wall-ratio, and heating and cooling systems of the buildings as it is illustrated in Table 3. It should be noted that geometric parameters of the building are not included in the archetype coding since the 3d geometry will be considered in the white box energy modeling in EnergyPlus and their specific context. In the second step, six highly uncertain variables (introduced in Table 2) will be defined within specific ranges and the calibration process in the next steps will define the values of the uncertain variables for every archetype.

1 Air Change per Hour

2 Square Meter Per Person

Table 3 shows the coding guideline of the building, for example, code A1234512 shows that this building is a residential, built-in 1901-1920, a multi-family house, with Northeast- Southwest orientation, and 40-50% window-wall-ratio, facilitated with "gas central" heating system and "combined heating and DHW system" as the DHW system.

Table 3: Classification of known and physics-based features

Archetype coding	Function	Building age	Building type	The orientation of facades with openings	WWR	Heating system	DHW system
1	Residential	Before 1900	Single-family house	East-West	Less than 10%	Gas-central heating	Individual DHW sys per apartment
2	Office	1901-1920	Terraced house	South-North	10-20%	Gas-decentral-heating	Combined heating and DHW
3	Retail	1920-1946	Multi-family house	Southeast-Northwest	20-30%		Gas-fired instantaneous water heater
4	Hospital	1946-1960	Apartment Block	Northeast-Southwest	30-40%		Gas central DHW system
5	School	1961-1975		All orientations	40-50%		
6	Hotel	1976-1990			50-60%		
7		1991-2005			60-70%		
8		After 2006			70-80%		

2.3. Initial value setting and sampling of initial calibration

After archetype identification, a set of values should be generated as prior distribution set for training the model. To ensure robust performance, the set of samples must cover the full training range equally. In the proposed methodology, Latin Hypercube Sampling (LHS) has been employed. LHS can generate different realizations of dependent random variables with any probability distribution shape. An N-dimensional LHS ensures that every combination of N conditions is sampled equally, while it is likely that a random sampling pattern misses a few combinations of conditions and samples other combinations more than once per repetition.

2.4. Sensitivity analysis

To identify influential parameters on the building energy demand among six uncertain parameters, a sensitivity analysis should be calculated for every archetype separately since parameters' ranks can vary from one archetype to another depending on the known parameters. This study employs standardized regression and random forest importance variables to consider linearity and non-linearity variation of the data for ranking the importance of the parameters based on the annual energy consumption of archetypes. R sensitivity package [52] has been used in this study for bootstrapping and calculation of the intervals of sensitivity index.

2.5. Emulation

Due to the complexity of building energy modelling in iterative calibration, a surrogate is employed to reduce the computation time. GP model has been selected for this step to combine simulated and observed data. For a GP emulation, a mean (η) and a covariance (δ) functions should be defined for field measured parameters (x) with p number, and the target parameter for calibration (u) with q number. To do so, the equations are:

$$\Sigma_{\eta,mn} = \frac{1}{\lambda_\eta} exp\{- \textstyle\sum_{k=1}^{p} \beta_\kappa^\eta \, |x_{nk} - x_{mk}|^\alpha - \sum_{k'=1}^{q} \beta_{p+k'}^\eta |u_{nk'} - u_{mk'}|^\alpha\} \quad (1)$$

$$\Sigma_{\delta,mn} = \frac{1}{\lambda_\delta} exp\{- \textstyle\sum_{k=1}^{p} \beta_\kappa^\delta \, |x_{nk} - x_{mk}|^\alpha\} \quad (2)$$

Where:

λ_η is the precision hyper-parameter

$\beta_1,\ldots, \beta_{p+q}$ correlation hyper-parameter

The last equation for calculating the relationship between observation parameters (x) and prediction parameters (u) is the vector z with this definition below:

$$\mathcal{L}(z \,|u, \beta^\eta, \lambda_\eta, \beta^\delta, \lambda_\delta, \lambda_\varepsilon) \propto |\Sigma_z|^{-1/2} \exp\left\{-\frac{1}{2}\,(z-\mu)^T \,\Sigma_Z^{-1}(z-\mu)\right\} \quad (3)$$

$$\Sigma_z = \Sigma_\eta + \begin{bmatrix} \Sigma_\delta + \Sigma_y & 0 \\ 0 & 0 \end{bmatrix} \quad (4)$$

Σ_η matrix of the mean (η) in the GP which is the output of equation 1

Σ_δ matrix of the covariance δ in the GP which is the output of equation 2

Σ_y is the matrix of observation error

So, the joint posterior probability relies on GP correlation hyper-parameters and precision hyper-parameters, and prediction parameters [27].

2.6. Calibration

Bayesian calibration (Equation5) has been employed to analyze the uncertainty in every archetype, the analysis was carried out through a formulation introduced by Kennedy and O'Hagan [26]. The six unknown parameters will go through the calibration process to demonstrate whether the outputs of the simulation are compatible enough with observed data. The Bayesian inference equation is as follows:

$$P(u|x, M) = \frac{P(x|u, M)\,.\,P(u|M)}{P(x|M)} \quad (5)$$

Where:

x is the observed data

u is the target uncertain parameter

M is the building energy model

For posterior distribution to ease sampling No-U-Turn Sampler (NUTS), an extension of the Hamiltonian Monte Carlo (HMC) for the MCMC sampling has been selected[53].

In this paper, separate GP models have been employed to emulate the simulator and the discrepancy. The trained emulators will be new clusters for the next step of correlation. The iteration number was set to 40,000 and validation has been proceeded by one data set from the test data and has been considered as the target archetype code. The assessment was achieved through the Coefficient of Variation of the Root Mean Squared Error (CVRMSE, Equation 6) and the Mean Absolute Percentage Error (MAPE, equation 7).

$$CVRMSE = \sqrt{\frac{\frac{\sum_{t=1}^{n_t}(y_t - y_t^*)^2}{n_t}}{\bar{y}}} \quad (6)$$

$$MAPE = \frac{\sum_{t=1}^{n_t}\left|\frac{y_t - y_t^*}{y_t}\right|}{\boldsymbol{n_t}} \quad (7)$$

3. Step-wise description of the method implementation in the city of Bologna

The case study of this paper is the building stock in the Saffi area in the Saragozza-Porto quarter of the city of Bologna. 1156 buildings have been classified into 11 representatives. The input data is collected through the municipality of the city of Bologna, ARPAE Emilia-Romagna [54], local weather data, and some other public datasets in urban databases.

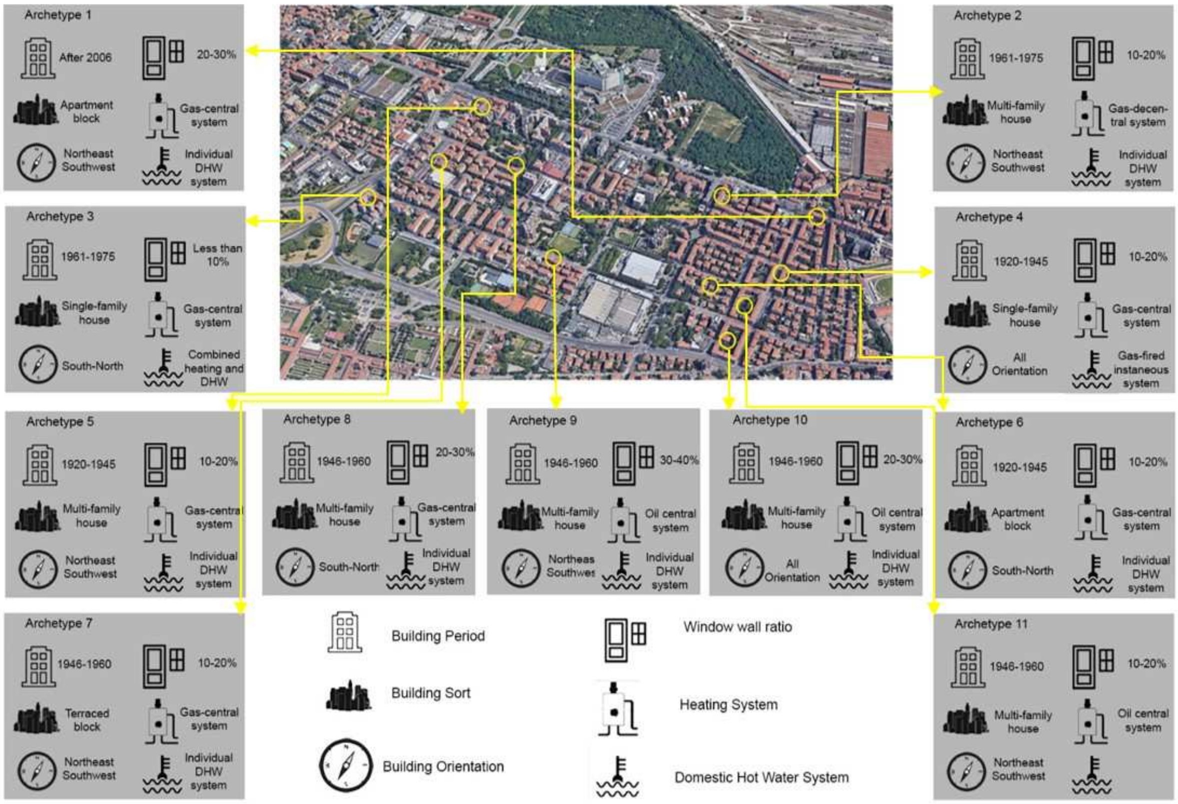


Figure 3: Identification of the 11 archetypes and the sampled building for every archetype

3.1. Developing a GIS database

For this case study, the municipality of Bologna has provided a dataset for the case studies of this UBEM, which includes (a) Building geometry; consisting of the 3d shape and characteristics of the buildings from the GIS Shapefile. (b) Features of the building; overview of the building's conditioning and heating systems, restoration dates, exterior conditions and openings, type of the fuel used, as well as materials for façades. Fig 2 shows the steps for developing the GIS dataset for the city of Bologna. For energy simulation, an hourly weather file based on the year 2019 dataset from a local weather station near the selected neighborhood was employed. TABULA [51] has been considered as the source of the properties for archetypes' materials and also conditioning systems of the buildings and lastly, the generated dataset has been modified with the latest changes in the neighborhood based on the official GIS file of the municipality.

3.2. Archetype coding

The buildings in the neighborhoods have been classified through the archetype coding algorithm. archetypes are defined according to Table 3. Table 4 shows the properties of every archetype. Based on the generated code and properties, every building will be simulated in EnergyPlus, and Energy Use Intensity (EUI) for every archetype is calculated.

Table 4: Identification of the 11 defined archetypes based on the property details

Component	Input Parameters	Arch 1	Arch 2	Arch 3	Arch 4	Arch 5	Arch 6	Arch 7	Arch 8	Arch 9	Arch 10	Arch 11
Envelope	Gross floor area	832	299	594	335	301	678	673	388	254	196	594
	Floor levels	7	4	4	4	4	5	5	4	4	3	5
	Room height	2.8										
	Gross Volume	17871	1646	11076	3750	3160	2818	5120	6197	4337	1975	11076
	Window to wall ratio	20-30%	10-20%	Less than 10%	10-20%	10-20%	10-20%	10-20%	20-30%	30-40%	20-30%	10-20%
	Thermal Zoning	Central zone and perimeter zones										
	R-Value floor	2.88	0.89	0.89	0.11	0.11	0.4	0.4	0.4	0.4	0.4	0.4
	R-Value Roof	2.88	0.89	0.89	0.11	0.11	0.4	0.4	0.4	0.4	0.4	0.4
	R-Value Wall	3.34	0.5	0.5	0.47	0.47	0.57	0.63	0.63	0.63	0.63	0.63
	U-Value Windows	2.87	2.87	5.55	5.05	5.05	5.55	5.05	5.05	5.05	5.05	5.05
	Solar heat gain coefficient SHGC	0.35	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
HVAC systems	DHW system	Individual DHW sys per apartment	Individual DHW sys per apartment	Combined heating and DHW	Gas-fired instantaneous water heater	Gas central DHW system	Gas central DHW system	Individual DHW sys per apartment	Individual DHW sys per apartment	Individual DHW sys per apartment	Individual DHW sys per apartment	Individual DHW sys per apartment
	Heating system	Gas-central heating	Gas-decentral-heating	Gas-central heating	Gas-central heating	Gas-central heating	Gas-central heating	Gas-central heating	Gas-decentral-heating	Oil central heating	Gas-central heating	Gas-central heating

3.3. Initial value setting and sampling of initial calibration

A total of 400 sets of unknown parameters are sampled employing the LHS. From this list, 300 samples were used for training the model and 100 for testing it. The samples were then simulated in EnergyPlus to calculate EUI. The annual gas and electricity usage (kWh/m^2) of every archetype is illustrated in Fig 4. Gas usage is limited to the heating and DHW systems due to the data availability. As Fig 4 shows, the minimum gas usage belongs to archetype 1. The reason is probably the material properties of this archetype, as it is demonstrated in Table 4 the materials' R-value of archetype 1 is higher than other ones. On the other hand, archetype 2 has the highest level of gas consumption. Besides, the electricity consumption of all the archetypes is at the same level, except in archetypes 1 and 2 that consume the lowest and highest electricity.

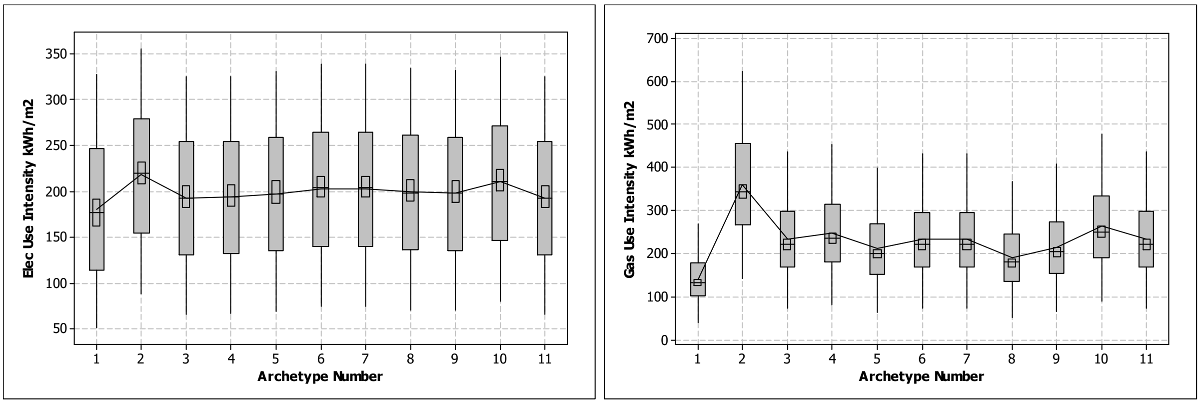


Figure 4: Annual Energy Usage Intensity of the archetypes, Electricity Use Intensity in left and Gas Use Intensity in right

3.4. Sensitivity analysis

As mentioned in section 2.4, sensitivity analysis in this study is calculated through two different methods: standardized regression coefficient and random forest variable importance. Electricity, gas, and total energy usage data of archetypes are employed to rank every parameter. Fig 5 shows the results of sensitivity analysis based on annual datasets. The results show the dominant parameter varies in different archetypes. EPD and CSP are constantly the most dominant parameters in electricity consumption in all the archetypes. On the other hand, the importance ranks for HSP, EPD, and OCC are the highest for gas usage in all the archetypes. The least important parameters in both gas and electricity usage are DHW and INF. However, the ranking figure for annual energy usage shows a stable trend. The four most important parameters in this ranking are EPD, HSP, CSP, and OCC, while DHW and INF have the least impact on annual energy consumption in all the archetypes. This ranking eases the calibration process, for instance, we know in the calibration of gas energy usage, the DHW does not significantly affect the model.

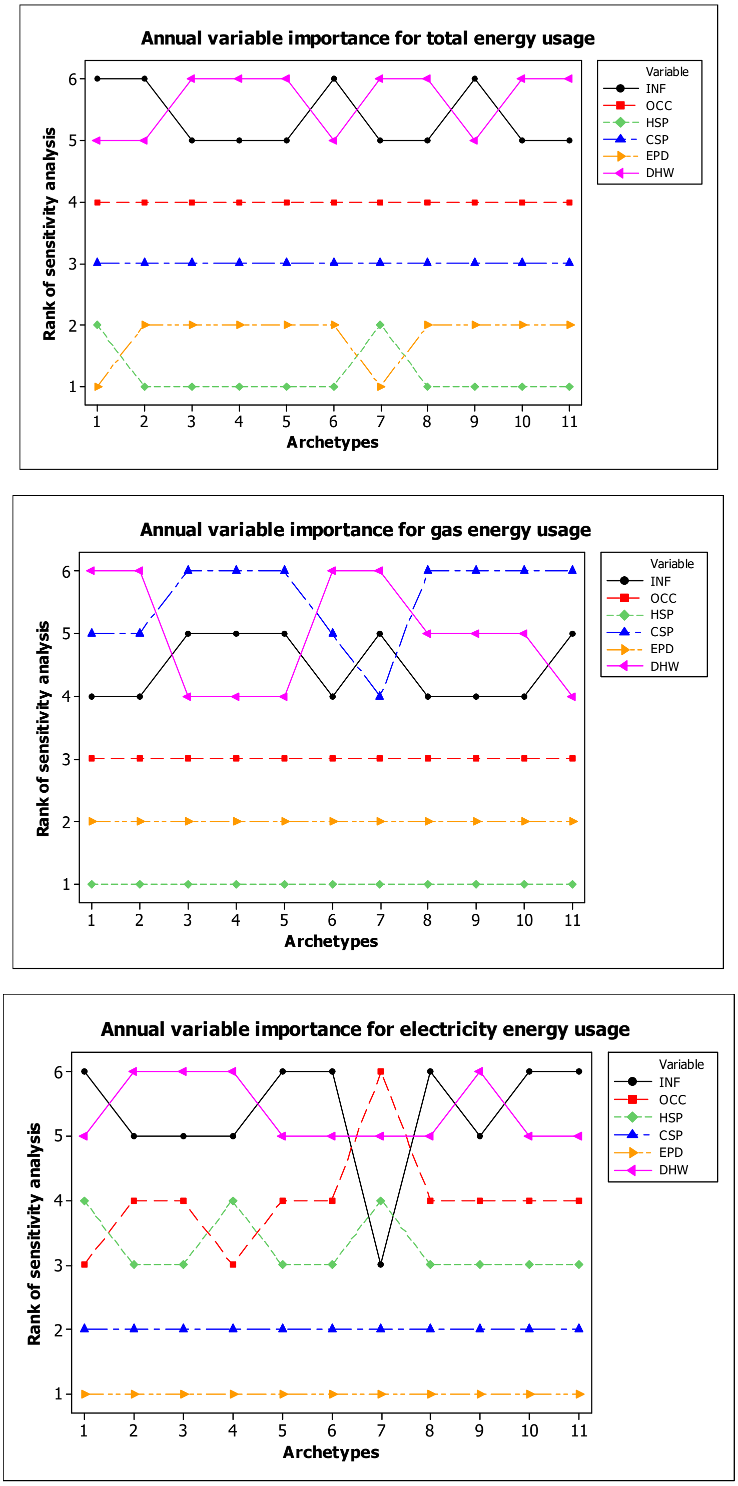


Figure 5: The results of the sensitivity analysis for six highly uncertain parameters

3.5. Calibration

After listing the uncertain variables and ranking them, the calibration starts with the GP. As it is described in section 2.5, GP trains an emulator to produce a combined set of observations and simulation data. The output of this step will be a group of emulators by which the calibration is assessed later. HMC is applied for drawing samples out of the posterior distribution of parameters. The sampling is being iterated until a desired number of samples is collected.

The prior and posterior distributions of six uncertain variables are shown in Fig 6. One archetype from every period of the archetypes is selected to illustrate the density in both prior and posterior distributions. The blue line demonstrates prior distribution and the red line shows the posterior distribution. It is noteworthy that when a parameter is not an informative variable for the calibration, it shows a wider distribution for that archetype. Therefore, in archetype 1, DHW and EPD are the most informative variables, these results are in accordance with the R-value of the construction properties in Table 3 that shows the R-value of the materials for this archetype is lower than other archetypes. On the other hand, CSP and HSP are the most informative parameters for archetype 6 which is the oldest building archetype (1920-45). In all the defined archetypes, CSP is the most effective parameter.

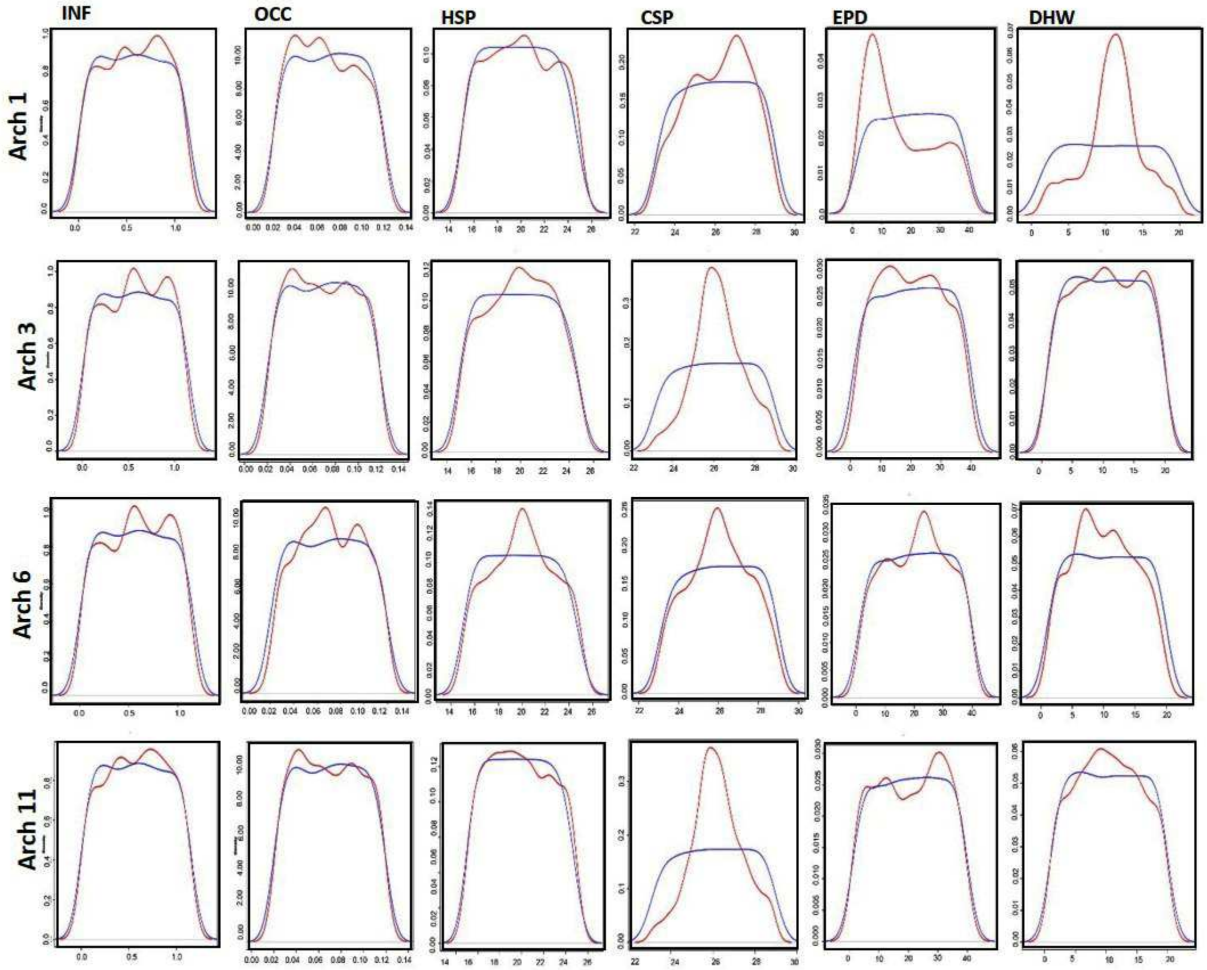


Figure 6: prior and posterior distribution of 4 archetypes, every archetype belongs to a specific built period for the sake of comparison. The X-axes show the value of the variable and the Y-axes show the density of the distribution. The blue line belongs to prior distribution and the red line stands for the posterior distribution

The results of the calibration process are shown in Fig 7. Each histogram shows the prior and posterior predictive distribution of EUI values. The EUI values of posterior predictive estimations (y_{pred}) in the histograms are based on 1000 draws out of the posterior predictive distribution for every archetype. It is noteworthy that the range of the EUI values of the archetypes have been limited by the illustration frame of the prior distribution. In most of the histograms, the ranges for the prior distributions are compatible with the predictive values of EUI, however, for archetype 2 the predictive range of EUI (y_{pred}) is not quite into the defined axes by the prior distribution. Possibly, the reason is the poorly designed excitation signals in the training that can happen in a data-driven model or simply the prior definition of the training set is not well suited to the actual data.

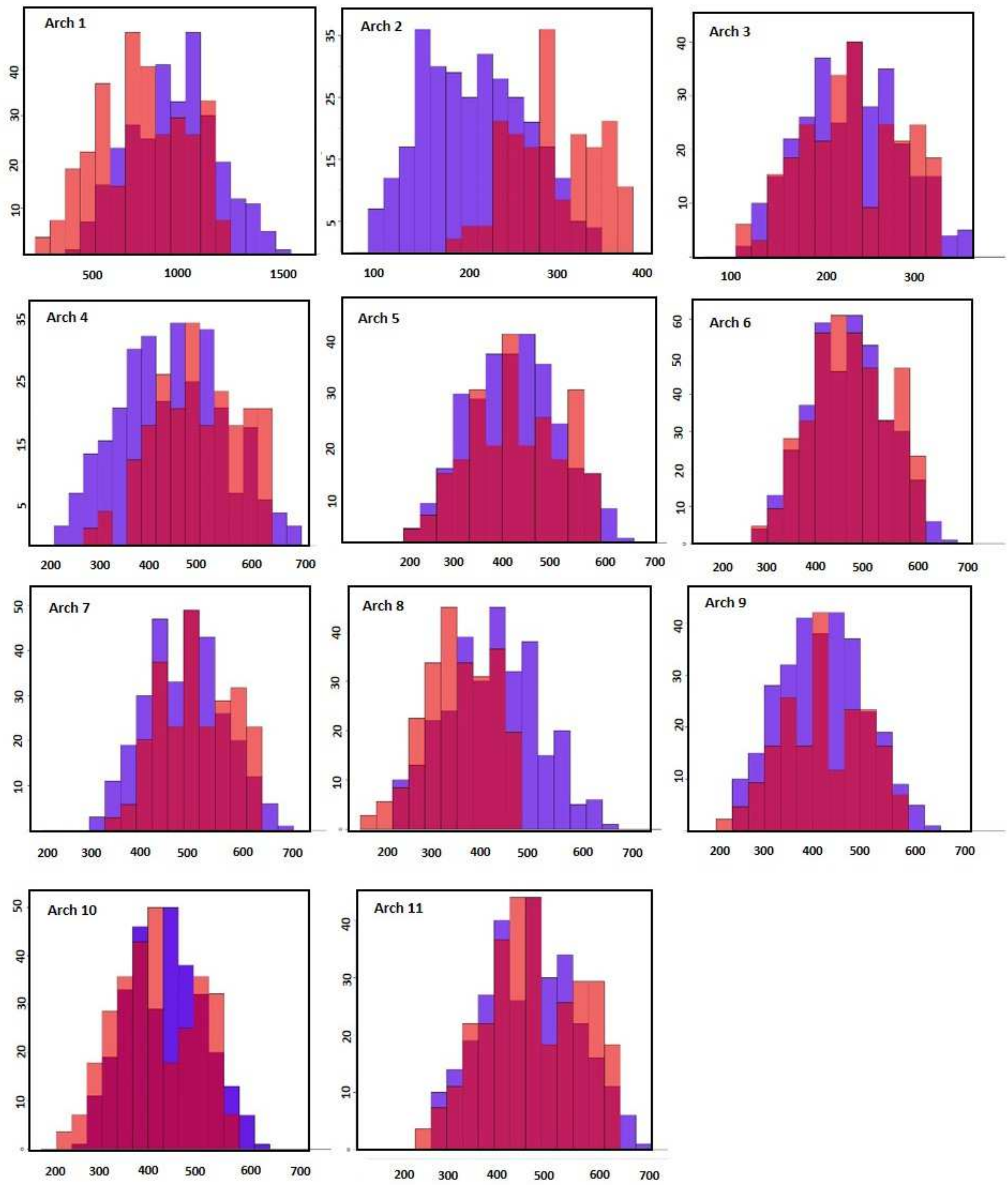
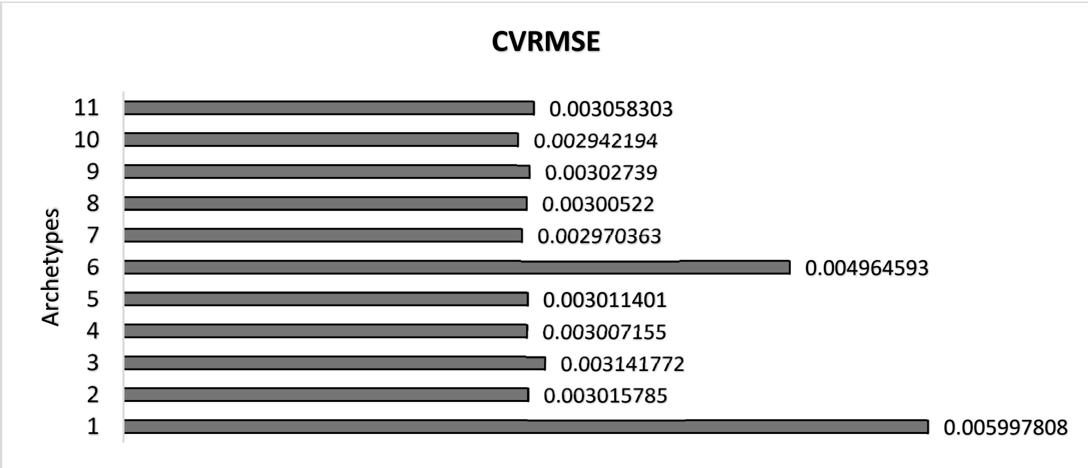


Figure 7: prior and posterior predictive distribution of EUI values. Predictive estimations (y_{pred}) are based on 1000 draws out of the posterior predictive EUI. The X-axes show the value of the EUI and the Y-axes show the frequency of the distribution. The blue columns illustrate prior EUI values and the red columns show the predictive values for EUI.

3.6. Evaluation of model performance

The accuracy of the method for forecasting the EUI corresponded to every archetype was tested through random draws out of the y_{pred} from the posterior distribution. The evaluation for each archetype was performed on its building energy model and specific building properties. The archetypes are evaluated through two

methods, the Coefficient of Variation of the Root Mean Squared Error (CVRMSE) and the Mean Absolute Percentage Error (MAPE) as illustrated respectively in equations 2 and 3. MAPE is a measure of error, an acceptable range for an excellent forecast in MAPE is less than 10%. However, based on the ASHRAE guideline the acceptable range for CVRMSE for energy prediction is less than 15% [55].
Fig 8 shows the variation of energy prediction from the actual values of EUI based on CVRMSE and MAPE. The CVMRSE of all the archetypes is less than 0.5% except Archetype 1. This archetype is a new-built building model that is simulated based on TABULA [51]. The reason for this gap could be simply a difference in the defined structure, R-value of the materials in practice and simulations, or imprecise defined ranges for unknown parameters in input data.
The outputs of MAPE also show the same results for Archetypes 6 and 1. To achieve a better understanding of the evaluation results, probably it is helpful to calculate the level of accuracy for the variables in the archetypes.



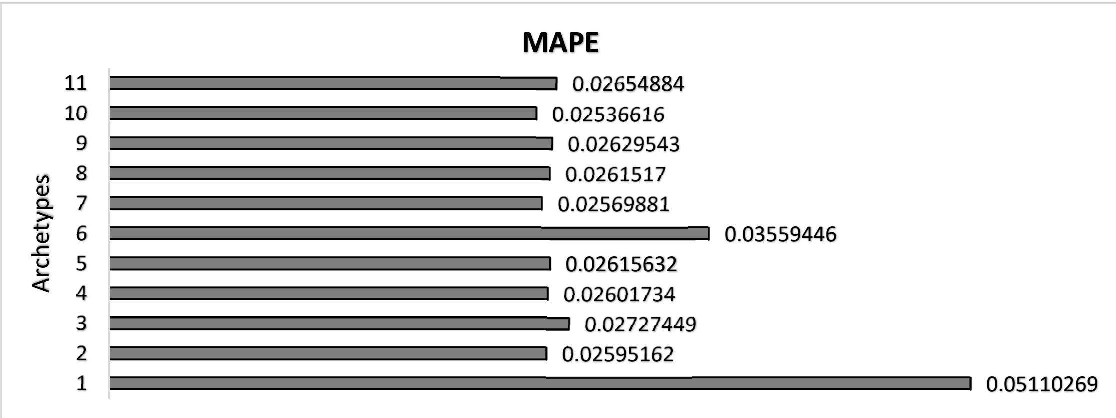


Figure 8: Performance metrics of the 11 defined archetypes for energy demand forecasts of the training buildings and testing buildings

Fig 9 shows the CVRMSE of the 6 unknown variables for every archetype in 1000 draws of the posterior distribution and the measured values. The results show that HSP and CSP are the most accurate estimated parameters in almost all the archetypes. The CVRMSE for OCC alternates in the different archetypes from 0.0035 in archetype 4 to 0.65 in Archetype 1. This means that the model is not precise in predicting the occupancy density in most of the archetypes. The results show that archetype 1 demonstrates the highest level of error in all the six variables among the archetypes. The reason is probably due to the large floor area in this archetype that has reduced the level of accuracy in modeling zones, heating and conditioning systems, and also the level of insulation.

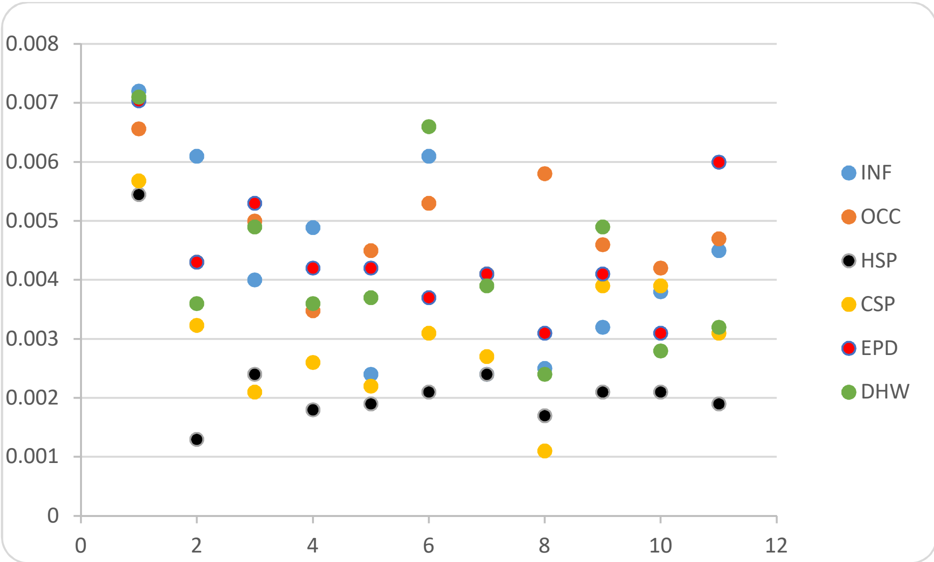


Figure 9: Performance metrics of the 6 uncertain variables in the 11 archetypes

4. Conclusion

This paper proposed an automated calibration method for long-term energy forecasting at the city scale. The proposed archetype-based energy model has been applied in a neighborhood in the city of Bologna in Italy. The following conclusions can be obtained from this research:

1- The presented archetype-based coding framework for the city of Bologna is based on 7 physical features that can be applied systematically to any urban region for classifying the urban buildings. These 7 features are available in most urban databases. Then, the values for six highly uncertain variables (INF, OCC, CSP, HSP, EPD, DHW) are estimated through Bayesian calibration. Therefore, every archetype has been defined based on 7 pre-calibration features and a tight range of six calibrated variables which are the most effective parameters in estimating building energy consumption. The coding framework is flexible and can be applied in any neighborhood containing hundreds of buildings with any uncertain parameters for forecasting energy modeling. This method can be also considered for energy forecasting of unseen buildings.

2- Automated calibration can calculate the importance of parameters concerning the building energy consumption. Informative parameters in the calculation of EUI are estimated based on 1000 draws out of the posterior predictive distributions. This method provides a forecasting framework for reliable prediction results.

3- The proposed model has proved a high level of accuracy with almost no bias in almost all the defined archetypes. The evaluation has been calculated both in EUI and also in the 6 highly uncertain variables. The comprehensive investigation in performance metrics clarified the concerned errors in uncertain parameters and the EUI.

The proposed UBEM prevents monotheism in applying the same strategies in various buildings. The reliability of the model is proven in predicting energy demand based on CVRMSE and MAPE. The model is capable of testing scenarios and recognizing the most effective retrofitting strategies and accelerating the urban-scale calibration. The simple archetype coding makes the method appropriate for energy policymaking on the urban scale and analysis of various retrofitting strategies on large scale for various types of buildings.

Yet, there are many other aspects that this paper did not cover in the calibration of the urban energy forecasting models. Future studies may consider more measures for the robustness of the Bayesian calibration, and also to take into consideration noisy urban datasets in processing hourly and monthly databases and optimize them. Besides, some efforts are needed to extend the functionality of the UBEMs for high-dimensional outputs. Many proposed models on the building-level scale cannot be performed on urban scales due to the required computation time, thus, future studies can explore solutions to eliminate this gap.

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References:

[1] Gholami M, Barbaresi A, Torreggiani D, Tassinari P. Upscaling of spatial energy planning, phases, methods, and techniques: A systematic review through meta-analysis. Renew Sustain Energy Rev 2020;132. doi:10.1016/j.rser.2020.110036.

[2] Reinhart CF, Cerezo Davila C. Urban building energy modeling - A review of a nascent field. Build Environ 2016;97:196–202. doi:10.1016/j.buildenv.2015.12.001.

[3] MacGregor WA, Hamdullahpur F, Ugursal VI. Space heating using small-scale fluidized beds: A technoeconomic evaluation. Int J Energy Res 1993;17:445–66. doi:10.1002/er.4440170602.

[4] Kohler N, Schwaiger B, Barth B, Koch M. Mass flow, energy flow and costs of the German building stock. Karlsruhe; 1999.

[5] Huang YJ, Brodrick J. A Bottom-Up Engineering Estimate of the Aggregate Heating and Cooling Loads of the Entire US Building Stock Prototypical Residential Buildings. 2000 ACEEE Summer Study Energy Effic Build 2000:135–48.

[6] Snäkin JP. An engineering model for heating energy and emission assessment. The case of North Karelia, Finland. Appl Energy 2000;67:353–81. doi:10.1016/S0306-2619(00)00035-0.

[7] Shipley D, Todesco G, Adelaar Ottawa, ON (Canada)] M [Marbek RC. Modelling a nation of buildings : estimating energy efficiency potential for large building samples, Canada: International Building Performance Simulation Association, Canadian Chapter, Ottawa, ON (Canada); 2002.

[8] Carlo J, Ghisi E, Lamberts R, Para N, Ahorro EL. THE USE OF COMPUTER SIMULATION TO ESTABLISH ENERGY EFFICIENCY PARAMETERS FOR A BUILDING CODE OF A CITY IN BRAZIL LabEEE – Energy Efficiency in Buildings Laboratory Federal University of Santa Catarina. Methodology 2003:131–8.

[9] Shimoda Y, Fujii T, Morikawa T, Mizuno M. Residential end-use energy simulation at city scale. Build Environ 2004;39:959–67. doi:10.1016/j.buildenv.2004.01.020.

[10] Wan KSY, Yik FHW. Representative building design and internal load patterns for modelling energy use in residential buildings in Hong Kong. Appl Energy 2004;77:69–85. doi:10.1016/s0306-2619(03)00104-1.

[11] Palmer J, Boardman B, Bottrill C, Darby S, Hinnells M, Killip G, et al. Reducing the environmental impact of housing Final Report Consultancy study in support of the Royal Commission on Environmental Pollution’s 26 th Report on the Urban Environment 2006.

[12] Nishio K, Asano H. A residential end-use demand model for analyzing the energy conservation potential of new energy efficient technologies. Proc Energy Effic Domest Appliances Light 2006.

[13] Petersdorff C, Boermans T, Harnisch J. Mitigation of {CO}2 Emissions from the {EU}-15 Building Stock. Beyond the {EU} Directive on the Energy Performance of Buildings (9 pp). Environ Sci Pollut Res - Int

2006;13:350–8. doi:10.1065/espr2005.12.289.

[14] Clarke JA, Johnstone CM, Kim JM, Tuohy PG. Energy, Carbon and Cost Performance of Building Stocks: Upgrade Analysis, Energy Labelling and National Policy Development. Adv Build Energy Res 2009;3:1–20. doi:10.3763/aber.2009.0301.

[15] Jonas Tornberg LTA. A GIS energy model for the building stock of Goteborg Jonas 2012.

[16] Ballarini I, Corgnati SP, Corrado V. Use of reference buildings to assess the energy saving potentials of the residential building stock: The experience of {TABULA} project. Energy Policy 2014;68:273–84. doi:10.1016/j.enpol.2014.01.027.

[17] Cerezo C, Dogan T, Reinhart CF. TOWARDS STANDARIZED BUILDING PROPERTIES TEMPLATE FILES FOR EARLY DESIGN ENERGY MODEL GENERATION Massachusetts Institute of Technology , Cambridge , MA 2014.

[18] Yang G, Li Z, Augenbroe G. Development of prototypical buildings for urban scale building energy modeling: A reduced order energy model approach. Sci Technol Built Environ 2017;24:33–42. doi:10.1080/23744731.2017.1328943.

[19] Tian W, Heo Y, de Wilde P, Li Z, Yan D, Park CS, et al. A review of uncertainty analysis in building energy assessment. Renew Sustain Energy Rev 2018;93:285–301. doi:10.1016/j.rser.2018.05.029.

[20] Cerezo Davila C, Reinhart CF, Bemis JL. Modeling Boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets. Energy 2016;117:237–50. doi:10.1016/j.energy.2016.10.057.

[21] Sokol J, Cerezo Davila C, Reinhart CF. Validation of a Bayesian-based method for defining residential archetypes in urban building energy models. Energy Build 2017;134:11–24. doi:10.1016/j.enbuild.2016.10.050.

[22] Chen J, Gao X, Hu Y, Zeng Z, Liu Y. A meta-model-based optimization approach for fast and reliable calibration of building energy models. Energy 2019;188:116046. doi:10.1016/j.energy.2019.116046.

[23] Li H, Li X, Qi M. Field testing of natural ventilation in college student dormitories (Beijing, China). Build Environ 2014;78:36–43. doi:10.1016/j.buildenv.2014.04.009.

[24] Huang P, Huang G, Wang Y. HVAC system design under peak load prediction uncertainty using multiple-criterion decision making technique. Energy Build 2015;91:26–36. doi:10.1016/j.enbuild.2015.01.026.

[25] Tian W, Choudhary R. A probabilistic energy model for non-domestic building sectors applied to analysis of school buildings in greater London. Energy Build 2012;54:1–11. doi:10.1016/j.enbuild.2012.06.031.

[26] Kennedy MC, Hagan AO. Bayesian calibration of computer models. J R Stat Soc B 2001:425–65.

[27] Chong A, Menberg K. Guidelines for the Bayesian calibration of building energy models. Energy Build 2018;174:527–47. doi:10.1016/j.enbuild.2018.06.028.

[28] Fernández M, Conde B, Eguía P, Granada E. Parameter identification of a round-robin test box model using a deterministic and probabilistic methodology. J Build Perform Simul 2018;11:623–38. doi:10.1080/19401493.2017.1420824.

[29] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 2002;6:182–97. doi:10.1109/4235.996017.

[30] Taheri M, Kingdom U, Tahmasebi F. A Case Study of Optimization-Aided Thermal Building Performance Simulation Calibration A CASE STUDY OF OPTIMIZATION-AIDED THERMAL BUILDING PERFORMANCE SIMULATION CALIBRATION Mahnameh Taheri , Farhang Tahmasebi , Ardeshir Mahdavi Vienna University

of Techn 2013.

[31] Wetter M. GenOpt®-A Generic Optimization Program GenOpt Ö-A Generic Optimization Program. 2001.

[32] Li W, Tian Z, Lu Y, Fu F. Stepwise calibration for residential building thermal performance model using hourly heat consumption data. Energy Build 2018;181:10–25. doi:10.1016/j.enbuild.2018.10.001.

[33] Yang T, Pan Y, Mao J, Wang Y, Huang Z. An automated optimization method for calibrating building energy simulation models with measured data: Orientation and a case study. Appl Energy 2016;179:1220–31. doi:10.1016/j.apenergy.2016.07.084.

[34] Asadi S, Mostavi E, Boussaa D, Indaganti M. Building energy model calibration using automated optimization-based algorithm. Energy Build 2019;198:106–14. doi:10.1016/j.enbuild.2019.06.001.

[35] Chaudhary G, New J, Sanyal J, Im P, O'Neill Z, Garg V. Evaluation of "Autotune" calibration against manual calibration of building energy models. Appl Energy 2016;182:115–34. doi:10.1016/j.apenergy.2016.08.073.

[36] Chen J, Gao X, Hu Y, Zeng Z, Liu Y. A meta-model-based optimization approach for fast and reliable calibration of building energy models. Energy 2019;188:116046. doi:10.1016/j.energy.2019.116046.

[37] Manfren M, Aste N, Moshksar R. Calibration and uncertainty analysis for computer models - A meta-model based approach for integrated building energy simulation. Appl Energy 2013;103:627–41. doi:10.1016/j.apenergy.2012.10.031.

[38] Lim H, Zhai Z (John). Influences of energy data on Bayesian calibration of building energy model. Appl Energy 2018;231:686–98. doi:10.1016/j.apenergy.2018.09.156.

[39] Lim H, Zhai ZJ. Comprehensive evaluation of the influence of meta-models on Bayesian calibration. Energy Build 2017;155:66–75. doi:10.1016/j.enbuild.2017.09.009.

[40] Booth AT, Choudhary R, Spiegelhalter DJ. Handling uncertainty in housing stock models. Build Environ 2012;48:35–47. doi:10.1016/j.buildenv.2011.08.016.

[41] Booth AT, Choudhary R, Spiegelhalter DJ. A hierarchical bayesian framework for calibrating micro-level models with macro-level data. J Build Perform Simul 2013;6:293–318. doi:10.1080/19401493.2012.723750.

[42] Booth AT, Choudhary R. Decision making under uncertainty in the retrofit analysis of the UK housing stock: Implications for the Green Deal. Energy Build 2013;64:292–308. doi:10.1016/j.enbuild.2013.05.014.

[43] Kim J-H, Augenbroe G, Suh H-S, Wang Q. DOMESTIC BUILDING ENERGY PREDICTION IN DESIGN STAGE UTILIZING LARGE-SCALE CONSUMPTION DATA FROM REALIZED PROJECTS 2015.

[44] Zhao F, Lee SH, Augenbroe G. Reconstructing building stock to replicate energy consumption data. Energy Build 2016;117:301–12. doi:10.1016/j.enbuild.2015.10.001.

[45] Evins R, Orehounig K, Dorer V. Variability between domestic buildings: the impact on energy use. J Build Perform Simul 2016;9:162–75. doi:10.1080/19401493.2015.1006526.

[46] Nagpal S, Mueller C, Aijazi A, Reinhart CF. A methodology for auto-calibrating urban building energy models using surrogate modeling techniques. J Build Perform Simul 2019;12:1–16. doi:10.1080/19401493.2018.1457722.

[47] Wang CK, Tindemans S, Miller C, Agugiaro G, Stoter J. Bayesian calibration at the urban scale: a case study on a large residential heating demand application in Amsterdam. J Build Perform Simul 2020;13:347–61. doi:10.1080/19401493.2020.1729862.

[48] McNeel R and others. Rhinoceros 3D, Version 7.0. Robert McNeel \& Assoc Seattle, WA 2021.

[49] U.S. Department of Energy. EnergyPlus | EnergyPlus. US Dep Energy 2020.

[50] Mathworks. Matlab R2017b 2017.

[51] Corrado V, Ballarini I, Corgnati SP. Typology Approach for Building Stock National scientific report on the TABULA activities in Italy. 2012.

[52] Bertrand Iooss A, Da Veiga S, Janon A, Pujol G, contribu-tions from Baptiste Broto with, Boumhaout K, et al. Package “sensitivity” Title Global Sensitivity Analysis of Model Outputs. 2020.

[53] Betancourt M. A Conceptual Introduction to Hamiltonian Monte Carlo. 2018.

[54] ARPAE. Hydro-Weather-Climate, dexter system 2020.

[55] Shailza. ENERGY MODELING OF MULTI-STORIED RESIDENTIAL BUILDINGS-A MANUAL CALIBRATION APPROACH. 2018 Build. Perform. Anal. Conf. SimBuild co-organized by ASHRAE IBPSA-USA, Chicago, IL: 2018.