Thesis

Towards a framework for developing fit-for-purpose Urban Energy Models: a case study for Ahmedabad

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DECLARATION

I am a bonafide student of CEPT University, Ahmedabad and declare that the thesis entitled **“Towards a framework for developing fit-for-purpose Urban Energy Models: a case study for Ahmedabad”**, submitted by me in partial fulfilment of the requirements for the award of the Degree of **Master of Technology in Building Energy Performance**, is my original work.

I declare that this thesis was composed by me, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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APPROVAL

Towards a framework for developing fit-for-purpose Urban Energy Models: a case study for Ahmedabad

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This thesis is hereby approved as a credible work on the approved subject, carried out and presented in the manner that is satisfactory to warrant its acceptance for internal and external examination as a partial fulfilment of the requirements for the award of the Degree of **Master of Technology in Building Energy Performance**, for which it has been submitted.

It is to be understood by this approval that the undersigned does not endorse or approve the statements made, opinions expressed, or conclusion drawn therein but approves the study only for the purpose for which it has been submitted.

Name of the Guide: Prof. Rajan Rawal

Guide’s signature:

Date: 30th April 2020

Abstract

By 2047, India's rapid urbanisation at 34%, will raise the energy demand & carbon emissions by 12 and 3 times respectively (NITI 2015). The Government's Smart City mission plans an urban renewal and retrofitting program by developing 100 citizen-friendly and sustainable smart cities across the country (MUD India 2015). Optimizing the existing building stock is a key strategy for cities to minimize energy consumption, GHG emissions, mitigating climate change and achieve the Nationally Determined Contributions. Understanding the dynamics of the urban building stock is essential to ensure phase-wise implementation of energy efficiency codes & policies like Energy Conservation Building Code (ECBC), Indian Cooling Action Plan (ICAP) and National Energy Policy. This can be achieved through a data-driven approach to develop specific action plans for different cities. Thus, adopting bottom-up Urban Energy Modelling (UEM) can advance urban and regional analyses, municipal planning processes, implementation of these policies and correlating them to optimize future cities.

Developing a UEM requires rich data sets providing both geometrical and semantic data (non-geometric) for the building stock. In the Indian context however, the current data on building stock & occupant behaviour is insufficient. The required data exists with different agencies and formats, some are missing or have limitations in terms of quality. The 3D geometry data for Indian cities need to be developed from scratch with a suitable Level of Detail (LoD). Semantic details like the construction assembly, occupancy pattern, type of HVAC systems, metered electricity, fuel & water consumption essential for a UEM must be accumulated from previously existing data sets or be exclusively collected and be linked together. At an Urban scale it is nearly impossible to have complete, accurate, and usable data, because of resource limitations and data-privacy regulations. Therefore, it is essential to know the influence of the different input data for different applications. Lack of data presses a need to shift focus towards a "fit-for-purpose" approach for developing UEM. Thus, there is a need of a framework which creates a meaningful correlation between geometrical & semantic attributes of the UEM.

This research expands the model characterization framework developed by Fennell, Ruyssevelt, Rawal, & Poola, (2019) identifying 13 characteristics defining the structure of the UEM. Each characteristic has different modelling approaches of increasing complexity and Level of Detail (LoD) of input data. This framework is developed through a robust review of existing projects. It lists the data required and the expected trade-off between higher accuracy and effective effort required for developing the UEM at different LoDs.

The framework is analysed for the city of Ahmedabad allowing to make the best use of the available data and estimate a suitable LoD for its UEM. An area 0.5sqKm of the Central Business District with 250 Residential & Commercial buildings is studied in detail to assess the impact of different LoDs of different model characteristics. The framework is aimed as a pilot study to inform research groups and local government on the methodology to develop the UEM for the entire city. This enables to control the result accuracy and recommend suitable data collecting strategies, focusing on the most important parameters. The framework conceptualises formation of the UEM for the entire city and lists the future scope of work. Ultimately it will guide the modeller to select suitable Levels of Detail (LoD) in the semantic (non-geometric) data and linking with geometrical LoD, minimizing the overall potential error by finding a compromise solution. The framework deployed and demonstrated for Ahmedabad has a potential for scaling up to other cities.

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1. Introduction

1.1. Urban Energy Modelling (UEM)

Urban energy modelling (UEM) refers to the computational modelling and simulation of the performance of a group of buildings in the urban context, to account for not only the dynamics of individual buildings but more importantly, the inter-building effects and urban microclimate (Hong et al. 2019). It can cover spatial scales from city block to district, and to an entire city. UEM typically covers temporal scales from hourly to annual. (Swan and Ugursal 2009) introduced two major approaches to urban energy modelling "**top-down**" models, which start from an aggregate view of a system that is broken down into constituent sub-systems, and the "**bottom-up**" models, which give a detailed representation of a system's constituent parts that are aggregated to the whole-system level. Kavgica (2010), adds a "**Hybrid**" approach that combines data- and simulation-driven approaches. Literature review suggests that top-down approach is suitable for large-scale analysis and not for the identification of the improvements at the building level; while the bottom-up approach has been recognized as suitable for urban and regional analyses. A bottom-up approach as explained in Figure 1 models building subsectors or down to individual buildings, using fully detailed dynamic building physics models (white box), reduced-order dynamic models (grey box), or data-driven models (black box). **Thus, for this research we opted to move forward with the bottom-up approach**. This used to simulate heat and mass flow in and around buildings UEM predicts operational energy use, indoor and outdoor environmental conditions for groups of buildings. A UEM creates a "geo-tagged" database (a city 3D model) of various characteristics of the buildings in the city. UEM provides quantitative insights on annual or seasonal energy use and demand, short-term demand response, the potential of renewable energy & district energy systems, GHG emissions, and impacts of climate change on energy demand. This simplifies the planning and evaluation of retrofits, building design & operation strategies and policy interventions for the urban building stock. In most UEM processes for simplification, similar buildings are classified into "archetypes". The semantic details are collected for sample buildings in the archetype and extrapolated using suitable assumptions to apply to all the buildings in that archetype. Geometry data is generated through remote sensing of the city. Other data from authorities, which exists in different formats and IDs, is filtered into cumulative data sets geotagged with a unique ID for each premise & building. After archetyping and allotting relevant non-geometrical characteristics the UEM is generated and simulated. UEM is calibrated using relevant energy use data. The error in simulated results is noted as the accuracy. A detailed description of UEM is given in the Literature review.

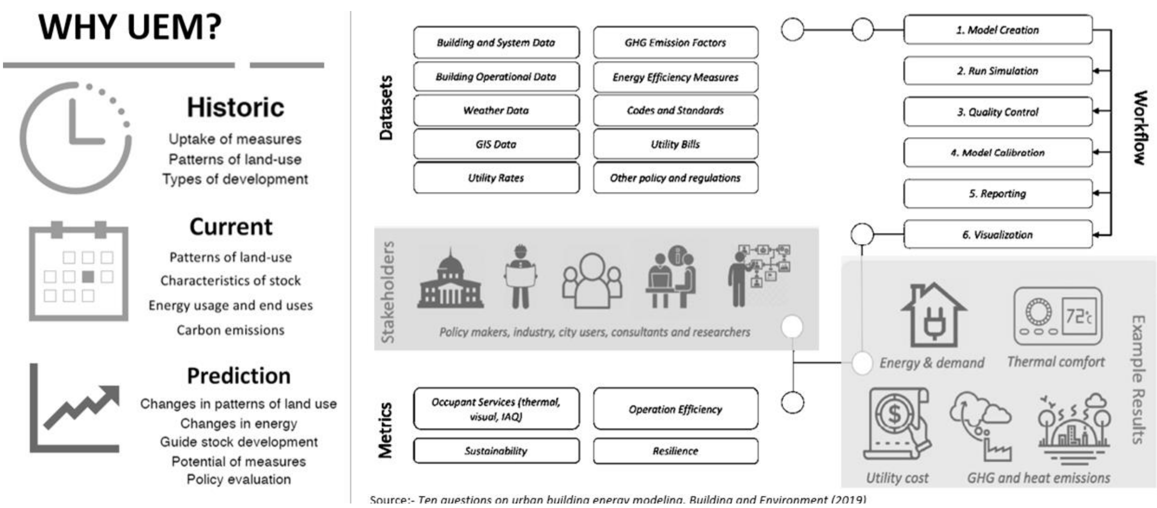


Figure 1-Typical workflow adopted for an Urban Energy Modelling (UEM) process. The figure depicts the probable uses for a UEM along with a methodology for data collection, simulation and analysis

1.2. Global coverage of Urban Energy Modelling (UEM)

Globally, several research institutes have made pioneering endeavours working along with their city governments to develop & research on UEM. Lawrence Berkley National Laboratory (LBNL) has developed a UEM with various retrofit scenarios considering a collection of 100 building technologies with performance and cost data for buildings in U.S. cities including Los Angeles, San Francisco & New York. They have created an online platform "CityBES – Building Energy Saver" which displays the model with various scenarios of energy efficiency in a comprehensive graphical interface.

MIT has analysed a citywide building energy performance and retrofit strategies for Boston. Along with that they have developed a software plugin for Rhinoceros 3D called Urban Modelling Interface (UMI) for creating urban energy models. University College London has developed models for London, Leicester and Swindon using LiDAR imaging to generate a 3D model and government data about building characteristics, use type, and energy consumption. In the USA, the Customer Optimization for Energy Efficiency (COFFEE) tool generates baseline energy models for buildings in the utility territory of the National Grid. It creates 3D building models using Google imagery to determine footprints, then refines models for financial analysis, using billing data and incentive data. It uses Open Studio for model creation, Building Component Library (BCL) for retrofit measures, and EnergyPlus for a simulation engine. Remmen et al., (2018) introduced TEASER that offers a city scale analysis and energy supply by district energy systems; a case study for about 3,000 buildings in German cities with combined heating and power plant was also provided. ETH Zurich is also a leading research institute in the field of Urban modelling with their projects for the district energy planning of several cities in Switzerland with their web based platform- City Energy Analyst (Fonseca et al. 2016). Technical University Munich (TUM) has estimated the heating demand from the UEM of Helsinki & Berlin. Helsinki has become one of the first cities to have an "energy-atlas", a real-time data base of the city's building stock with dynamic energy consumption trends. They are now on a way to develop a digital twin of the city and address integration of municipal services and transportation along with other interactions for effective planning and governance. Not only the existing building stock, but an analysis of future development is possible through UEM. Bergerson et al., (2015) developed LakeSim that provides an urban scale building energy analysis for various policy scenarios and urban morphology for 50,000 buildings in Manhattan, New York city. The International Energy Agency (IEA) Annex 70 also addresses the ongoing research to model urban building stocks by an international collaboration of researches. The Annex 70 emphasises on intensive and real-time building stock data accounting for the diversity of energy use and an appropriate combination of top down and bottom up approaches for UEM. The IBPSA (International Building Performance Simulation Association), as stated in (Wetter et al. 2019) is developing a BIM to GIS framework for Building Stock Modelling in Modelica. To summarize, UEM's growing popularity and importance as a planning tool has encouraged the exploration of this thesis.

1.3. Indian Context – Relevance of Bottom up Urban Energy Modelling

The urban building sector in India is experiencing an unprecedented growth. It has 38% (~208 mtoe) of India's total annual primary energy consumption and 31% (296 TWh) of the total annual electricity consumption (NITI Aayog & Prayas, 2017). While 40% of the stock is yet to be constructed, addressing human comfort through sustainable and energy efficient building designs is the key (BEE NITI 2017).

In India, the Smart cities mission aims to create more robust and sustainable cities, however they need a data-driven approach to develop action plans for the same. It becomes very important to understand the energy demand of the city and identify more efficient methods of utilizing available resources in catering the demands. Understanding the dynamics of the urban building stock is essential to ensure phase-wise implementation and mandate of energy efficiency codes & policies like the ECBC.

With view to this (BEE NITI 2017) prepared a roadmap to fast-track the implementation of Energy conservation building code (ECBC). Despite its launch in 2007 there was an extremely poor response to the voluntary adoption of the ECBC. Making the code mandatory required a deeper analysis of the level of awareness and economic viability of the end user to adopt it. Understanding the national and urban building stock dynamics is essential to ensure phase-wise implementation and mandate of the code. Thus, there is a need to amend the code at regional and local levels. This can be achieved through a data-driven approach to develop different action plans for different cities by assessing and understanding the variations incurring in the energy demands of the city through constant observation and analyses. Khosla & Janda, (2019) reviewed India's building stock for developing energy and climate change solutions. They focused on the need of data driven approaches to understand energy use patterns in cities for policy and research and highlighted the ongoing research addressing these issues.

There have been many studies to policy interventions analyse the national level impacts of ECBC & other energy efficiency measures on reducing the end-use energy consumption. Bhatnagar, Varma, Tathagat, & Diddi, (2017) assessed the national level energy savings by implementing the ECBC & Thambi, Bhatacharya, & Fricko, (n.d.) introduced the India Energy security scenarios – IESS 2047. Both studies used top-down statistical & simulation approaches based on already existing Growth rate & Economic models. Rawal, Pandya, and Shukla (2018) and again in (Rawal and Sharma (2019) presented a bottom-up, scaled dynamic simulation for the building stock of Ahmedabad. Classifying commercial buildings into 16 archetypes and implementing ECBC in phases based on the building's age, floor space and use type.

However, all these studies do not address the contextual & spatial characteristic of the energy use of the urban areas. The impact of the urban design of built spaces and efficient planning of municipal services like water supply, sewage and electricity supply on the source energy consumption is also not captured in such analysis. The solution lies in not scaling up energy modelling from one individual building to many buildings linearly, but capturing the dynamic and complex interconnection and interdependencies between buildings and the urban environment (Hong et al. 2019).

A bottom up Urban Energy Modelling (UEM) can thus enable city governments & stakeholders such as electricity DISCOMs, Energy Service Companies (ESCO), planners, architects and researchers to understand the existing building stock and the interrelated phenomena in the cities and evaluate realistically different combinations of policy interventions and levels of efficiency in energy demand-supply through a simulation-based approach. One of the ongoing research in the field of Urban Energy Modelling in Indian context is the iNUMBER Integrated Urban Model for Built Environment Energy Research project (Rawal et al. 2019). The key objective of the project is to develop a City Energy Model that includes the 3D building stock and the municipal services energy model. The project aims to achieve the same by linking the existing and new data sets and testing the validity of the developed model for a range of scenarios in accordance with different data availabilities.

1.4. Research Objective

The aim of this thesis is to develop a framework to make the best use of the available data and estimate a suitable trade-off between higher accuracy and effective effort required for developing the UEM, minimizing the overall potential error by finding a compromise solution. Based on the use case or scenario that needs to be analysed, a suitable accuracy and Level of Detail for both semantic and geometric data would be determined, prioritizing action plans for the cities.

- Identify the Level of Detail (LoD) for each model characteristics as developed in (Fennell et al., (2019) through an extensive review of the existing UEM projects.
- Understand how these have been applied in the literature and how they relate to model purpose
- Assess the impact of changing levels of detail on model accuracy and effort required through a case study of Ahmedabad.

1.5. Research question

- What are the possible combinations of Levels of Details (LoD) of both geometrical and semantic attributes applicable to a UEM?
- Are choices of LoD driven by model purpose or by data availability?
- What are the trade-offs between the accuracy and the complexity, and the effort required for these Levels of details?

1.6. Research scope

- This research will create intermediate Levels of Details through the various possible combinations of both geometric and semantic data applicable to a "bottom-up" simulation based Urban Energy Model, expanding the model characterization framework.
- The focus of the exercise will only be on "building level" attributes and will exclude municipal services and other phenomena of transportation from the scope. The research will only discuss building operational energy parameters and will not go into co-simulation exercises for complex problems.
- The accuracy and effort of only a selected combination of these LoDs based on the data and technical know-how available to the researcher will be performed on a 0.25 sqkm site of Ahmedabad city covering nearly 130 buildings of primarily residential use.
- The research will present a survey methodology as future scope of work for collecting data for the Ahmedabad UEM.
- The current thesis research will establish fit-for-purpose approach with choice of LoD for the three building types i.e. Commercial, Residential and Educational, as observed from the pilot study. This framework can be used in further researches to derive best LoD combinations for other building types in other parts of the city.

2. Literature review

Through the literature review several important themes for Bottom-up UEMs which make a huge impact on the modelling process's effort and its accuracy were studied in detail. The literature review was conducted in five stages as described in Figure 17.

2.1 Review of bottom up Urban Energy Modelling concepts

Reinhart & Cerezo Davila, (2016), reviewed the ongoing work in the field of bottom up UEM. The paper discussed points like, UEM generation process - data inputs, thermal model & validation, required datasets - building geometric & non geometric characteristics, Archetypes for grouping similar buildings for assigning non geometric properties. It lists previous UEM or related works where buildings have been archetyped, giving the number of buildings, the archetypes and the properties used to define them. It also lists which previous works have used dynamic vs static energy modelling. (Abbasabadi and Mehdi Ashayeri 2019) reviewed bottom-up simulation models and data-driven models incorporating Machine learning algorithms. It evaluates the strengths and limitations of each and presents the potential bottom-up hybrid data-driven and simulation-based techniques to reduce the modelling uncertainties. Hong et al., 2019 thoroughly reviewed existing scenario and presents ten questions that highlight significant UEM research and applications. The highlights of the paper are: - Description and importance of UEM, Review of available UEM tools, Available urban datasets and data representation standards, Sources of local weather data for use in UEM, Methods to couple multi-physics urban system models, Calibration methods of UEM, Example applications of UBEM and the main challenges of UEM. Through the literature review several important **themes emerged** which were studied in detail. These were: - Simulation methodology & tools, Data required for UEM, Model calibration & validation, Use case of the UEM, and other themes like use of Geo-spatial data & Level of detail for City 3D models, Co-simulation for microclimate and Urban heat island analysis and incorporating municipal services and transportation.

2.2. Use case of the UEM

Global coverage of Urban Energy Modelling (UEM) emphasised the wide application of UEM. Essentially the purpose of developing a UEM is to predict future scenarios and assess the impact of different Energy Conservation Measures (ECM) on the building stock. Development of urban design schemes, space syntax for effective planning and zoning of different urban areas and planning municipal can become more efficient by adopting the UEM. The LoD and accuracy of the model often determine how well the UEM can predict impact of different ECMs. According to (Hong et al. 2019) the use cases for UEMs are typically classified as: -

1. **End-use energy auditing & benchmarking** – Development of codes & standards.
2. **Existing building retrofits -** E.g.- CityBES (Hong et al. 2016) presents 1000 ECMs bundled through envelop, mechanical systems and operational strategy improvements for the city of San Francisco along with Life cycle cost implications.
3. **Demand energy forecasting** & predicting future growth scenarios and subsequent impact on energy & carbon footprint.
4. **District energy system optimization** – Pasichnyi, Wallin, & Kordas,(2019) presented two data-driven archetypes for Stockholm presented a method for analysing energy savings by adopting a waste-heat recovery for district heating system from the power plant.

2.3. Simulation Methodology & Tools

Cerezo Davila, Reinhart, & Bemis, 2016 of MIT and Chen, Hong, Luo, & Hooper, 2019 of LBNL talked about the modelling process for the cities of Boston and San Francisco with their bottom-up simulation-based tools called UMI (Urban Modelling Interface) & CityBES respectively. Both tools had a common approach. The 3D geometry data was taken from previously existing GIS data in City GML format. Non geometric attributes were collected through publicly available datasets like property tax, metered energy data, national level surveys (CBECS etc.) and other through sample surveys or literature. Similar buildings depending upon use type or construction / retrofit age are grouped together as **archetypes**. Different approaches were used to determine attributes to all buildings of one archetype (as discussed in Treatment of Uncertainty) and all the buildings are **simulated dynamically**. Rawal & Sharma, (2019) developed a **scaled-dynamic model** of Ahmedabad's commercial building stock, considering 16 archetype buildings. With more granular publicly available datasets (Evans, Liddiard, and Steadman 2017) discussed the 3D stock model for the city of London and (Coffey et al. 2015) discussed an **epidemiological** approach for UEM based on the London 3D stock model. Epidemiology treats every component individually and differently and strongly opposes a scaled-dynamic UEM approach and the creating deterministic archetypes which tends to overlook variations in building geometry, density and most importantly occupant behaviour. Apart from these **dynamic simulation** based approach another **Reduced order** approach was found in TEASER (Remmen et al. 2018) & CITYSIM (Robinson et al. 2009) which considers buildings and systems as a network of resistors and capacitors and use mathematical equations to determined Urban energy dynamics. There has been a constant focus on improving simulation accuracy while reducing the model complexity and computational effort. In view of this (Dogan and Reinhart 2017) presented "Shoe-boxer", an algorithm that abstracts an arbitrarily shaped set of building volumes into a group of simplified '**shoebox**' building energy models. It clusters the building's façade and creates smaller representative zones based on weighted area for each facade for ease of simulation Simulations are 200 times faster with a highest observed RMSE of around 11% to 20%. A similar approach was presented in (Zhu et al. 2019). This approach, based on the L-T method, decomposes floors from building geometry & creates zone clusters. Simulation results for typical zones are already inputted, the model just looks-up for the result for each zone cluster.

2.4. Data for developing UEM

It is essential to gather building asset data at the city scale from a wide range of sources (e.g., literature reports and studies, surveys, city projects, city datasets, and public records) and assemble them into a single open database with standardized formats and terms. Both geometric and semantic data needs to be collected and aggregated geographically to develop a UEM. Typically this includes- (a) building geometry, number of stories, and floor area; (b) year built / refurbished; (c) location and climate; (d) use type and occupancy; (e) HVAC, lighting, equipment & process systems & loads; (f) building construction details, window size, location, & type; and (g) actual energy consumption data. **Geometric data** is associated with creating 3D city models. According to Biljecki, (2013) these are traditionally classified into four LoD from 1 to 4 in increasing fineness of the details captured. It also introduces LoD 0 which is essentially 2D. However, LoD 1 to 3 are more popular for UEMs. City GML is a database which contains 3D geometry of various cities globally in a standard interoperable format. OpenStreetMap also provides data for exporting the 2D building footprint along with data like building type & height for a selected area. However, such data is unavailable for Indian cities. Thus, City 3D model needs to be generated. Data can be captured using LiDAR (Light detection & ranging) or Ariel photogrammetry. As previously worked upon by Oak ridge National lab for their Virtual EPB (New et al. 2018) project for the USA & Helsinki energy atlas, machine learning can be incorporated for image processing and creating building 3D models for energy simulations. Supervised machine learning can be incorporated for processing this data to extract buildings from streets, landscape and other features captured & can help creating 3D models for energy simulations.

Chen, Hong, Luo, & Hooper, (2019) discussed the development of **city level semantic datasets** for creating UEM of American cities. It reviewed the existing data from several cities and evaluated their adequacy for a UEM. San Francisco's DataSF provides building geometry, including the tax assessor's records, & building energy benchmarking data, which provides annual energy use and GHG emissions data for about 1,700 commercial buildings and 1,200 residential buildings. New York's NYC Open Data contains property data & the monthly energy cost for some of the city-owned buildings. Energy Information Administration's (EIA) survey on building characteristics and energy use for both commercial & residential buildings are also available. The data are represented in different formats and there is a need for a common key to make the data mapping easier.

2.5. Data availability in the Indian context

India's scale and stage of economic development with characteristics of both developed and developing countries requires a unique approach to derive a methodology for developing a UEM. Shnapp & Laustsen, (2013) poorly ranked the quality of data available in India for applicability in energy modelling. They suggest a need for a significant improvement of India's data. Data varies from region to region leaving many unfilled gaps in information and very difficult access to this information. Informal & organic development of our cities, regressive & unstandardized government data collection schemes in the past are chiefly responsible for this. This data-scarcity is worsened by the diversity of building stock which has only recently been subject to systematic building regulations and associated enforcement. Only after the formulation of ECBC in 2007 there has been some focus on the need for data to fastrack energy efficiency in the Indian building stock. Iyer et al., (2017) analysed all the previous attempts for data collection in India including Situation analysis of commercial buildings 2008, BEE Energy Benchmarking survey 2010 & 2016, and the ECO III & CBERD project 2015. They suggested a more systematic approach to collect data for commercial buildings derived from a case study of similar surveys around the world like CBECS & RBECS of USA, European Union survey and Singapore Building Energy Submission system dataset, etc.

2.6. Model Accuracy, calibration & validation

The most important aspect of a UEM is its accuracy in estimating the actual energy consumption profiles. Uncertainty in the input data is thus reduced through model calibration and subsequently the assumptions must be validated for consistency in obtained results. Krayem et al., (2019) discusses a case of Beirut, Lebanon with a **deterministic model calibration** strategy. The model was calibrated grouping buildings into clusters and then assigning coefficients to calibrate the simulated energy consumption of all buildings in the cluster. The result suggested strong correlation between the simulated & metered EUI after model calibration and was possible due to large availability of bi-monthly energy bills of almost all the buildings in the city. Berthou et al., (2019) discussed calibration with scarce data for French residences. It presented a national level UEM where residences where grouped by regions, floor space, occupancy profile, & economic status. Nine input parameters like heating set-point, infiltration rate, percentage of heated space, WWR, envelope U-value, were identified to be of highest uncertainty and were calibrated to match national residential energy consumption values. Validation was also based on strength of correlation coefficient with random samples of metred data from ten French cities. These calibration methodologies are often time consuming and deceptive since manual tweaking is done to match the results and the validity of these results may be questioned. To counter this Cerezo et al., (2017) presented a comparison between Deterministic and **Probabilistic**

calibration. It emphasised on how machine learning can improve calibration process and ensure validity. They presented three common archetype characterization methods for UEM and proposed a fourth **Bayesian method** for the calibration of unknown archetype parameters, using dynamic energy simulations and measured energy data. This method was applied to a case study of a residential district in Kuwait City which was later validated with metered data from existing buildings. The results showed that the proposed Bayesian method could produce a better simulated fit for the real EUI distribution, with a reduction of percentage errors for the 10 and 90 percentiles of 13–45% against deterministic methods, and 2–14% against other cases. The model was calibrated to match the monthly energy consumption profile using a Smirnov test and not just a single annual EUI number. This methodology was again explored in a UEM model of entire Cambridge city with over 2600 residential buildings by Sokol, Cerezo Davila, & Reinhart, (2017). These papers suggested that Bayesian method although was computationally expensive but saved time for ensuring better calibration and more accurate models. In all the above UEM approaches the model is just calibrated once based on historic data, but there needs a continuous model calibration for a long-term planning of building stock. Especially for large campuses like universities who often plan out renovation in phases. Thus Nagpal, Mueller, Aijazi, & Reinhart, (2019) proposed an auto-calibration process through monthly metered data for the MIT campus creating "**surrogate" models of the building stock**. This Machine learning algorithm learns from the simulations performed then creates mathematical models of the physical behaviour of the buildings to speed up this **auto calibration** process.

2.7. Challenges in the field of UEM

Developing a UEM requires rich data sets providing both geometrical and semantic data (non-geometric) for the building stock. At Urban scale it is nearly impossible to have complete, accurate, actualized and usable data sets, because of resource limitations and data-privacy regulations. Nouvel, (2017) stated that the diverse availability, uncertainty and Level of Details (LoD) of these data and the resources required to collect them, managing data quality is a common challenge of UEM. It emphasised on the importance of data quality and the need of a data recording standardization and improvement process. Also, the necessary simplification of UEM to perform energy studies in cities can impact their accuracy (Monteiro et al. 2017).

Looking at Indian context also, the current data on building stock & occupant behaviour is insufficient (Khosla and Janda 2019; Shnapp and Laustsen 2013). The required data exists with different agencies and formats, some are missing or have limitations in terms of quality. The 3D geometry data for Indian cities need to be developed from scratch with a suitable Level of Detail (LoD). Semantic details like the construction assembly, occupancy pattern, type of HVAC systems, metered electricity, fuel & water consumption essential for a UEM must be accumulated from previously existing data sets or be exclusively collected and be linked together. The spatial and temporal validity of this data while modelling cities with buildings which are built, refurbished and destroyed following the city evolution, is also important. Therefore, it is essential knowing the influences of the different input data for different configurations and applications. This enables to control the result accuracy and recommend suitable data collecting strategies, focusing on the most important parameters.

2.8. Research Gap Identified

There have been several methods and LoD of both geometric and semantic data used for developing UEMs by different research groups. As stated above in Challenges in the field of UEM, lack of essential data creates uncertainty and oversimplification of the reality of the event. At present each research group makes its own assessment of what is the required level of detail for their purposes. This is often implicit within the work rather and may be driven by practical considerations about what data is available, rather than the actual requirements of the study. Nouvel, (2017) assessed the impact of increasing levels of semantic detail versus increasing levels of geometric detail and highlighted the importance of prioritizing different input data. Lack of data presses a need to shift focus towards a “fit-for-purpose” approach for developing the UEM. Thus, there is an urgent need for a broader and more general assessment of how increasing detail in one aspect of a model affects overall model results. The aim is to make the best use of the available data and estimate a suitable trade-off between higher accuracy and effective effort required for developing the UEM. This will help the modeller select a suitable Levels of Detail (LoD) in the semantic (non-geometric) data and linking with geometrical LoD, minimizing the overall potential error by finding a compromise solution. This is particularly important for contexts like India where much data needs to be collected so there is a need for guidance on where to focus limited resources for data collection.

2.9. Probable solution - The intermediate Levels of Detail (LoD)

Fennell, Ruyssevelt, Rawal, & Poola, (2019) explored the characteristics of each different approaches for a UEM in more detail to understand how well they might meet the needs of a rapidly expanding city, such as Ahmedabad. They developed a unique model characterization framework defining four layers of interactions in a UEM – user, building, environmental and methodological. The building users & their interactions with the buildings they inhabit are at the core of the study. The building layer describes the envelope and systems which enclose and interact with the user. The environmental layer addresses the context in which each building is situated. Above all of these is a methodological layer capturing key choices on how models are structured, and the outputs are produced. Within these layers a total of 11 different characteristics were identified which addressed specific themes related to the layers. Each of the 11 characteristic/themes were then expanded into detailed approaches of varying complexity & granularity. Each UEM project reviewed by them could thus be identified with a combination of approaches, one from each of the 11 characteristics of this framework. This now leads to an important question- what is right balance between details & effort? – There can be many approaches to create a UEM as literature suggests. The model characterization framework must convey the implication of selecting a modelling approach on the accuracy they may expect, and the amount of effort required for it. For this we have come up to define these approaches / combinations as intermediate LoD between geometrical & semantic attributes. Thus, the modified model characterization framework will guide in assigning resources to the most important data required & help formulating an action plan to develop UEM for different cities.

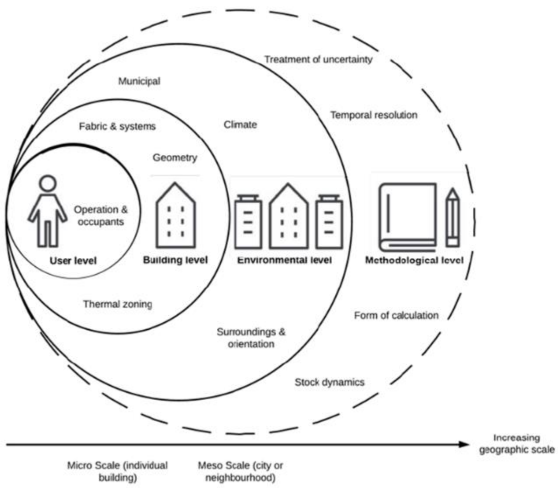


Figure 2- Model Characterization framework developed by Fennell et.al. 2019

3. Research Methodology

As discussed in the literature review section - Probable solution - The intermediate Levels of Detail (LoD) the model characterisation framework explains 11 pertinent characteristics that any UEM project is comprised of. These were: - Operations & Occupancy, Building Geometry, Archetypes or building fabrics and systems, Thermal Zoning, Surrounding context, Climate, Municipal services, Treatment of uncertainty, Stock dynamics, Temporal resolution and Form of calculation. In order to understand the different methods adopted by different projects across these characteristics an extensive literature review of the most cited 85 Urban Energy Modelling papers was carried out using a Data mining and literature review tool called Eppi Reviewer.

The existing UEM projects were studied to form a database. The papers were classified into this framework, & additional details about Number of buildings, level of calibration, model accuracy, existing data available, efforts made for developing that UEM, computational power, collecting data for it, and the use case of the model, were also noted. This review informed about the most commonly adopted UEM approaches, and the data required for each different approach.

The entire list of papers reviewed are summarized in section 5.3. The section below describes the findings from the literature review and highlights the different methodologies adopted in the different characteristics.

3.1. Defining the model characteristics and the different methodologies

The section discusses the model characterization framework in detail. Commencing with the description of the four layers of interaction as discussed above in section 2.9. it describes the characteristics and then elaborates the methodologies adopted.

USER

User describes the occupancy pattern / schedule defined in the model.

1. **Occupancy**: **-** It is known that occupants are responsible for a large share of a building's energy performance. Simulating occupant behaviour in Building energy simulations is carried out in largely two ways i.e.- occupant presence & movement and occupant actions. As discussed in (Gaetani, Hoes, and Hensen 2016) the influence of occupant behaviour on buildings' performance increases as the envelop becomes tighter & better or when the envelop gains are insignificant especially in large volume spaces. This influence can cause huge discrepancy between simulated and actual performance. For Urban energy models inappropriate choice of occupant behaviour model could result in oversized district energy systems, leading to over-investment and low operational efficiency (Happle, Fonseca, and Schlueter 2018). Thus, occupant behaviour can be modelled in broadly as a combination of deterministic or stochastic approach with space based or person/agent-based definition: -
   - **a) Single profile-** These are deterministic space-based defined occupancy schedules. Defined by a single profile of typical occupancy patterns set as numbers between 0 to 1 and occur as defined without any variation & considers occupancy movement and action the same. For.eg- A UEM which defines all residential buildings in one archetype and uses the same occupancy schedule irrespective of the diversity in different spaces to all the buildings in the archetype.
   - **b) Multiple profile-** Also deterministic in nature & defined like single profile but account for variation in spaces or with time. For.eg- A UEM which defines all residential buildings in one archetype and uses the different occupancy schedule for different spaces in the building or different for weekends / weekdays / different times of the year, but essentially remain the same as defined

c) **Probabilistic / Stochastic-** Probabilistic space-based schedules. Works with a probability distribution likeliness of variations to be accounted for & defined with a range of probable outcomes. For.eg- A UEM which defines occupant density in an office can vary between 0.5 - 0.8 at the same time in different office buildings or there is a 40% probability of the occupant opening the window if the outdoor temperatures are in the comfort band etc.

d) **Agent Based –** It is a highly complex definition for occupancy patterns based on a stochastic person-based modelling where interactions between each individual occupant can be accounted for. It also requires intense amount of data to carry out machine learning algorithms to predict occupancy patterns. Due its complex & computationally intensive nature it is not very popular in UEMs but it is actively being researched to be incorporated (Barbour et al. 2019).

BUILDING

This layer describes the physical & geometrical attributes of the building stock in a UEM.

1. **Geometry**: - The characteristics of the buildings are defined as their external geometry / massing / shape / form. As defined in (Biljecki 2013) there are predominantly 4 levels of detail in defining building geometry for city 3D models. However, there was also a mention of LoD 0 i.e. Non volumetric geometries in many of the research papers. Thus, it is considered as a part of the framework.
   a) **LoD 0 / Non-Volumetric -** In the context of city 3D models a hypothetical / arbitrary volume of geometry assumed is considered in this category. Typically, UEM projects having a scaled dynamic approach who do not have geometry data assume an arbitrary volume for a prototype building and perform simulations through that.
   b) **LoD 1 / 2.5D extrusion-** Described by Extruding the footprint / typical floor plan of the building to its average height, a 2.5D geometry. It assumes all buildings a cuboidal and neglects variation in 3 Dimensions. This geometry can be easily created by image processing of 2D satellite images, extracting footprints and extruding them to height as detected through the image or inputted through previously collected GIS data.
   c) **LoD 2 / 3D geometry -** Consists of the exact 3D geometry of the building which considers the variations in 3 Dimensions. For e.g.- it considers sloped roofs and having different footprint on different floors.
   d) **LoD3 / Detailed 3D geometry**– Adds on to the LoD2 geometry with detailed external features like overhangs, projections and exact WWR of the building, LoD3 model if developed through photogrammetry will also show the textures and materials on the building.
   e) **LoD 4 -** Details out an LoD3 model with interior layout as well.

   An LoD2 & LoD3 model will need specialized techniques like LiDAR & Photogrammetry to collect the data. LoD4 will require typical floor plans in even more detail for the buildings.

2. **Archetypes: -** Simulating at an urban scale inherently comes with an assumption to group similar buildings and define their physical attributes like construction materials, type of mechanical systems, typical occupancy & operation schedules, EPD & LPD and others. These groups are referred to as Archetypes & help in determining typical attributes. Archetypes are created as a result of segmentation and characterization. In segmentation, the investigated building stock is divided into groups according building shape, age, use, climate and systems. In characterization, a complete set of thermal properties including construction assemblies, usage patterns and building systems must be defined for the archetype buildings representing the previously defined groups.
   a) **Single Archetype-** for simplicity all the buildings can be grouped under a single Archetype based on use/age/energy consumption etc. For e.g.- All buildings in the model can be grouped as Residential & Non-Residential irrespective of their diverse uses.

b) **Multiple Archetypes** – Architypes can be segmented based on multiple uses e.g.- Commercial, retail, hospitality, Apartments, row houses or based on age/construction period.
c) **Multiple (combining different attributes to segregate)-** Segmentation can be done at third level based on combinations of different attributes like use & age e.g.- Apartments (pre 1970), Apartments (After 2000), Retail stores (pre 1970) & Retail store (after 2000).

3. **Zoning: -** Describes the way the thermal zones are defined in a building.
   a) **Single Zone per Building –** Considering the entire building as a single thermal zone and simulating it entirely at once.
   b) **Zones per floor or peruse -** Creating a separate zone for each floor, considers the difference in ground floor and top floor due to different exposure to exterior. This may use a zone multiplier for middle floors. Another way can be to zone a building based on use in case of a mixed-use building.
   c) **Core & perimeter zones –** Zones created on each floor can be segregated as core & perimeter zones and be assigned as conditioned or unconditioned spaces. For e.g.- in an office building the core zone may represent the staircase/lift lobby area & perimeter zones are occupied and conditioned.
   d) **Detailed interior zoning –** Zones are divided according to the detailed interior layout.

ENVIRONMENT

This layer describes the interactions of the buildings with their context.

1. **Climate**: - Describes how the outdoor conditions are considered and simulated
   a) **Steady state –** Assumes a long-range average value for outdoor conditions
   b) **TMY –** Uses a Typical Meteorological year or historic weather data stored in an EPW collected generally at the nearest airport.
   c) **Local Microclimate-** Uses microclimate data for the specific urban location considering the effects of Urban heat island. This can be either measured or calculated using simulations or weather generation tools.

2. **Context: -** Describes the interaction of the neighbouring buildings and other structures.
   a) **Volumetric/Standalone-** Does not consider any impact of neighbouring structures.
   b) **Context as shading –** Considers neighbouring buildings as shading elements only.
   c) **Trees & vegetation as shading –** Includes the dynamic shading effect of vegetation.
   d) **Detailed context with mutual interactions -** Includes the dynamic interactions between the building and neighbouring structures including long-wave radiant heat exchange. This may require a co-simulation between thermal simulation and outdoor weather data in form of CFD.

3. **Municipal Services: -** Describes the interaction of urban level infrastructure with the dynamics of building stock. This may include municipal services like water-supply, sewage, electricity grid, gas pipelines district energy systems, transportation (mass transit) etc.
   a) **Not included**
   b) **Included without spatial mapping-** Components of the municipal services like pumps for water supply, electricity substations & transformers etc. are accounted for their energy consumption in the urban area assuming them as aggregated / averaged.
   c) **Included with spatial mapping –** Networks and layouts of these services are included, and their dynamic interaction in-terms of demand & supply responses is captured in the model. This

helps in understanding concepts like Water-energy nexus, modifying services layouts and optimizing grid interaction with active demand management.

METHODOLOGY

This layer describes the aspects related to the method of modelling, simulating and reporting the results of the UEM.

1. **Stock dynamics –** Describes the dynamic nature of the building stock with changes in floor-space, use patterns, redevelopment and future projects.
   a) **Snapshot-** Assumes the current / historic building stock at a single instance. Does not include changes in the building stock and develops an as-is-case. Temporal validity of the input data is thus not questioned in this type of simulation.
   b) **Time Series-** Develops several snapshot models from different time-steps for the building stock, eg- depicting decadal changes in the building stock and developing future scenarios of proposed planning schemes.
   c) **Dynamic-** Accounts for dynamic changes in the building stock & keeps updating the changes as they happen in the model. Temporal validity of the model becomes important in this case.

2. **Temporal Resolution-** Describes the time-step at which the results are obtained from Annual to Hourly increasing from LoD1 to 3 respectively. Commonly UEMs report results in annual resolution due to lack of calibration data at finer time steps.

3. **Treatment of Uncertainty-** It is one of the most crucial aspects of determining the accuracy and calibration of a UEM. It describes how the uncertain input parameters of the model are assumed and tweaked for calibrating the model. Since simulation at urban scale will lead enormous uncertainties in many building & occupants related characteristics due to a diverse nature of a vast building stock, several assumptions are taken for values in the input parameters. As explained 2.6 in “model calibration” the uncertain inputs like Infiltration rate, set-point temperature, exact glazing ratio in a LoD1-2 geometry, occupant density and for that matter all the semantic data can treated in three ways: -
   a) **Deterministic-** Uncertain parameters are defined with a specifically determined value with no probability of variations.
   b) **Probabilistic-** Parameters are defined with a range of probable values that be assigned randomly (stochastic) or with a defined probability. For eg- Infiltration rate in residential buildings constructed prior to 1970 can vary between 1.2-0.6 ACH with equal probability.
   c) **Bayesian-** It uses a probabilistic approach coupled with Bayes theorem to iterate input parameters based on previous results and tries to tweak the input value till a desired level of accuracy is achieved. It typically uses a machine learning algorithm.

4. **Form of simulation-**

a) **Reduced Order Model-** which considers buildings and systems as a network of resistors and capacitors and use mathematical equations to determined Urban energy dynamics.
b) **Scaled Dynamic –** Dynamically simulates the Archetype or prototype buildings and then scales the result to all the buildings falling in that archetype
c) **Shoebox -** It clusters the building’s façade and creates smaller representative zones based on weighted area for each facade for ease of simulation
d) **Dynamic –** Performs a dynamic simulation on all the buildings accounting for diversity in location, context, geometry and operation patterns.

MODEL CALIBRATION

This layer has been added to the existing framework to account for how the model is calibrated & validated. This will inform of the quality and usability of the model apart from its accuracy, since the accuracy of the model is dependent on the data to which it is calibrated and validated.

1. **Calibration level-** Determines the data to which the model's simulated results are being calibrated to. The temporal resolution of this data generally governs the same for the model simulation.
   a) **Annual average values-** Typically data derived from literature or benchmarking studies. Gives annual energy consumption of the total building stock, based on building uses (e.g.- total for residential) or end use types (e.g.- total energy for cooling/heating etc.) or Average EUI (kWh/m2) for the different building uses. This data is useful if detailed data for each building is not available.
   b) **Annual Metered data-** Annual metered energy data for all or several buildings in the UEM project.
   c) **Monthly metered data-** Helps in calibrating to not only a total value but the monthly consumption trend.
   d) **Hourly/Daily metered data –** This data can help calibrate the model to use the UEM for controlling Peak Demand and different Grid interaction scenarios.

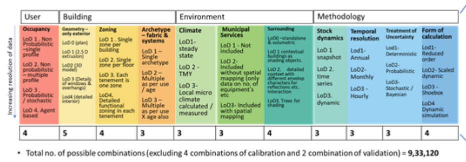
2. **Model Validation –** Determines the level of confidence and consistency in the UEM model and its applicability in different locations.
   a) **Validated on the study area-** The UEM is developed for a study area/area of interest with all the relevant calibration data available for that. Some of the data is used to train the model and calibrate it, the remaining data is used to test the consistency of the trained model to other buildings in the study area.
   b) **Validated on & outside the study area-** If the inputs/assumptions of the trained model are to be applied on a larger scale for which entire data is not available but data for random samples is available then this approach is useful. For eg- If the UEM for a zone/ward in a city is developed as representative of the entire city's building stock then this model must be validated with enough test cases outside the training set to determine its validity

3.2. The intermediate Levels of Detail (LoD)

Evaluating the literature and assessing the granularity of each method these characteristics were defined into intermediate 'Levels of Details'. Considering that **calibration data & validation** are equally important for UEM process two more characteristics were added to a new '**Model Calibration**' layer, thus creating 13 Model characteristics. Based on increasing granularity and complexity the approaches within each character were assigned LoD from 1 to "n", 1 being the simplest and "n" being the most complex. As shown in the first, second & third rows represent the **Layers**, the **characteristics** & the Modelling approaches / **intermediate LoDs** for each characteristic. To elucidate, a model having Considered all the combinations of these LoDs there are a possible number of approximately **60 lack combination of approaches** to create a UEM. The Figure 3- Intermediate LoDs expanded from the model characterization framework of 11 characters below describes the model characterisation framework with the Levels of Details assigned to each characteristic. Figure 5 - Frequency of papers compiled from the Literature review of 85 projects, having different LoDs in different characteristics indicating the most adopted methodologies below highlights the number of papers opting for different LODs across different characteristics. This analysis helps to better understand the most commonly adopted LoDs.

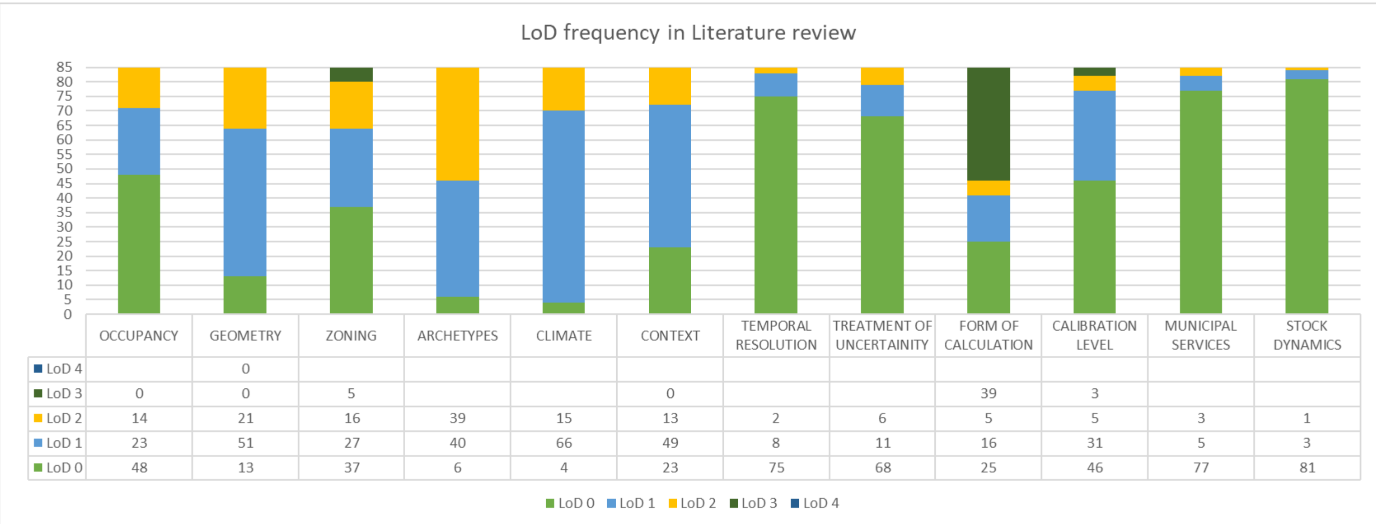
LAYERS	USER	BUILDING			ENVIRONMENT			METHODOLOGY			
CHARACTERISTICS	OCCUPANCY	GEOMETRY	ZONING	ARCHETYPES	CLIMATE	CONTEXT	MUNICIPAL SERVICES	STOCK DYNAMICS	TEMPORAL RESOLUTION	TREATMENT OF UNCERTAINITY	FORM OF CALCULATION
LoD1	Deterministic-Single profile	2.5D extrusion	Single Zone /Building	Single	Steady state	Stand alone/volumetric	Not included	Snapshot	Annual	Deterministic	Reduced order
LoD2	Deterministic-Multiple profile	3D geometry	Zone / floor or use type	Multiple with use type/age/other characteristic	TMY	Context as shading only	Included without spatial mapping	Time series	Monthly/ Bimonthly	Probabilistic	Scaled Dynamic
LoD3	Probabilistic	Detailed 3D with external features	Zone / floor or use type core & perimeter	Multiple with use type x age x other characteristic	Microclimate (measured / calculated)	Trees for shading	Included with spatial mapping	Dynamic	Hourly / Daily	Bayesian	Shoebox
LoD4	Agent Based	Detailed with interior layout	Detailed internal zoning			Detailed context with mutual interaction					Dynamic
Total = 7,46,496	4	4	4	3	3	4	3	3	3	3	4

Figure 3- Intermediate LoDs expanded from the model characterization framework of 11 characters



LAYERS	MODEL CALIBRATION	
CHARACTERISTICS	CALIBERATION DATA	MODEL VALIDATION
LoD1	Annual calibration through reference EUI (literature)	Validated on the study area
LoD2	Annual metered data	Validated outside the study area
LoD3	Monthly / bimonthly metered data	
LoD4	Hourly metered data	
Total = 59,71,968	4	2

Figure 4- - Model calibration added as an additional layer to the existing framework



	OCCUPANCY	GEOMETRY	ZONING	ARCHETYPES	CLIMATE	CONTEXT	TEMPORAL RESOLUTION	TREATMENT OF UNCERTAINITY	FORM OF CALCULATION	CALIBRATION LEVEL	MUNICIPAL SERVICES	STOCK DYNAMICS
LoD 4		0										
LoD 3	0	0	5			0			39	3		
LoD 2	14	21	16	39	15	13	2	6	5	5	3	1
LoD 1	23	51	27	40	66	49	8	11	16	31	5	3
LoD 0	48	13	37	6	4	23	75	68	25	46	77	81

Figure 5 - Frequency of papers compiled from the Literature review of 85 projects, having different LoDs in different characteristics indicating the most adopted methodologies

3.3. Developing the UEM

Developing a UEM requires the geometric data to be linked with the semantic data collected from different sources and be processed as one single dataset.

Simulation workflow

(Krietemeyer and Kontar 2019) discussed a simple methodology to integrate UEM with **GIS data** which is commonly practiced for most UEM projects. Essentially all **geometrical and semantic details are geotagged**. A custom Python script is written to extract these details and produce "idf" (Intermediate Data Format) files for input to Energy Plus. Since this thesis will not test "co-simulation" scenarios, thus UEMs will be simulated on **Energy Plus** considering context as only shading objects.

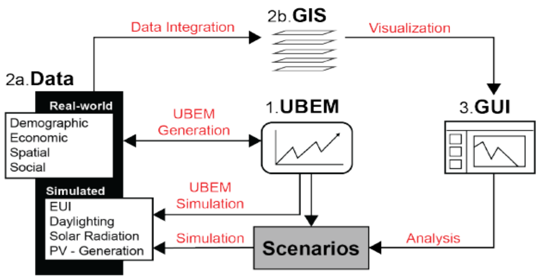


Figure 6- Typical workflow for generating a UEM

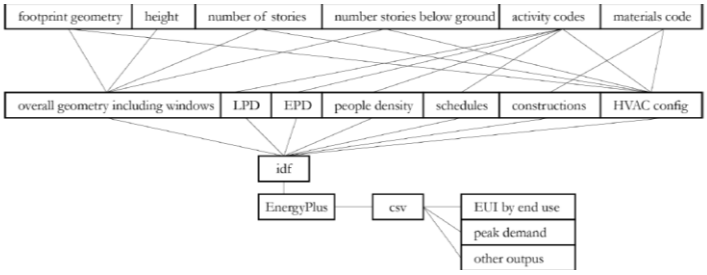
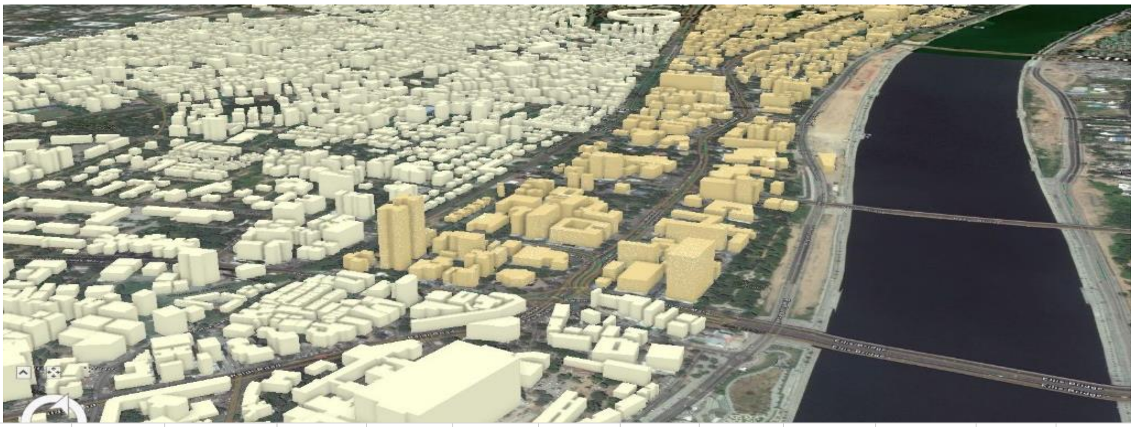


Figure 7- Connecting all essential data to generate the Energy Plus input files

1. Data Integration - Creating a Geo-tagged database for UEM

The first step is to link the building attributes with their geometry. This data will help identify important attributes derived from Property tax database like building use, age, number of floors etc. All these attributes are linked to the building footprint with a "FID" and stored in .shp (shapefile) extension file format. This data for Ahmedabad is developed in **ArcGIS s**oftware. The figure below shows an LoD1 geometry model of the Central Business District, highlighted in yellow having 935 buildings. This geometry contains attributes that will be used to assign further properties to each building for running the simulations.



FID	Bldg_Use	Bldg_Use_2	No_Floors	Groundfloo	Bldg_age	No_of_DU	Builtup_Ar	Mixed_Use	Shape_Leng	Shape_Area	Building_H	Bldg_cond
0	Residential	Row Houses	2	Residential	38	2	243.926	0	44.635582	121.963033	6.4	Fair
1	Commercial	Semi-Detached	3	Retail	18	0	501.186	0	52.421544	167.061936	9.6	Good
2	Residential	Row Houses	2	Residential	38	2	246.405	0	44.771713	123.202271	6.4	Fair
3	Residential	Row Houses	2	Residential	38	2	227.084	0	42.727825	113.541905	6.4	Fair
4	Residential	Row Houses	2	Residential	38	2	210.753	0	41.46342	105.376472	6.4	Fair
5	Residential	Row Houses	2	Residential	38	2	156.385	0	36.174127	78.192535	6.4	Fair
6	Residential	Row Houses	2	Residential	38	2	183.916	0	39.107517	91.9581	6.4	Fair
7	Residential	Row Houses	2	Residential	38	2	242.273	0	44.311037	121.136526	6.4	Fair
8	Residential	Row Houses	2	Residential	38	2	196.205	0	39.826611	98.102695	6.4	Fair
9	Residential	Row Houses	2	Residential	38	2	188.991	0	39.007308	94.495327	6.4	Fair
10	Residential	Row Houses	2	Residential	38	2	198.925	0	40.17666	99.46259	6.4	Fair

Figure 8- LoD1 geometry model for the Central Business District of Ahmedabad with attribute table indicating essential semantic data derived from Property tax records.

2. Defining templates to Archetypes based on use type & building age.

Based on the building's use, building's age and condition described in columns Bldg_use, Bldg_age & Bldg_cond in Figure 8- LoD1 geometry model for the Central Business District of Ahmedabad with attribute table indicating essential semantic data derived from Property tax records. the attributes like construction/material assembly, schedules, system specifications etc are defined in an .idf file. The idf will be linked to the shapefiles using another python program. The usage schedules, occupant density, EPD & LPD are defined based on the building's use whereas the construction assembly is assigned based on Building condition- good, fair & basic which is derived from the building's age as shown below.

```
! AMD basic roof
Construction, basic_flat_roof,
    Ceramic glazed_0.01,                               !- .01m
    Tile Bedding_0.025,                                !- .025m
    Concrete cast - lightweight Moist_0.17,            !- .17m
    Cement/plaster/mortar - cement plaster_0.01;       !- .01m

! AMD good roof
Construction, good_flat_roof,
    Ceramic glazed_0.01,                               !- .01m
    Tile Bedding_0.025,                                !- .025m
    Concrete cast - lightweight Moist_0.17,            !- .17m
    Cement/plaster/mortar - cement plaster_0.01;       !- .01m

! AMD improved roof
    Construction, improved_flat_roof,
    Ceramic glazed_0.01,                               !- .01m
    Tile Bedding_0.025,                                !- .025m
    Concrete cast - lightweight Moist_0.17,            !- .17m
    Cement/plaster/mortar - cement plaster_0.01;       !- .01m

! AMD basic wall
Construction, basic_wall,
    Cement/plaster/mortar - cement plaster_0.018,      !- .018m
    Brick - burned_0.215,                              !- .215m
    Cement/plaster/mortar - cement plaster_0.018;      !- .018m

! AMD good wall
Construction, good_wall,
    Cement/plaster/mortar - cement plaster_0.018,      !- .018m
    Brick - burned_0.215,                              !- .215m
    Cement/plaster/mortar - cement plaster_0.018;      !- .018m

! AMD good wall
Construction, improved_wall,
    Cement/plaster/mortar - cement plaster_0.018,      !- .018m
    Brick - burned_0.215,                              !- .215m
    Cement/plaster/mortar - cement plaster_0.018;      !- .018m
```

Figure 10- Construction assemblies defined as per building's condition

```
! office occupancy updated

People,
    People Office,               !- Name
    Office,                      !- Zone or ZoneList Name
    Office_Occ,                  !- Number of People Schedule Name
    People/Area,                 !- Number of People Calculation Method
    ,                            !- Number of People
    0.111,                            !- People per Zone Floor Area {person/m2}
    ,                           !- Zone Floor Area per Person {m2/person}
    0.3,                         !- Fraction Radiant
    AutoCalculate,               !- Sensible Heat Fraction
    Activity Schedule 98779,     !- Activity Level Schedule Name
    0.0000000382,                !- Carbon Dioxide Generation Rate {m3/s-W}
    No,                          !- Enable ASHRAE 55 Comfort Warnings
    ZoneAveraged,                !- Mean Radiant Temperature Calculation Type
    ,                            !- Surface Name/Angle Factor List Name
    Work efficiency,             !- Work Efficiency Schedule Name
    ClothingInsulationSchedule,  !- Clothing Insulation Calculation Method
    ,                            !- Clothing Insulation Calculation Method Schedule Name
    Clothing Schedule 98779,     !- Clothing Insulation Schedule Name
    AirVelocitySchedule,         !- Air Velocity Schedule Name
    Fanger;                      !- Thermal Comfort Model 1 Type

People,
    People Ed,                 !- Name
    Ed,                        !- Zone or ZoneList Name
    Ed_Occ,                    !- Number of People Schedule Name
    Area/Person,                 !- Number of People Calculation Method
    ,                            !- Number of People
    ,                            !- People per Zone Floor Area {person/m2}
    3,                           !- Zone Floor Area per Person {m2/person}
    0.3,                         !- Fraction Radiant
    AutoCalculate,               !- Sensible Heat Fraction
    Activity Schedule 98779,     !- Activity Level Schedule Name
    0.0000000382,                !- Carbon Dioxide Generation Rate {m3/s-W}
    No,                          !- Enable ASHRAE 55 Comfort Warnings
    ZoneAveraged,                !- Mean Radiant Temperature Calculation Type
    ,                            !- Surface Name/Angle Factor List Name
    Work efficiency,             !- Work Efficiency Schedule Name
    ClothingInsulationSchedule,  !- Clothing Insulation Calculation Method
    ,                            !- Clothing Insulation Calculation Method Schedule Name
    Clothing Schedule 98779,     !- Clothing Insulation Schedule Name
    AirVelocitySchedule,         !- Air Velocity Schedule Name
```

Figure 9- Occupancy & other attributes defined by building use (office & education uses shown here)

3. Pre-processing the building shapefiles & creating idf for Building Islands

The shapefiles are processed to remove redundant edges, clean the shapes for intersection and generate clear volumes for energy simulations. This process creates Building Islands by combining attached buildings together and creates separate .idf files for each building island with their respective shading context. Glazing ratios (WWR) are also defined here.

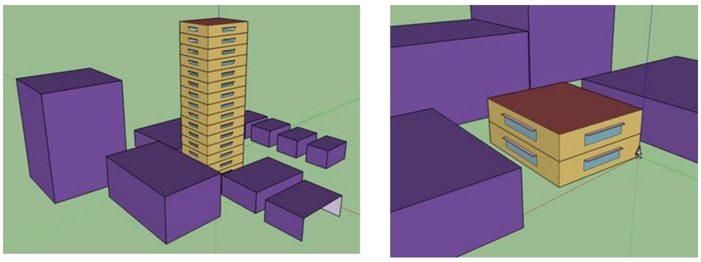


Figure 11- Building islands created as separate .idf files. Shading context is kept within an arbitrarily defined radius of 30m

4. Running the simulations in EnergyPlus

The idf created for each building island has been created with one zone per floor of the building. These multiple idfs are now batch-simulated using a library in python called eppy which is based on Energy plus. The results are reported as .html files for individual buildings and each zone's end use energy consumption in terms of cooling, lighting, equipment etc. can be extracted separately and be reported for comparison.

4. Results - Case study of Ahmedabad, Gujarat

The city of Ahmedabad is the largest city in the state of Gujarat. It has been one of the most important trade centres in western India and a major industrial and financial hub. Ahmedabad, at present, is divided into 6 zones which is further split into wards. There are, 64 wards in all. There are 1.86 million properties with 51.81 million m2 of commercial and 81.21 million m2 of residential floor space in Ahmedabad. 37.94 million m2 (26.91%) floor space are newer than 10 years & 33.67 (23.88%) million m2 older than 40 years. Electricity consumption in Ahmedabad in FY 2014-15 was 5165 million kWh and 2419 million kWh in commercial and residential sector respectively. Owing to this huge building stock and rapid development at a Compounded Annual Growth Rate (CAGR) of 3.18 for commercial & 3.61 in residential stock respectively, a robust planning through a UEM is required for achieving energy efficiency, analysing the impact of implementing different policies and tailor them to suit both the existing and the upcoming building stock. Thus, an attempt is made to understand the existing data and infrastructure available for Ahmedabad. Rawal et al., (2018) analysed the previously collected data by CEPT University & publicly available datasets.

4.1. Public Datasets in Ahmedabad

In Ahmedabad, Gujrat Development Control Regulations (GDCR) controls the development of the land use of a city. It provides details of development regulations including the FSI for the land depending on its typology. It also determines building height and plot margins depending on the road length and FSI. The town planning scheme is developed by Ahmedabad Urban Development Authority (AUDA). They develop Local Area Plan (LAP) for different wards in the city with detailed plot layouts with permissible land use. LAPs can be overlaid with GDCR & transit zone maps to extract buildings, roads & plots to determine building use & height. Individual property assessment data is collected by the Ahmedabad Municipal Corporation (AMC). It contains essential information about the property's address, use type, carpet area and year of construction all linked with a unique Tenement Number. Data regarding actual energy consumption can be obtained from the electricity bills. Torrent Power Distribution company (DISCOM) servers most of Ahmedabad's electricity requirement. The bill is issued bi-monthly & states the connected load & the units consumed every cycle in the previous year, thereby giving a complete year's energy consumption in a single bill. It is identified that the property's address & owners name can serve as a common key to link all the above data. In a previous effort by CEPT Geomatics Lab (2017) the administrative data along with satellite imagery was used to extract building footprints and develop a GIS database. The plot's details on its permissible use, FSI, setbacks & year of ownership were used to derive building use, footprint, building height & building age. The commercial building uses were further classified into 16 categories or archetypes and their characteristics were derived from baseline buildings described in ECBC 2017 & Rawal et al., (2018) predicted energy saving potential of various ECM scenarios. However, there are several challenges in this data extraction linking them in a GIS database and developing a UEM. There are several gaps and inaccuracies in this available dataset as identified by Rawal, Sharma, Poola, Ruyssevelt, & Fennell, (2019).

The major challenges identified were: -

1. The building footprints extracted didn't match the plot boundaries and overestimated building area by including projections like balconies, porch, temporary structures and unoccupied areas like lift/staircase cores, shafts & corridors.
2. Building heights were estimated based on maximum permissible FSI and not on the actual building as existing.
3. The Address on the tax assessment data was insufficient to locate the property on the GIS map for many properties

4. Archetype characteristics were assigned from literature studies due to lack of actual surveyed data for Ahmedabad.

5. Energy bills were inaccessible due to data privacy regulations. Only total energy sales in Ahmedabad was known from reports published by Torrent Power.

To overcome these challenges a robust action plan is required to collect, process and assimilate essential data for Ahmedabad to be able to develop a UEM. For this the data required for each intermediate LoD within these 13 model characteristics was compared with the existing Ahmedabad data and the additional efforts required for advancing to a higher LoD or a more granular approach. Table 7 shows in the columns 4,5&6 the data required; data available & additional efforts required respectively. Following this the most appropriate LoD for each of the 13 model characteristics is suggested and highlighted in the Table 7.

4.2. Comparison of Different LoDs through simulations

As discussed in Table 7, the LoDs highlighted can be developed with the available data for Ahmedabad city. In order to understand the impact of different LoDs on the model's simulation results, with respect to the simulation time a case study was conducted. A simulation exercise was carried on a 0.5 sqkm area of the Central Business District of Ahmedabad consisting of 250 buildings area to test the script and the methodology. The area consists of buildings of 6 primary uses i.e. 1) Residential, 2) Commercial offices, 3) Retail / Mixed use, 4) Education, 5) Hotels and 6) Healthcare. The 0.5sqkm area can be easily distinguished into three typical clusters of buildings, referred to as Zone A – Predominantly residential, Low-rise and High density of buildings, Zone B- Predominantly commercial area, High rise and high density and Zone C – Predominantly educational buildings, Mid-rise and low density. The aim of this simulation exercise was: -

1. Analyse the difference in energy consumption (EUI-kWh/m2) of Residential buildings with different urban clusters / zone, i.e. to study the impact of context building's heights and density and scale of the urban area.
2. Analyse the effective difference in EUI distribution in the residential buildings with change in LoD.
3. Find out a suitable trade-off between simulation time and closeness of results between different LOD combinations.

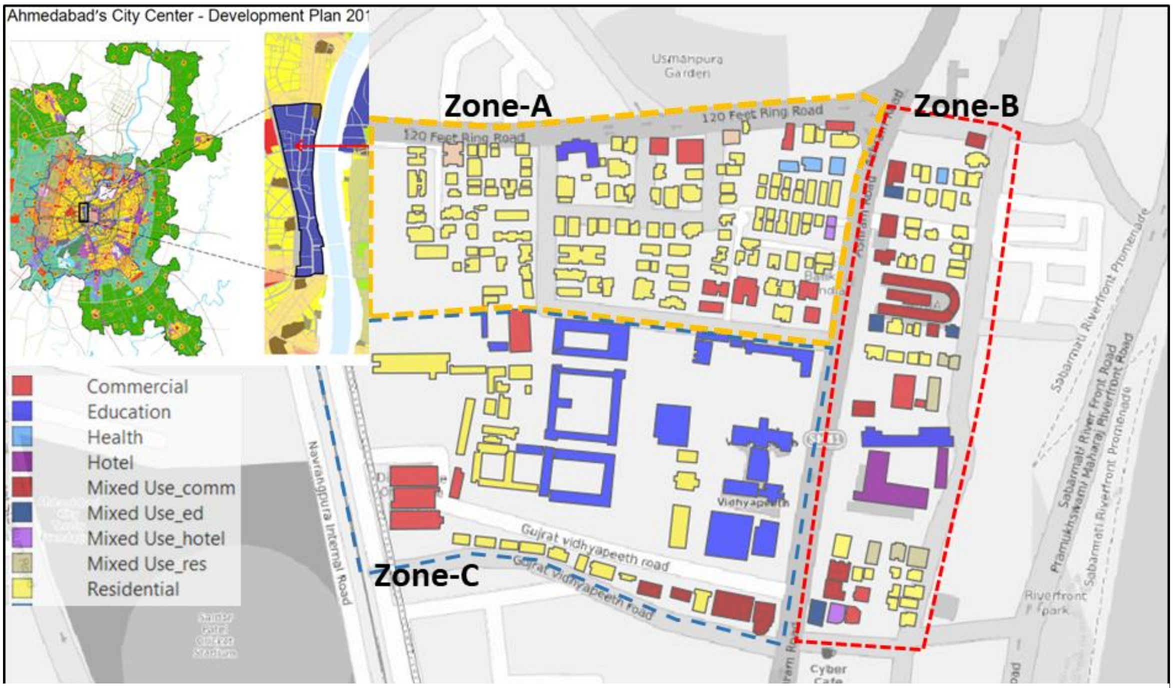


Figure 12- Selected site for UEM simulations. The site can be divided into 3 zones based on the urban fabric.

As a preliminary exercise only residential buildings in all these 3 zones are being studied, however other building types must also be studied on similar patterns.

4.3. Simulation iterations / combinations of different LoDs

For the exercise the following iterations / combinations of LoDs were studied in an incremental fashion from least to a higher granularity or Level of detail. All other LoD in the previous iterations were retained in the following iteration, and only one Characteristic was changed in every successive iteration. In this way it becomes intuitive as a sensitivity analysis of changing only characteristic while others are kept same.

OCCUPANCY	GEOMETRY	ZONING	ARCHETYPES	CLIMATE	CONTEXT	MUNICIPAL SERVICES	STOCK DYNAMICS	TEMPORAL RESOLUTION	TREATMENT OF UNCERTAINITY	FORM OF CALCULATION	CALIBERATION DATA
Deterministic- Single profile	LoD1	Zone / floor or use type	Multiple with use type/age/other characteristic	TMY	Context as shading	Not included	Snapshot	Annual	Deterministic	Dynamic	Annual calibration through reference EUI (literature)
Deterministic- Multiple profile	LoD1	Zone / floor or use type	Multiple with use type/age/other characteristic	TMY	Context as shading	Not included	Snapshot	Annual	Deterministic	Dynamic	Annual calibration through reference EUI (literature)
Deterministic- Multiple profile	LoD1	Zone / floor or use type	Multiple with use type/age/other characteristic	TMY	Context as shading	Not included	Snapshot	Annual	Deterministic	Dynamic	Annual calibration through reference EUI (literature)
Deterministic- Multiple profile	LoD1	Zone / floor or use type	Multiple with use type/age/other characteristic	TMY	Context as shading	Not included	Snapshot	Annual	Probablistic	Dynamic	Annual calibration through reference EUI (literature)

Table 1- Simulation iterations adopted

Comparison between single & multiple occupancy profiles. Occupancy patterns make a significant difference in the urban area's energy consumption. The occupancy patterns were modelled as

Iteration 1 (I1) - Single Profile – same schedule throughout the year &

Iteration 2 (I2) -Multiple Profile – Seasonal variation in the schedule. The effect of varying AC & Evaporative cooler schedule in Residential building stock was studied with the schedules as shown

	Annual
Natural Ventilation	6am-1pm & 5pm-11pm
Fans	ALWAYS ON (follows occupancy)
Evaporative cooling	OFF
Air Conditioning	**1pm – 4pm & 10pm-1am**

Table 2- Single profile HVAC schedule

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Natural Ventilation	REM	REM	REM	REM	REM	REM	REM	REM	REM	REM	REM	REM
Fans	ON	ON	ON	ON	ON	ON	ON	ON	ON	ON	ON	ON
Evaporative cooling	**12pm – 4pm & 10pm-6am**	**12pm – 4pm & 10pm-6am**	**12pm – 4pm & 10pm-6am**	**12pm – 4pm & 10pm-6am**							**12pm – 4pm & 10pm-6am**	**12pm – 4pm & 10pm-6am**
Air Conditioning				1pm – 4pm	1pm – 4pm & 10pm-1am	1pm – 4pm & 10pm-1am	1pm – 4pm & 10pm-1am	1pm – 4pm & 10pm-1am	1pm – 4pm & 10pm-1am	1pm – 4pm & 10pm-1am		

Table 4- Multi-profile HVAC schedule

Iteration 3 (I3) -Multiple Archetypes based on age – The building's construction templates were varied in according to three age groups. This impacted the thermal properties along with the infiltration rates.

Iteration 4 (I4) -Probabilistic treatment of uncertainty – The WWR were varied according to building's use type as shown: -

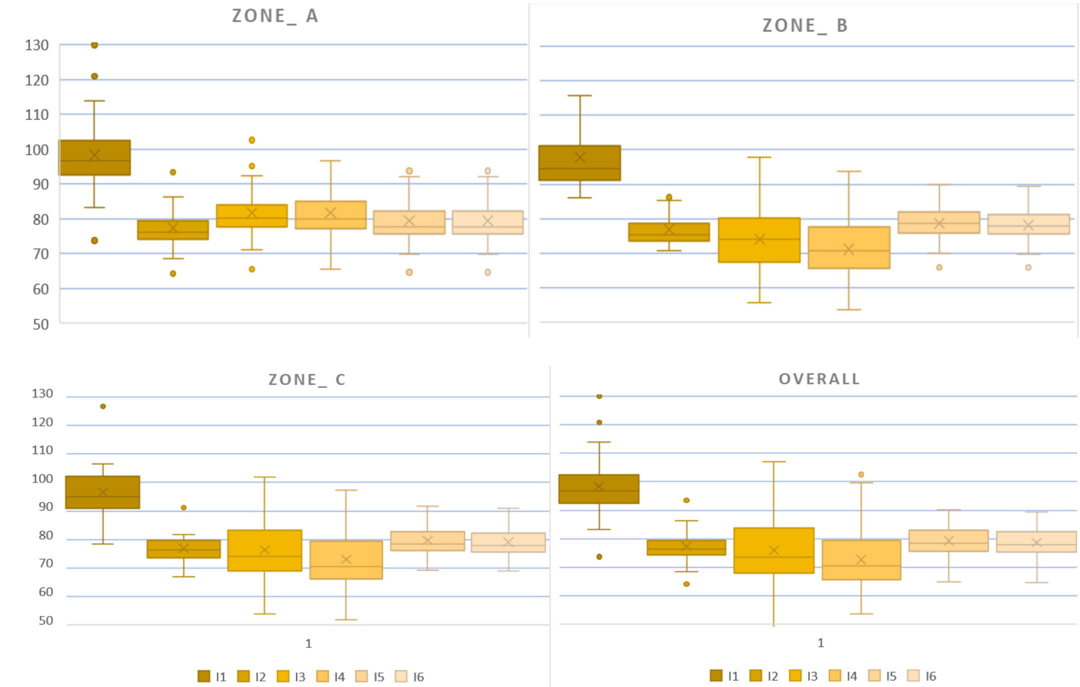
Table 6- Probabilistic WWR based on building types

Use Types	Deterministic WWR	Probabilistic WWR
Residential	20%	10-20% (interval of 10)
Commercial	60%	50-70% (interval of 10)
Others	30%	20-30% (interval of 10)

Iteration 5 & 6 (I5, I6) -Probabilistic treatment of uncertainty – Overhangs were added to the residential buildings at 0.3m depth in iteration 5 and then stochastically from 0.2-0.6m depth in iteration6.

4.4. Simulation observations

The results of the simulation were analysed in two levels. At first the EUI (kWh/m2) of all the buildings in different zones were compared with a reference EUI value derived from the study conducted by GBPN & CEPT (2014). The aim here was not to calibrate or to report model accuracy since one calibration value cannot be a representative of the diverse number of building, but for a sanity check of the simulation results. The results were studied Zone by Zone and then from overall area. The box plot shown in Figure 14 depicts the median values of EUI in Residential buildings for different zones and then combined.



Zone A data

		Iteration1		Iteration2		Iteration3		Iteration4		Iteration5		Iteration6	
	Measured	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference
Minimum	70	73.7	5.0%	64.2	-9.1%	65.4	-7.0%	65.4	-7.0%	64.9	-7.9%	64.6	-8.4%
Q1	70	92.5	24.3%	74.2	5.7%	77.7	9.9%	77.1	9.3%	76.0	7.9%	75.5	7.3%
Median	70	96.7	27.6%	76.1	8.0%	80.0	12.6%	79.8	12.3%	78.3	10.6%	77.6	9.8%
Q3	70	102.3	31.5%	79.3	11.7%	84.0	16.7%	84.9	17.5%	82.8	15.5%	82.0	14.6%
Maximum	70	179.8	61.1%	152.2	54.0%	158.4	55.8%	158.4	55.8%	156.9	55.4%	156.3	55.2%

Zone B data

		Iteration1		Iteration2		Iteration3		Iteration4		Iteration5		Iteration6	
	Measured	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference
Minimum	70	86.0	18.6%	70.8	1.1%	68.2	-2.7%	66.4	-5.4%	66.0	-6.1%	65.8	-6.4%
Q1	70	91.4	23.4%	73.6	4.8%	77.3	9.5%	77.1	9.2%	75.9	7.8%	75.5	7.2%
Median	70	94.5	26.0%	75.3	7.0%	79.3	11.7%	80.2	12.8%	78.5	10.9%	77.8	10.1%
Q3	70	100.7	30.5%	78.3	10.6%	82.8	15.5%	83.0	15.6%	81.3	13.9%	80.6	13.1%
Maximum	70	145.8	52.0%	87.4	19.9%	94.8	26.2%	92.0	23.9%	90.0	22.2%	89.3	21.6%

Zone C data

		Iteration1		Iteration2		Iteration3		Iteration4		Iteration5		Iteration6	
	Measured	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference
Minimum	70	78.4	10.7%	67.0	-4.5%	69.0	-1.5%	70.1	0.1%	69.1	-1.3%	69.0	-1.4%
Q1	70	91.0	23.0%	73.5	4.7%	77.0	9.1%	77.8	10.0%	76.2	8.2%	75.8	7.6%
Median	70	94.9	26.2%	76.4	8.4%	80.5	13.1%	80.2	12.7%	78.4	10.8%	77.8	10.0%
Q3	70	101.1	30.8%	79.4	11.8%	83.9	16.6%	83.9	16.6%	82.0	14.6%	81.5	14.2%
Maximum	70	126.7	44.7%	91.1	23.2%	99.6	29.7%	94.1	25.6%	91.7	23.7%	90.9	23.0%

Overall data

		Iteration1		Iteration2		Iteration3		Iteration4		Iteration5		Iteration6	
	Measured	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference	Value	% difference
Minimum	70	73.7	5.0%	64.2	-9.1%	65.4	-7.0%	65.4	-7.0%	64.9	-7.9%	64.6	-8.4%
Q1	70	92.5	24.3%	74.2	5.7%	77.7	9.9%	77.1	9.3%	76.0	7.9%	75.5	7.3%
Median	70	96.8	27.7%	76.2	8.2%	80.1	12.6%	79.9	12.4%	78.3	10.7%	77.7	10.0%
Q3	70	102.3	31.5%	79.3	11.7%	84.0	16.7%	84.9	17.5%	82.8	15.5%	82.0	14.6%
Maximum	70	179.8	61.1%	152.2	54.0%	158.4	55.8%	158.4	55.8%	156.9	55.4%	156.3	55.2%

Figure 14 - Simulation results comparing EUI values obtained from different iterations (I1 to I6) in different Zones

4.5. Kolmogrov-smirnov test for EUI (kwh/m2) distribution

The aim of the simulation exercise was to identify the effective difference between the simulation results from different LoDs adopted. Thus, the distribution of EUI values was studied as a measure of difference. The statistical test of normality, called the Kolmogrov-smirnov test was conducted to find the difference between the distributions. In this a null hypothesis is assumed that if the value of D, which is the maximum distance between two Cumulative Distribution functions is greater than D∞ (where ∞ is the level of acceptance) then the two distributions are considered different. The value of D as close to 0 will mean more similarity between the distributions. Since an Urban Energy Model can never be calibrated building by building it is more suitable to calibrate the distribution of EUI values or Total energy consumption between the simulated & the measured sample data. Thus, KS test will inform us for the given case study for Residential buildings the difference between two LODs and comparing this with simulation time will give us a trade-off between more effort and maximum similarity. Each iteration is compared to the succeeding one in this exercise

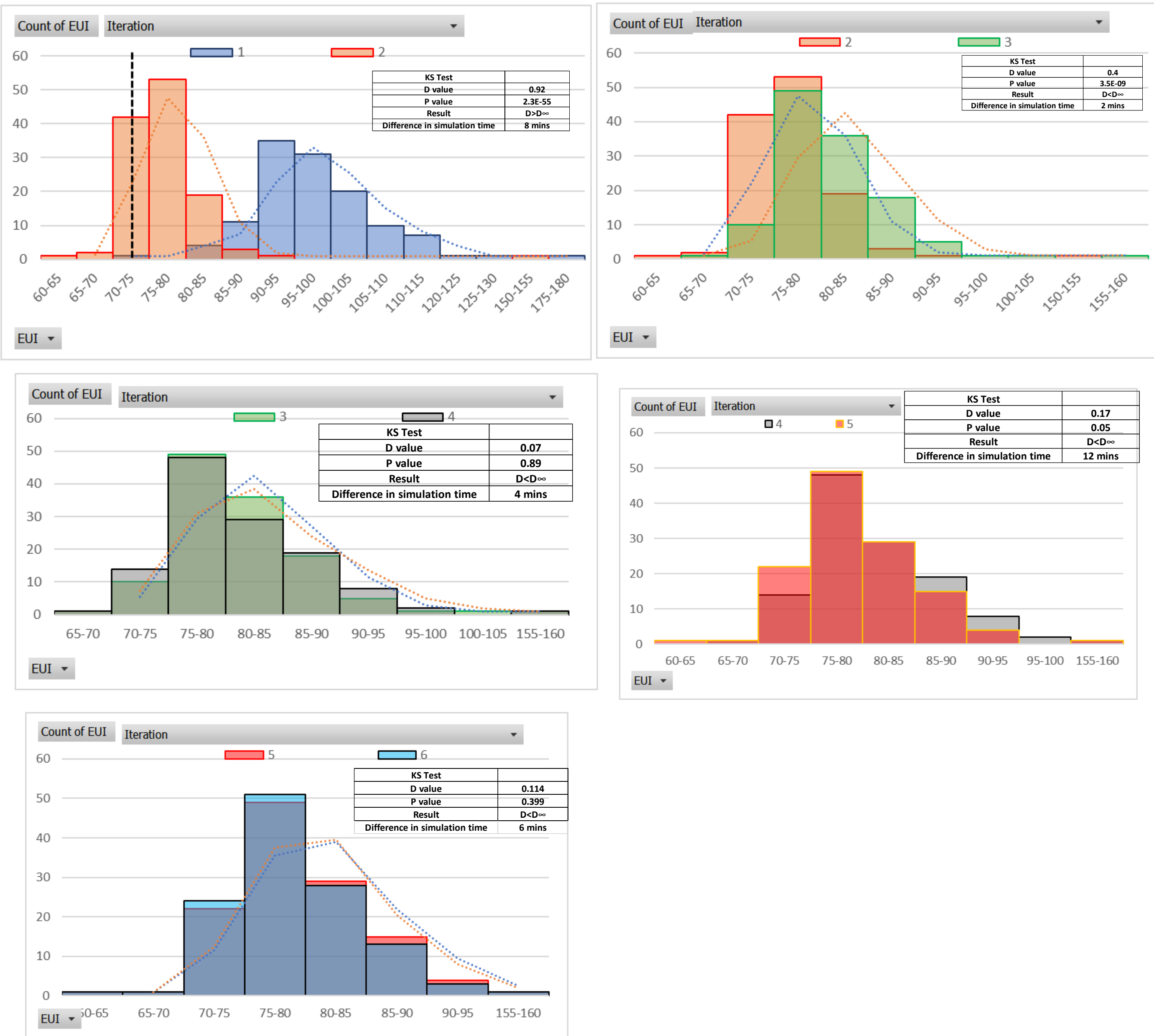


Figure 15 - KS Test for Zone 1 Residential buildings, comparing the EUI frequency

5. Conclusions

The simulation results from the 0.5 sqkm of site are indicate the following results: -

1. Impact of Multiple profile occupancy schedule is the on the EUI values. This is evident as the cooling energy consumption significantly increases upon considering the entire year to be operated on ACs which is very uncommon in Ahmedabad. The KS test shows that with an increment in 8 mins of simulation time the iteration 2 i.e. Multiple profile occupancy has a difference of D=0.92 from iteration 1 i.e. Single profile occupancy. Thus, both are significantly different, and Iteration 2 is closer depiction of the real scenario. Also, the median value of EUIs in this case is only 8% deviated from the benchmark EUI of 70kWh/m2.
2. The impact of other iterations is barely significant as there is not much difference in the distributions. Thus, for this exercise we can assume that keeping all characteristics at a coarser LOD but only detailing the occupancy schedules we are getting more accurate and reliable results.
3. It is also observed that combining the results from the three zones tend to average out the EUI values and is not a very reliable method. The understanding here is that while performing simulations on the city scale, urban areas of similar use types, density and urban fabric must only be grouped together, leaving out significantly different urban areas in a different group.
4. This exercise is limited to a small area and only residential buildings thus no statement can be made on the methodology or LoD combination most suitable for the entire city, however similar studies for other use types can help inform the most significant model characteristics and thereby moving towards a trade-off between higher accuracy and higher modelling effort.

To summarise on the data collection protocol, Table 7 in the Appendix lists the most feasible LoD of each characteristic that can be adopted for Ahmedabad with the available data. Thus, a pilot study is proposed to develop a UEM for the 0.25 km2 of the Central Business District to develop an action plan for the entire city. The errors in the existing GIS database are rectified manually following walkthrough surveys as shown in 5.4. The shapefiles for LoD1 geometry model created in ArcGIS were associated with the attributes like building use, age & height which are used for assigning archetypes and generating energy models.

The archetypes are defined in section 5.5 with by grouping buildings into 10 use types like Residential, Commercial retail & business, Mixed use etc. originated from the GDCR and 3 construction periods. The building use determines the occupancy patterns, equipment, lighting, process and HVAC loads. The building's age determines its condition as good, fair & poor which is used to assign envelop construction details and type of mechanical systems. The details for developing these archetypes are derived from literature study. Owing to a lack of calibration data the validity of the results from this UEM is not validated. Thus, the model characterization framework will guide in assigning resources to the most important data required & help formulating an action plan.

Future course of action

Analysing the existing dataset for Ahmedabad through the Intermediate LoDs, it is understood that there is a lack of data for defining archetype properties and actual energy data for calibrating & validating the model results. To collect this data two kinds of survey forms and protocols are developed as shown in section 5.6, the link to online survey form is also shared for looking into the details. The first survey is performed to collect calibration data. It is a voluntary, crowd sourced data collection form which allows respondents to mark their property on Google maps and share information like their address, property type, pictures of electricity and property tax bills. This survey will help enrich the GIS model linking the building's details with its location and provide enough data for calibrating the UEM and validating the results. Through this survey respondents are also asked to give their consent for a detailed survey which will be used to develop the Archetypes. This form is developed through the recommendations suggested by Iyer et al., (2017).

For Archetypes shown in section 5.5 the 10 building uses as per GDCR are expanded into 27 detailed use-types and 5 construction periods thereby leading to 135 Archetypes. Based on the properties in each archetype a suitable number of sample sets will be determined. This survey will collect details on occupancy patterns, envelop details, operation schedules, equipment, lighting, HVAC & process loads and specifications. Rawal et al., (2019) suggests a Photogrammetric survey using a UAV to collect accurate geometrical data for Ahmedabad. However, before proceeding with elaborate surveys, the model accuracy will be evaluated after the data collected from the above-mentioned surveys & following the process shown in Figure 16 - Framework for Data input and model generation for Ahmedabad. The potential application of a UEM is enormous for optimizing future cities. The intermediate LoDs proposed can be refined further into a global standard framework for developing UEMs and would be especially useful for developing nations like India.

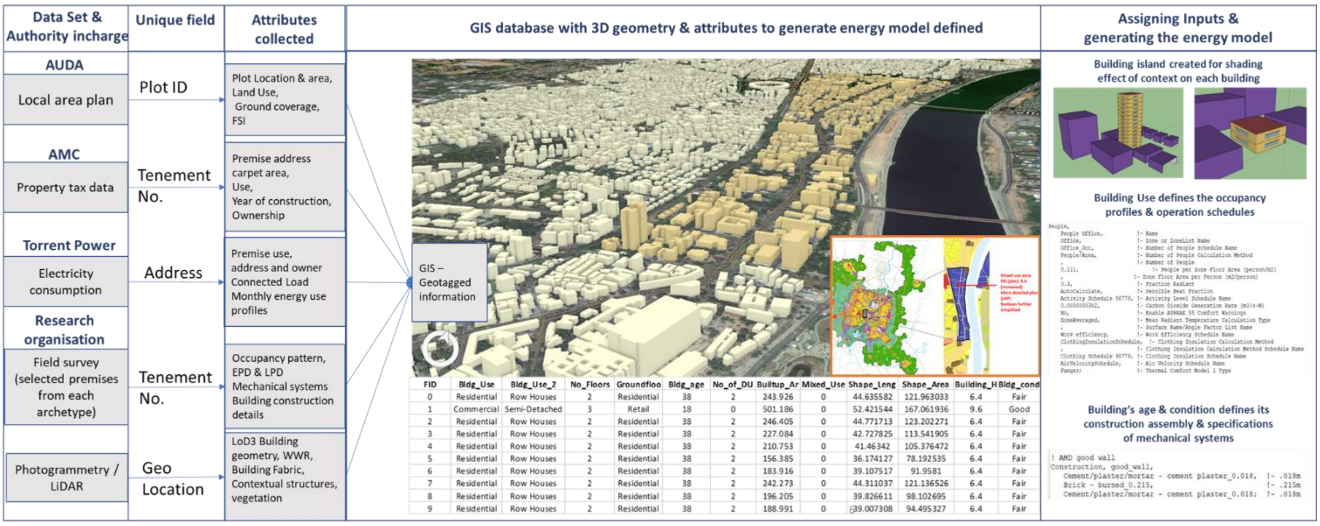


Figure 16 - Framework for Data input and model generation for Ahmedabad

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5. Appendix

Table 7 Model Characterization framework of intermediate LoDs with suitable approaches highlighted for Ahmedabad

Layer	Characteristic	LoD	Nubmer. of projects & e.g.-(Title)	Data required	Data available for Ahmedabad	Additional efforts required for collecting data
User	1. Occupancy	Deterministic Single profile	**9 –** e.g. (Berthou et al. 2019; Cerezo Davila et al. 2016; T. (LBNL) Hong et al. 2016)	Typical occupancy patterns without any variations. Derived from literature or surveys of typical buildings.	Schedules for Indian commercial buildings are defined in **ECBC 2017** based on sample surveys. (literature)	Conducting field surveys for occupant behaviour of a typical building from each Archetype in Ahmedabad. Details like occupant density, hours of operation should be noted. Collected building-vise or space-vise to generate single or multi profile respectively.
		Deterministic Multi profile	**17-** (Krayem et al. 2019; Nagpal, Hanson, and Reinhart 2018)	Occupancy patterns for different uses / spaces / days of the year – fixed / deterministic schedules.	**ECBC 2017** schedules are available for different spaces in commercial buildings.	
		Probabilistic	**6-** (Cerezo et al. 2017; Cerezo Davila et al. 2017; Sokol et al. 2017)	Occupancy patterns for many similar buildings to account for variations and probability of occurrence.		Surveys for large sample set from each Archetype to account for a range of schedules.
		Agent Based	**4-** (Barbour et al. 2019; Happle et al. 2018)	Mapping Occupant's daily activities to account for their unique behaviour & interaction.		Mapping individual occupant movement for daily activities like travel routes & times from place of work to residence etc.
Building	2. Geometry	2.5D extrusion	**15-** (Cerezo Davila et al. 2016; T. (LBNL) Hong et al. 2016)	GIS data (.shp/.gdb) of Building footprint and height / Number. of floors	**CEPT Geomatics lab's** GIS data from satellite imagery & Town planning scheme.	Rawal et al. (2019) propose a **photogrammetry model for Ahmedabad using a UAV.** The challenge lies in geometry extraction i.e footprint for LoD1 & wireframe mesh for LoD2&3 from the reality mesh model. Owing a dense & organic urban morphology of the city this requires ML algorithms & extensive training data.
		3D model	**3-** (Kaden and Kolbe 2014; Nouvel et al. 2017)	LiDAR/Photogrammetry model for the buildings in the city. Detailed architecture drawings / as built drawings submitted to the ULB for sanction.		
		3D with external features	**1-** (Saretta, et.al 2020)			
		3D with Detailed interior Layout	**0**	Location & size of each property along with its interior layout along with the above data.	**AMC's** database of properties with their address, use-type, area & Unique ID.	Address matching from AMCs database. Extensive field survey of the buildings to mark their interior layout.
	3. Zoning	Single zone / building	**10-** (Hong et al. 2016; Robinson et al. 2009)	Use type of the building to assign the zone properties	**Ahmedabad GIS data** contains building use. No. of floors & use type on each floor.	Field survey required to assure validity of this data. Accounting for modifications in the building use and addition of floors if any.
		Zone / floor or use	**16-** (Cerezo et al. 2017)	No. of floors & their uses individually		
		Detailed internal zoning	**1-** (Evans, et.al 2017)	Detailed interior layout		
	4. Archetypes	Single	**3-** (Cerezo et al. 2017; Sokol et al. 2017)	Building envelope, HVAC systems equipment &, lighting for typical use type building. Operational schedules are assigned as per building use and construction details as per building age / condition.	Building use classified as per **AMC** can be used.	A **survey methodology & protocol has been proposed** by the researchers to effectively collect details on building construction, equipment, lighting, HVAC & other necessary attributes.
		Multiple with Use type / age / other attributes	**16-** (Berthou et al. 2019; Robinson et al. 2009)		Detailed classification of 39 use types and 5 construction periods as per GDCR can be used.	
		Multiple with Use type x age	**8-** (Cerezo Davila et al. 2016)			

Environment	**5. Climate**	Steady state	**8 –** e.g. (Gupta 2009)	Long range average weather data	Hourly data collected from weather station at the airport.	
		TMY	**20-** (Rawal et.al 2019)	Weather data from nearest weather station		
		Microclimate	**4-** (Cerezo Davila et al. 2017)	Local weather station		Install local weather station and monitor data for a year.
	6. Context	Volumetric	**9-** (CEPT 2015)	No contextual data		
		Context shading	**12-** (Cerezo et al. 2016)	At least LoD1 geometry	GIS data of CEPT Geomatics Lab	Photogrammetry model.
		Trees shading	**0**	Location & details like tree type, crown size, height, transmissivity, leaf density		Photogrammetry model. Images can be processed to determine physical attributes of the trees.
		Detailed with mutual interactions	**3-** (Katal, Mortezazadeh, and Wang 2019)	Co-simulation to exchange weather, radiation, loads & other impacts		Details of building envelop, landscape & hardscape materials (road, pavers etc).

	7. Municipal Services	Not included	**20-**	Not required		
		Included without spatial mapping	**2-** (Pasichnyi et al. 2019; Remmen et al. 2018)	Details for services like electricity grids, sewage, water supply, mass transit		Collaboration with ULBs like AUDA & AMC, and service providers like Torrent power for electricity. Data for consumption, generation & transmission of the services
		With spatial mapping	**0**	Location & transmission network of these services		
Methodology	**8. Form of Calculation**	Reduced order	**17-** (Remmen et al. 2018; Robinson et al. 2009)	Standard calculation methods & normative equations.		Measured electricity data is required for a large number of buildings to establish correlation and normative equations.
		Scaled dynamic	**7 -** (Bhatnagar et al. 2017; Rawal et al. 2019)	Total floorspace & archetype data	Total commercial & residential building stock area.	To develop more archetypes, a bifurcation of the building stock is required.
		Shoebox	**2-** (Dogan et al. 2017)	Algorithm to create representative zones	UMI (Urban modelling interface) can be used.	
		Dynamic	**20-**(T. Hong et al. 2016)	Energy model of the urban area of interest	GIS data can be used	
	9. Treatment of Uncertainty	Deterministic	**20-** (Krayem et al. 2019)	At least one sample from each archetype		A **survey methodology & protocol has been proposed** by the researchers to effectively collect details on building construction, equipment, lighting, HVAC & other necessary attributes.
		Probabilistic	**4-** (Cerezo Davila et al. 2017)	Multiple samples from each archetype		
		Bayesian	**2-** (Cerezo et al. 2017)	Bayesian algorithm & calibration data along with requirements above		
	10. Temporal resolution	Annual	**16-** (Berthou et al. 2019; Hong et al. 2016)	Require actual metered data of equal granularity for validation of results	Benchmark EUI values collected in ECO III & IIM-Ahmedabad project.	Data in electricity bills (collected through surveys) or given by Torrent power for sample buildings to calibrate the model.
		Monthly/Bi-monthly	**2-** (Krayem et al. 2019; Robinson et al. 2009)			
		Daily/Hourly	**0**			Smart metering for real time data.
	11. Stock Dynamics	Snapshot	**20-** (Rawal et al. 2019)	Building stock at a given point in time	CEPT GIS data for current building stock	
		Time series	**0**	Historic evolution of building stock at annual or decadal level.	Historic data on building stock & Future development plans from town planning schemes.	Data incomplete or lacks validity. Needs more literature review.
		Dynamic	**0**	Real time Evolution of Building stock.		Monitoring of changes in building stock at shorter time intervals.

5.2. Appendix 1 - Structure of Literature review

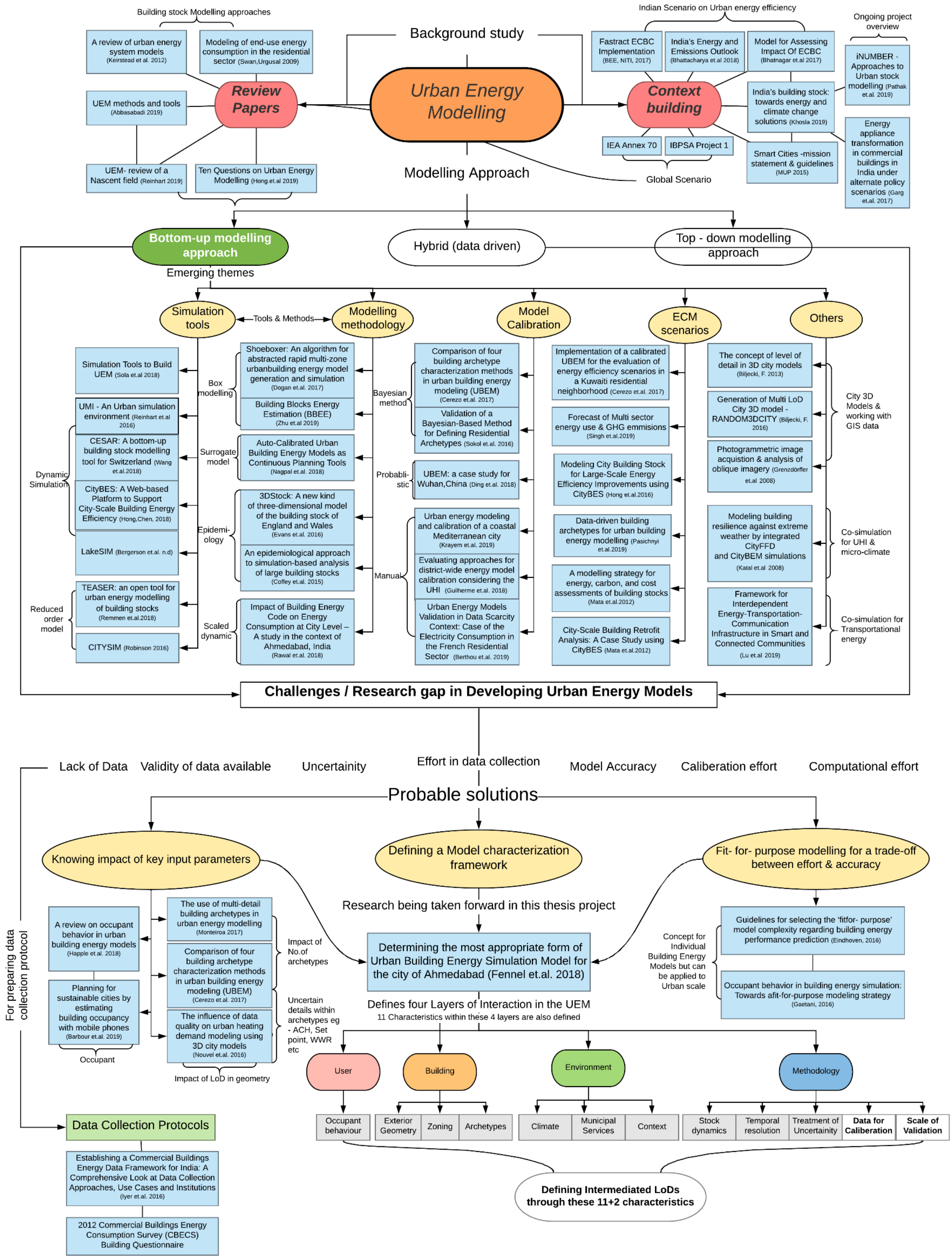


Figure 17- Structure of literature review

5.3. Appendix 2 – Classification of existing UEM projects

LoD 0 LoD 1 LoD 2 LoD 3 LoD 4

Model Characteristic framework

OCCUPANCY	GEOMETRY	ZONING	ARCHETYPES	CLIMATE	CONTEXT	TEMPORAL RESOLUTION	TREATMENT OF UNCERTAINITY	FORM OF CALCULATION	CALIBRATION LEVEL	MUNICIPAL SERVICES	STOCK DYNAMICS	**No. of buildings**	**Percentage Error**	**Data Available**	**Use of UEM**
0	1	1	2	1	1	0	0	3	0	0	0	83,541	40%	All three	Energy benchmark
0	1	1	0	2	1	0	0	3	1	0	0	336	16%	All three	Retrofit
0	1	1	2	2	1	0	0	3	1	0	0	336	4%	All three	Retrofit
2	1	1	2	2	1	0	1	3	1	0	0	336	4%	All three	Retrofit
2	1	1	2	2	1	0	2	3	1	0	0	336	1%	All three	Retrofit
2	2	0	1	1	1	0	0	3	1	0	0	7400	Null	Public & survey	Energy benchmark
2	2	1	1	1	1	1	0	3	3	1	0	7400	Null	Public & survey	District energy
1	0	1	1	1	0	0	0	1	1	0	0	4000	7.80%	Literature & public	Energy benchmark
0	2	1	2	1	1	0	0	1	0	0	0	7050	60%	Public	Retrofit
1	1	0	1	1	1	0	0	3	0	0	0	540	Null	Public	Retrofit
1	1	2	2	1	1	0	0	3	0	0	0	940	10%	Literature & public	Retrofit
2	0	2	1	1	0	0	1	1	0	0	0	351	7%	Literature & public	Energy benchmark
0	1	1	2	1	1	1	0	3	2	0	0	3630	Null	All three	Energy benchmark
1	1	1	2	1	1	0	0	3	0	0	0	3145	40%	Literature & public	Energy benchmark
1	1	2	1	1	1	0	0	3	1	0	0	100	Null	Public & survey	Energy benchmark
1	0	2	1	1	0	0	0	1	1	0	0	100	Null	Public & survey	Energy benchmark
0	1	0	1	1	1	0	0	3	0	0	0	8600	37.30%	All three	Energy benchmark
0	2	0	1	1	1	0	0	3	0	0	0	8600	30%	All three	Energy benchmark
0	2	0	1	1	1	0	1	3	1	0	0	28	17%	All three	Energy benchmark
0	2	0	1	2	1	0	0	3	1	0	0	28	10%	All three	Energy benchmark
0	1	1	0	1	1	0	0	3	1	0	0	339	47%	Literature	Energy benchmark
0	1	1	1	1	1	0	0	3	1	0	0	339	27.70%	Literature & public	Energy benchmark
0	1	0	2	1	1	0	2	3	1	0	0	339	12.30%	All three	Energy benchmark
0	1	0	2	1	1	1	2	3	2	0	0	339	19.40%	All three	Energy benchmark
0	2	2	2	1	0	0	0	2	0	0	0	8	6%	Literature	Energy benchmark
0	2	2	2	1	0	0	0	2	0	0	0	8	3%	Literature	Energy benchmark
0	2	2	2	1	0	0	0	2	0	0	0	8	1%	Literature	Energy benchmark
0	1	1	2	1	1	0	0	3	1	0	0	940	1.30%	All three	Energy benchmark
0	1	2	2	1	1	0	0	3	1	0	0	940	0.10%	All three	Energy benchmark
0	0	2	2	1	0	0	0	1	1	0	0	940	3.60%	All three	Energy benchmark
0	1	2	1	1	1	0	0	2	0	0	0	121	3%	Literature & public	Future scenario
0	1	1	1	1	0	0	0	3	0	0	0	20	20%	Literature	Energy benchmark
0	1	1	1	1	1	0	0	3	0	0	0	20	15%	Literature	Energy benchmark
0	1	1	1	2	2	0	0	3	0	0	0	20	9%	Literature	Energy benchmark
0	1	0	2	1	0	0	0	1	0	0	0	6	17.00%	Literature & public	Energy benchmark
0	1	0	2	1	0	0	0	1	0	0	0	6	26%	Literature & public	Energy benchmark
0	2	0	2	1	0	0	0	1	0	0	0	6	6%	Literature & public	Energy benchmark
0	1	0	2	1	1	0	0	3	1	0	0	2237	24.50%	Literature & public	Energy benchmark
0	1	0	1	1	1	0	0	0	0	0	0	123	Null	Public & survey	Energy benchmark
0	2	0	1	1	2	1	0	0	0	0	0	26	Null	Public & survey	Energy benchmark
0	2	0	1	1	2	1	1	0	0	0	0	26	Null	All three	Retrofit
0	2	0	0	1	1	0	0	0	1	0	0	1	5.10%	All three	Energy benchmark
0	1	0	1	1	1	1	1	0	2	0	0	6200	Null	All three	Retrofit
0	1	0	0	1	1	0	0	3	0	0	0	410	Null	Literature & public	Energy benchmark
1	0	3	2	2	0	1	0	1	2	0	0	659	Null	Literature & public	Future scenario
0	1	1	1	1	1	0	0	3	0	0	0	30	Null	Literature & public	Energy benchmark
0	1	0	1	1	0	0	0	0	1	0	0	17	9.80%	Literature & survey	Energy benchmark
2	1	1	1	1	1	0	1	3	1	0	0	78	1.05%	Literature & public	Energy benchmark
2	1	1	1	1	1	0	1	3	1	0	0	441	1.05%	Literature & public	Retrofit
2	1	1	1	1	1	0	1	3	1	0	1	441	Null	Literature & public	Future scenario
0	2	0	0	1	1	0	0	3	0	0	0	5600	Null	Literature & public	Energy benchmark
1	1	3	2	2	1	2	0	0	0	0	0	24	Null	Literature & public	Energy benchmark
1	1	1	2	2	1	2	0	0	3	0	1	200	5.60%	Literature & public	Future scenario
1	2	1	1	1	1	0	0	0	3	0	0	2866	Null	Literature & public	Energy benchmark
1	1	1	1	2	1	0	0	3	1	0	0	172	16%	All three	Energy benchmark
2	1	1	1	2	1	0	2	3	1	0	0	172	4%	All three	Energy benchmark
0	2	0	1	1	2	0	0	0	0	1	0	40	Null	All three	Energy benchmark
0	2	0	1	1	2	0	0	0	0	1	0	40	Null	All three	Energy benchmark
1	0	0	0	1	0	0	0	0	0	0	0	12241	Null	All three	Retrofit
1	1	0	2	1	2	0	0	0	0	1	2	1392	22.50%	All three	Retrofit
2	2	2	1	1	1	0	0	3	1	0	0	7184	Null	All three	Energy benchmark
1	0	0	1	0	0	0	0	0	0	0	0	318	Null	All three	Energy benchmark
1	0	0	1	0	0	0	0	0	0	0	0	NA	Null	All three	Energy benchmark
0	1	0	1	0	0	0	0	0	0	0	0	NA	Null	All three	Energy benchmark
1	0	0	1	0	0	0	0	0	0	0	0	NA	Null	All three	Energy benchmark
1	1	0	2	1	2	0	0	0	0	2	0	26	33%	All three	Energy benchmark
1	1	0	2	1	2	0	0	0	0	2	0	26	33%	All three	Retrofit
1	1	0	2	1	2	0	0	0	0	2	0	26	33%	All three	District energy
0	1	0	2	2	0	0	0	1	1	0	0	NA	9.80%	All three	Energy benchmark
1	1	2	2	2	0	0	2	0	1	0	0	100	2%	All three	Energy benchmark
0	1	2	2	1	1	0	0	0	1	0	0	22	Null	All three	Energy benchmark
1	2	3	2	1	1	0	0	1	0	0	0	750	16%	Literature & public	Energy benchmark
2	2	3	2	1	1	0	0	1	0	0	0	751	2%	Literature & public	Energy benchmark
2	2	3	2	1	1	0	1	1	0	0	0	752	0	Literature & public	Energy benchmark
0	0	0	1	2	2	0	0	3	0	0	0	9	Null	Literature	Energy benchmark
0	1	0	1	1	2	0	0	0	1	1	0	45000	23%	Literature & public	Energy benchmark
0	1	1	1	1	1	0	0	2	0	0	0	150	Null	Literature & public	Energy benchmark
1	1	0	2	1	1	0	2	0	1	0	0	2178	8.30%	Literature & public	Energy benchmark
1	1	0	2	1	1	0	0	0	1	0	0	2178	25.00%	Literature & public	Energy benchmark
2	1	1	2	1	1	0	1	3	0	0	0	143	Null	All three	Energy benchmark
0	1	1	1	2	2	0	0	3	0	0	0	20	9%	Literature	Energy benchmark
2	0	2	2	1	0	1	1	1	2	0	0	5400	5%	Literature & public	Energy benchmark
0	0	2	2	1	0	0	0	1	0	0	0	NA	4%	Literature & public	Retrofit
0	1	0	2	1	2	0	0	3	0	0	0	100	Null	All three	Energy benchmark
0	0	2	1	1	0	0	0	1	0	0	1	NA	Null	Literature & public	Future scenario

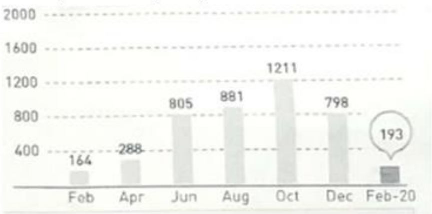
5.4. Appendix 3 – Calibration Data

Benchmark studies

Typology	Source	Granularity of data
Residential	1. ECO -3 Load research for residential & commercial establishments in Gujrat	Annual Profiles, Average EUI , Lighting cooling & equipment data
	2. GBPN -RESIDENTIAL BUILDINGS IN INDIA: ENERGY USE PROJECTIONS AND SAVINGS POTENTIALS	
Commercial	1. ECO -3	
	Energy appliance transformation in commercial buildings in India	Hourly profile for surveyed buildings
	BEE Benchmark EUIs	Annaul
Hotels	CBERD - Exploratory Data Analysis of Indian Hotel Benchmarking Dataset: Key Findings and Recommendations	Annual Data

Energy bill data

- Sample consumption pattern



Typology	Connected load range (kw)	Average Annual consumption (kWh)
Flats (2-3BHK)	6 - 4	7000 -4000
Flats (1BHK)	3-2	3500
Individual bungalow	10- 14	10,000

Walkthrough survey

Data Discrepancy

- Building ID:928 (Under Construction)
  - Survey: Mixed, G+20
  - Taxation data: Residential,G+1
- Building ID:936
  - Survey: Front portion of the building was G+1 whereas Back portion of building was G+2
  - Taxation data: G+1
- Building ID:942
  - Survey:G+2
  - Taxation data: G+1
- Building ID:930
  - Survey:G+4
  - Taxation data: G+1

Material

NEW CONSTRUCTION (Commercial

AAC block, Tinted glazing, Stone Cladding

OLD CONSTRUCTION

BRICK Masonry

5.5. Archetypes developed for Ahmedabad based on GDCR

	Main Type	Sub-Categorgy	Given name	Eg.
1	Residential	**Dwelling-1**	Detached / semi	Plotted house, detached homes,row houses
		Dwelling-2	Apartment (affordable middle class)	multistoried (1-2-3bhk affordable/middle class)
		Dwelling-3	Apartment II (Luxury)	High end apartment residences with luxurious amenities
		Dwelling-4	Shared housing	Non AC hostels, dharamshala, informal settlement, slums
2	Commercial-mercentile	**Mercentile 1**	Small retail stores & service establishments	grocery, barber, stationery, chemist, optician, garments eg- daily needs, small eating joints mechanic, laptop/mobile repair
		Mercentile 2	Shopping mall -large retails stores, display showrooms,	Jewelery, watch, garments, electronics, hyper markets
		Mercentile 3	Restaurants	Fine dining, food courts, cafes etc.
3	Commercial-business	**Business-1**	Offices with regular business hours	Private / public offices, consultants, corporate offices, coaching centres, tuitions, etc
		Business -2	Round the clock offices, call centres, customer care, IT, data centres	Private / public offices, consultants, corporate offices
4	Educational / institutional	**Educational-1**	Preschools, Primary Schools, Secondary Schools, Higher Secondary Schools,	
		Educational-2	College, Polytechnic, University, research labs	
5	Hospitality	**Hospitality-1**	No star hotel, motels, guest houses bed & breakfast	
		Hospitality-2	Premium hotels 4,5,7 star hotels with luxurious facilities	
6	Healthcare	**Health 1**	Primary Health Care, clinic, pathlab, dentist, dispensary	
		Health 2	Single speciality,	Indoor Hospital up to 20 Bed, Surgical Hospital, Nursing Home
		Health 3	Super Speciality, multi speciality	Civil Hospital, Medical College and Research Centre, Hospital of more than 20 Bed,

7	Industrial	**Industrial 1**	Small scale - Workshops, Repair facilities Storage & warehouse & MSMEs	Auto Repair ,Workshop, Wood Workshop, Fabrication, WORKSHOP, Public-Garage All type of Light, Service Industries, Small Factories, Warehouses, Newspaper Printing Press, Concrete Batching Plant, stone cutting and polishing; Poultry Farm, Dairy, Assembly Plant
		Industrial 2	All industries except obnoxious & hazardous materials	Junk Yard, Textile units, Ice Factory, Quarrying of Stone, Quarrying of Gravel , Quarrying of Clay, Dumping of Solid Waste, Steel re-rolling, Metal Manufacturing/sorting etc.,Oil Processing/ Storage
		Industrial 3	Obnoxious & Hazardous industry	Fuel Storage, Storage of inflammable materials, Thermal Power Plant, Power Plant, Gas Plant, Storage of Hazardous Materials, Obnoxious and Hazardous Industries, Chemical Industries, Obnoxious and Hazardous Uses, Dying House
8	Assembly / large gathering	**Assembly 1**	Courts, Government assembly, Community hall, banquet halls, marriage halls, town hall, open air event grounds, festival grounds, religious buildings, monuments	
		Assembly 2	Convention Center, Exhibition Hall, Auditorium, Movie hall, Planetarium, Museum, Large marriage halls,	
		Assembly 3	Stadiums, Indoor sports, gym etc.	
9	Public Utitiy	**PU1**	Transportationn eg- Airport, Bus terminal, Railway station	
		PU2	Other utilities - Petrol pump, Electricity substation, etc)	
10	Mixed Use	**Mixed Use 1**	Residential + Commercial retail / commerical business	Only need to be surveyed for which use is on which floor, normalize values as per percentage of use type
		Mixed Use 2	Commercial business + commercial retail	
		Mixed Use 3	Commercial business + commercial retail + Hospitality	

5.6. Survey Methodology for data collection

Survey collection plan- Survey for Calibration data

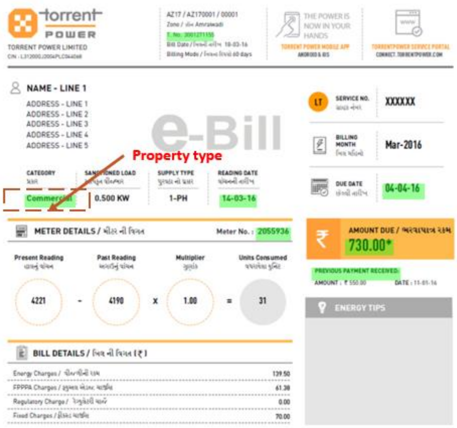
Link to view survey: - *https://forms.gle/tJXGMZqntatvuDzbA*

- **Survey type1- Voluntary responses to a google form for uploading electricity bills – Helpful for Calibration of model**

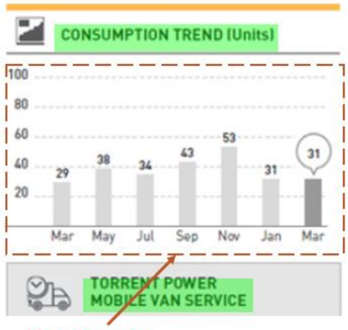
This survey will be circulated through as many means as possible to as many people in Ahmedabad. It asks people if they are interested in & give their consent in getting a detailed energy survey of their property.

The survey will ask them to share a photo of energy bills, water bill & property tax bill / tenement no.

We will also ask respondents to give their consent for a detailed survey (Survey for Archetypes) If they agree we will perform a detailed survey at their building



Front page



Bi-monthly trend to match profile & Total Energy consumption in the last year

Back side – most important

Impt information extracted from Tenement No.

Assessment Book for 2019-20

Tenement Number : 05180903810002I

The tenement number is the 15 digits number of the following format : 012345678900001T

Search

Tenement Details

Tenement Number	: 05180903810002I
Occupier Name	: KIRITBHAI MANILAL BABU .
Owner Name 1	: SEC SARDAR PATEL COLONY CO OP HOU SOC LTD
Owner Name 2	: KIRIT MANILAL BABU ASHA KIRIT BABU GITA RAJNIKANT BABU
Owner Name 3	: MILONI KIRIT BABU
Owner Name 4	: NIKSHU CHETANKUMAR SHINDHVAN
Address	: 73, SARDAR PATEL COLONY NAVJIVAN , AHMEDABAD-380014 , Pincode-0
Property Status	: Active

Detailed Property type & Building Age For assigning Archetype

Property Tax Calculation for Tenement Number : 05180903810002I

Survey Number	Census Number	TP Number	FP Number
00143-142/1-2-3	153	152/1-2152	-

Factor	Description	Rate
Type of Property	Residential	16.00
Building Type	Tenement	1.00
Type of Occupancy	Self	1.00
Location Factor	Very Prosperous (30000)	1.60
Government Building	No	-
Water Zone	Yes	-
Building Age	67 Years	-
Construction Year	1952	-
Age Factor Rate	-	0.50

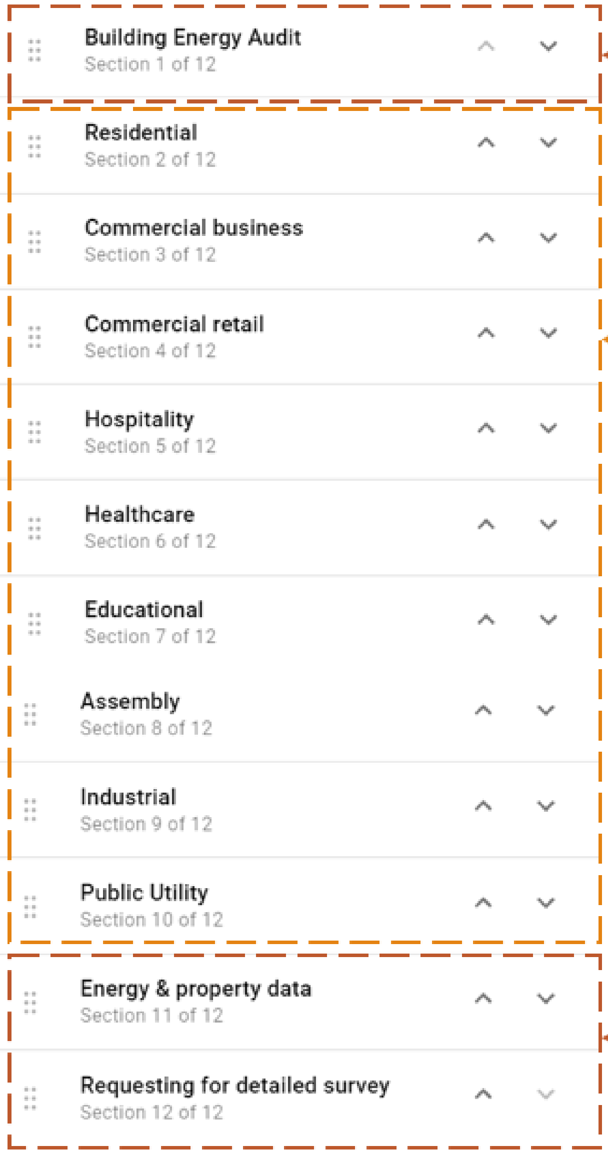
Sr. No.	Floor Description	Construction Year	Age Factor Rate (F2)	Carpet Area	Gross Tax = R*F1*F2*F3*F4	Discount Rate %	Net Tax
1	First Floor	1952	0.50	91 sq.mtr	1165	0.00	1165
			Total Area	91 sq.mtr		Total Tax	1165
						Net Tax	1165
						Water Tax	350
						Conservancy Tax	350
						Usage Charge	366
						Education Cess	117
						Service Tax	0
						Estate Rent	0
						Total Property Tax	2348

Building Area to calculate EUI (kWh/m2)

Energy bills & Property tax no are two essential terms for deriving maximum information.

Address can also be extracted by asking people to pin their location on the map

Survey 1- structure



Common to All
Part 1- Asking about building type
Based on selected answer the respondent will be directed to the respective sub section

Specific to Use type
Part 2- Further details on the building type
This will help in assigning Archetype
After this all sections will be directed to Part 3

Common to All
Part 3- Asking to upload Electricity bill photograph & property tax Tenement no.
Finally asking consent for a detailed survey

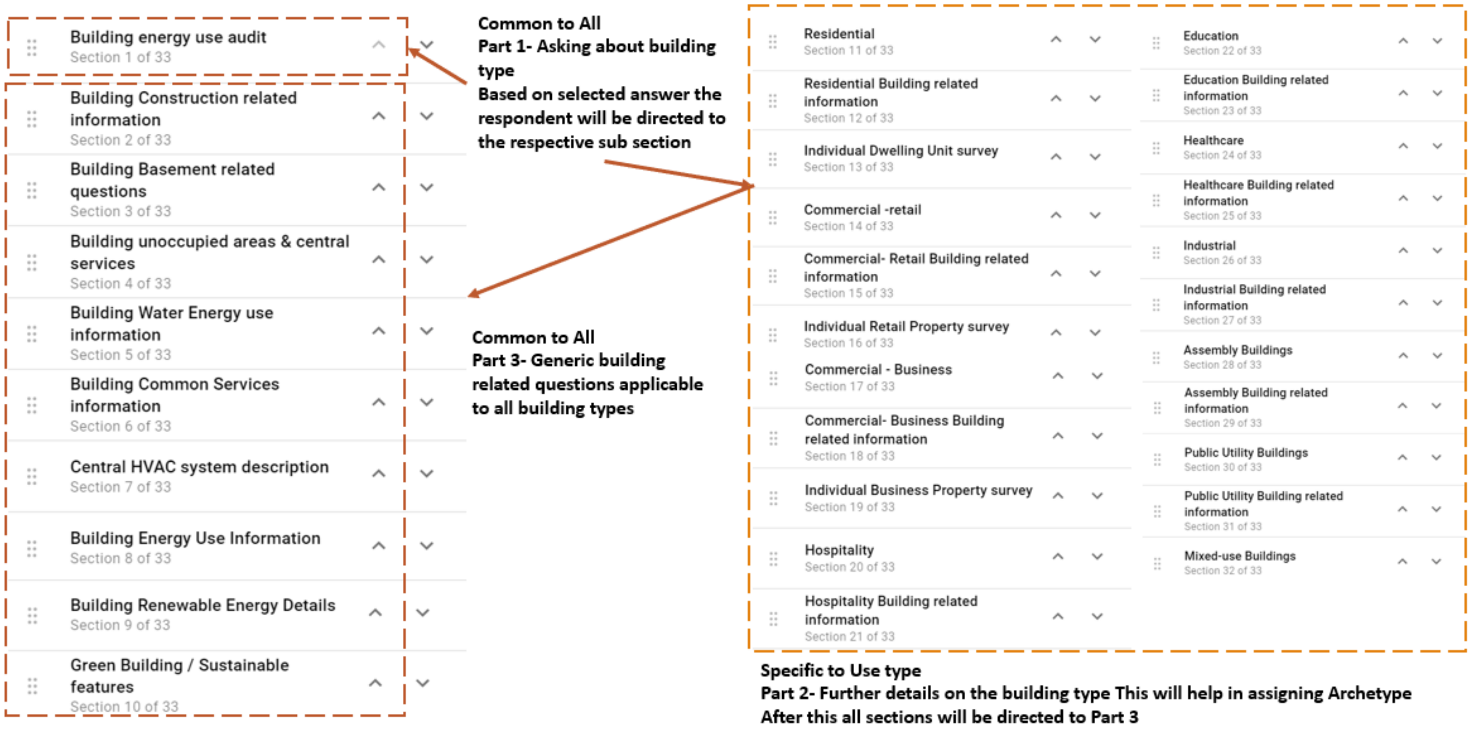
Survey collection plan- Survey for Archetype data

Link to view survey: - *https://forms.gle/e791FWH468TXJjgN9*

Survey collection – Detailed data for Archetypes

- **Survey type 2 – Detailed Physical survey to a sample from each archetype** https://forms.gle/e791FWH468TXJjgN9

The objective of this survey is to collect detailed information to derive input parameters of each archetype for energy simulations.



- **Generic Building related question**

This section will cover details for building characteristics like typical ratio of conditioned vs unconditioned spaces, typical construction materials, HVAC systems, etc

- **Individual Building type subsection**