A review of residential building archetypes and their applications to study building energy consumption

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Abstract

In developing economies, residential energy consumption patterns have rapidly transformed with better energy access and service quality. Unlike other building types, residential buildings are more complex due to wide variations in their consumption patterns influenced by various factors. Researchers have characterised residential building stock based on distinct building archetypes. This paper presents a comprehensive review of relevant published research focusing on the classification of residential buildings based on their energy consumption. This review also focuses on residential archetype studies in the context of building science. The methodologies adopted by different researchers to characterise the energy use of residential building stock using an archetypal approach at different spatial scales (building to city scale and local to national scale) have been critically reviewed in this study. The paper will provide the researchers with a holistic understanding of the current directions and magnitude of ongoing research in this domain.

Keywords: Housing stock, building archetypes, classification methodology, building energy consumption, energy modelling

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1. Introduction

1.1 Background

United Nations estimates the number of urban dwellers to be growing at a rate of two million per week globally until 2030 (UN-DESA, 2020). If this growth continues with business as usual scenarios of informal settlements, haphazard densification and fewer environmental concerns can lead to a poor economy and meagre quality of life (UNCHS 2001; Bredenoord, Lindert, and Smets 2014). The effect of global climate change on any country's building stock depends on its size and scale, rate of growth and stage of development (Khosla and Janda 2019).

In any country, the building sector generally accounts for substantial parts of energy demand and emission of greenhouse gases. Transformation of inefficient buildings to efficient buildings with more sustainability can significantly reduce both energy consumption and greenhouse gas emissions. The annex 31 report by P. Russell and S. Moffatt in 2001, discussed the environmental benefit of the adaptability of buildings (Russell and Moffatt 2001). It is estimated that 20-30% more resources are required when buildings cannot adapt. It happens due to the low performance of the old building envelope (especially walls & windows) with the gradual rise in energy demand of the building (occupants). Hence, the construction of adaptable buildings (provisions for retrofitting in future) is the key to sustainability in building and construction industry.

Such transformations will not only enhance the usage of resources but also improve the integration of buildings at the city level (Ali et al. 2019). The limited information on energy consumption and other details of building characteristics (such as building envelope and physical parameters) available for the existing building stock could be useful in developing building energy modeling. These energy models help identify the energy reduction measures that can improve the building's energy performance (Reinhart and Davila 2016). However, data availability with required granularity is a significant constraint in this practice. Available larger data sets contain information at the household level, it lacks user level and equipment levels granularity. In many cases, the granular datasets collected by researchers, government agencies and utility companies are less useful for future studies, as they all have different formats. The limited information about energy modeling of existing building stock can be availed using the available database.

The energy performance of various design and retrofit scenarios can also be measured using these energy models. Several studies (de Vasconcelos et al. 2015; TABULA 2013) in the literature have described building stock for energy modeling. Moreover, data availability in the required form has been a significant issue. To deal with it, the building stock is usually characterized into different building types representing the typical characteristics of array of buildings. The building stock can be classified mainly into three categories viz. building typologies, reference buildings and building archetypes (Monteiro et al. 2017; Mata, Kalagasidis, and Johnsson 2014). Building typologies classify buildings based on the criteria of building function. The building stock can be classified mainly into three categories: building typologies, reference buildings and building archetypes (Mata, Kalagasidis, and Johnsson 2014). Reference buildings are the concept based on European Union Energy Performance of Buildings Directive. It deals with cost effective measurement of minimum energy performance needs for buildings (European Union 2018). Lastly, the building archetypes are theoretical buildings composed of various characteristics within the class of buildings with similar parameters. It considers geometric and non-geometric (occupancy, household income, equipment ownership etc.) parameters to specify building stock. Building archetypes are widely used in energy modeling at urban level (Galante and Torri 2012; Famuyibo, Duffy, and Strachan 2012).

Famuyibo et al. (2012) illustrated building stock modelling based on archetypes and found it helpful in exploring resources and reducing greenhouse gas emissions. These models can play a promising role in building stock aggregation and identifying the potential of energy retrofit measures for a sustainable future. They also help to estimate GHG emission potential at a larger scale. Some studies (Corgnati et al. 2013; Ballarini, Corgnati, and Corrado 2014) have yet to find a consensus between the common approach used for defining the data of reference buildings and existing buildings, which can therefore result in several problems at the national level. The TABULA (Typology Approach for Building Stock Energy Assessment) project used a similar approach for identifying reference buildings, particularly the residential buildings, based on two variables viz. period of construction and type of building (TABULA 2013) (Loga, Stein and Diefenbach 2016). Later the EPISCOPE project inherited the research from TABULA and continued with building stock monitoring. In building stock segmentation, the three parameters i.e. climatic zone, period of construction and type of building plays a critical role in deciding the selection criteria (Monteiro et al. 2017) Various other parameters should also be considered to develop the robust energy model and determine the reference buildings. According to U. S. Department of Energy, the additional parameters can be classified into four sets viz. geometry (form), construction (fabric), systems (equipment) and operation (program) (Deru et al. 2011). These parameters' definitions for each set depend on the energy modelling data requirements. In some cases, the purpose of energy modeling may only be served by adding sets of parameters to ensure the building stock classification process. Moreover, there is a fundamental need for a flexible method that accounts for different parameters relevant to each country and city's characteristics.

1.2 Availability of residential building stock data

The present study reviews building stock, particularly the residential building archetypes. The building stocks are categorized into two types namely, residential buildings (houses and apartments) and non-residential buildings (industries and commercial sectors) (Mata, Kalagasidis, and Johnsson 2014). Both terms often need to be clarified when studying buildings' energy aspects. Most macro-level studies consider buildings as one group without classifying them. However, with the addition of more equipment, and transformation in operational schedules, the classification of building types made more sense. High-energy consuming non-residential buildings need different strategies than small residential units. However, the paper focuses on Residential housing stock. Few Non-residential or mixed-use building studies are referred, only as methodological references. The intent is to identify critical factors associated with energy consumption in residential buildings through existing literature. Residential buildings seem easier to specify as they cover everything, which deals with energy demand of householders for their dwellings. The residential sector has gained more government attention through various initiatives such as social housing in recent decades (Bredenoord, Lindert, and Smets 2014). This has resulted into better statistics and knowledge about the residential sector. However, reliable Energy consumption data for residential buildings has been a long-standing challenge for researchers.

Two basic approaches widely used to gather information on housing stock are census and survey data (Mata, Kalagasidis, and Johnsson 2014). Census data is the compilation for inception of a register which includes the construction statistics of all buildings and usually provides the basic information (such as area of the building, use of the building, no. of building etc.) on housing stock. Census data provides a wide range of statistical data varying from small areas (or district scale) to national and international scales. On the other hand, sample survey data provides specific information about selected buildings and is generally carried out on a selected population of the existing building stock. Specific information includes a wide range of post-occupancy information along with details of technical characteristics, occupant behavior and fuel usage. Survey-based studies impart information needed for categorising building stock and are primarily required for building energy modeling.

The United States building performance database is the largest dataset that provides information on the energy performance of residential and commercial buildings (Building Performance Database 2020). European statistical system of Europe has developed a tool named 'Census Hub' that contains a national census database (European Statistical System 2020). Building performance institute Europe also surveyed and collected details of the existing building stock in Europe. Also, a data hub portal was created to gather statistical data related to building stock characteristics across Europe (Buildings Performance Institute Europe 2017). Another project assessed the implementation aspects of the Energy performance of buildings directive and identified potential problems. Most of the state's members in Europe are issued energy performance certificates containing information about their respective building stocks. The available database and research project reflect a broad overview of existing building archetypes, but the information related to the physical characteristics of buildings usually needs to be updated.

In literature, several studies and databases are available for energy modeling of building stock at a national level for different countries. These databases include ODYSSEE-MURE (ODYSSEE and MURE Data Bases, accessed in 2020), Eurostat (Statistical Office of the European Union, accessed in 2020), TABULA (TABULA 2013), CRB (Commercial Reference Buildings, accessed in 2020), ENTRANZE (Intelligent Energy Europe program, accessed in 2020) and BPIE (Buildings Performance Institute Europe, accessed in 2020). The existing database mostly covers the top-level archetypes and disregards crucial information about district or city level archetypes. The assumptions considered for energy modeling of national level building stock may not hold true for district or city level archetypes. This might lead to invalid predictions of building energy consumption. Some studies (de Vasconcelos et al. 2015; Monteiro et al. 2017; Theodoridou, Papadopoulos, and Hegger 2011; Cerezo et al. 2017) used national level archetypes for energy modeling of urban areas and found a lack of investigations due to scarcity of fine temporal resolution data. Other studies (Li et al. 2018; Torriti 2014) used survey based building stock data for predicting profiles of building energy consumption. These studies however, furnished energy models using updated information and but lacked scalability usually in 'Urban Building Energy Modeling'. Even at the urban level, the building archetypes comprise several parameters (i.e. geometry and physical parameters), and the development of a single model that quantifies every characteristic of existing buildings could be more feasible.

It is necessary to restrict the number of buildings for detailed analysis which of course needs settlement between feasibility and accuracy. Moreover, the multi-scale approach is needed to develop the improved energy modeling of different levels of building stocks (Ali et al. 2019). Other national representative datasets like the Census of India identified and listed systematically the partly residential or non-residential buildings. The housing census in India provides statistics on housing stock, details about basic amenities in each household and the status of human settlements (Ahmad, Mathai, and Parayil 2014). It helps evaluate the housing deficit, quality of housing units and people's living status. The National Sample Survey Organization (NSSO) provides a scenario of socio-economic aspects, information on the condition of dwellings and construction details of the building structure (NSSO 2005). The housing census and NSSO might not cover the information required to address inquiries. Billing and metering data can easily be used as supportive detail for building stock characterization.

In 2013, the global buildings performance network published a report that compared data robustness in four regions i.e. India, China, European Union and the United States (Shnapp 2015). The report concluded that there is significant potential for improvements in the data quality of building stock across various regions. Recently, energy certificates and geographical information systems have been widely used for data gathering, particularly on a regional scale (Dascalaki et al. 2010; Keirstead, Jennings, and Sivakumar 2012). 3D urban stock models quantifying building morphology can be used for local and national policy formulation. Such models deal with data complexity and provide opportunities to understand building stock (Evans, Liddiard, and Steadman 2017). However, their structural complexity and inter-relations among sociocultural and socioeconomic aspects are significant bottlenecks to achieving comprehensive knowledge about any building stock (Kohler and Hassler 2002). These aspects play a crucial role in determining the effects of climate change on the sustainable development of building stock.

1.3 Objective of present review

The present review encompasses the following main objectives:

1. Identify the approaches used to classify residential building stock into representative archetypes.
2. Discover the key factors that can characterise the energy performance of residential archetypes.
3. Understanding linkages between building archetypes and building energy performance through relevant literature.

2. Literature search

Various studies on residential building archetypes were identified using the Relevant keywords related to the "residential building archetypes" on electronic databases like Google Scholar, Science Direct and Scopus. Searching relevant studies fitting this review paper's scope were conducted from January 2004 to June 2021. Boolean operators were used with the logical combinations such as "residential archetypes" AND "methodology" OR "building stock data" AND "residential building" AND 'dwellings" OR "residential energy demand" AND "building energy consumption", for identification of studies specific to this review paper. Another search approach was used based on the "reference by reference" in which the reference sections of the extracted studies were focused to identify more relevant studies available in the literature. All the peer-reviewed papers published in the English language that apposition with the objective of present review paper were considered. The grey literature such as anecdote papers, reports, editorials, discussion papers and presentations was discarded in this review. The paper referred to some of the national and international databases that are most relevant to the existing topic. The figure below shows the distribution of literature sources through a pie chart.

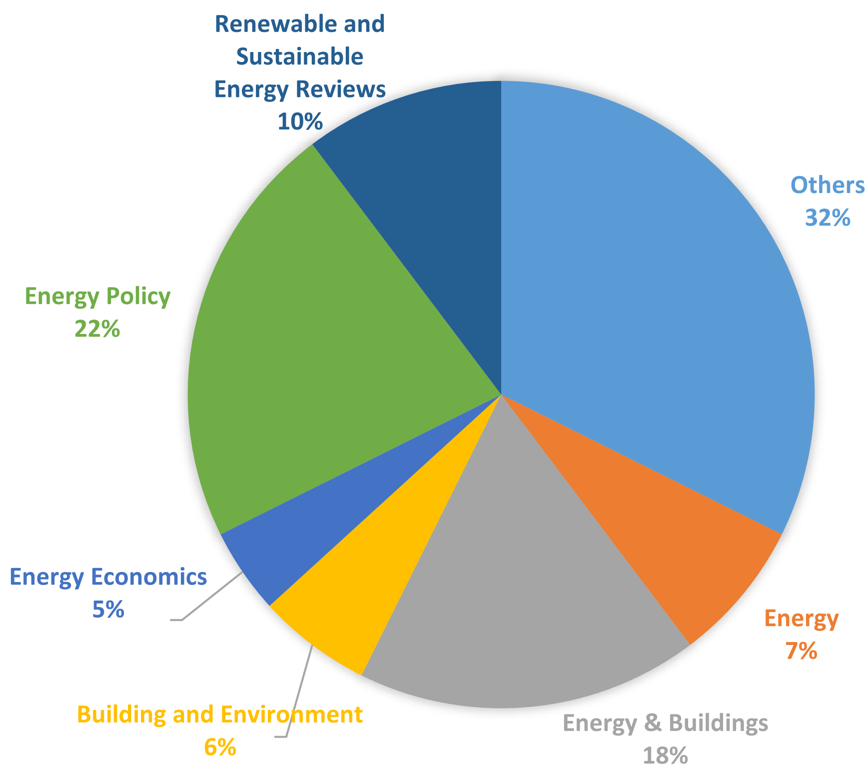

Figure 1: Contribution of Journals in the Meta data

Literature type	No.	Time period	Remarks
Refereed Journals	74	2004 - 2021	Only peer reviewed, high impact, Scopus indexed journals.
Conference	12		Conferences with reviewed papers (Eg. IBPSA)
Reports, guideline and Books	17	2008 - 2020	Project reports supported by reputed bilateral funding agencies, governments and reputed NGOs/think tank

Table 1: Types and quantity of Literature reviewed.

The residential energy demand studies are divided into two parts based on the methodology i.e. top-down approach and bottom-up approach (Swan and Ugursal 2009). The top-down studies give a generalised overview of energy consumption at a macro level, whereas bottom-up studies focus on user-level consumption patterns and other influencing factors. Several bottom-up studies recently relied on equipment-level monitoring to get more detailed insight. This paper will specifically focus on the archetype methods used in bottom-up approach studies. A brief introduction to various approaches to studying building energy consumption can help set up the context (Lim and Zhai 2017).

The “Archetype” models include all known and measurable parameters contributing to the energy consumption into a representative model. That essentially represents a specific class of building type, with parametric values oscillating within a specific range. This method offers the flexibility to classify buildings on various parameters, geometry, materials, size, occupancy etc. It offers the flexibility to accommodate new parameters into the model in future. Which is undoubtedly going to change the archetypical character of the model, but this flexibility is necessary to update the old models as per the advent of new equipment and building technologies (Lim and Zhai 2017; Willmann et al. 2019; Li et al. 2017; Kavgic et al. 2010; Kumar et al. 2009).

Before exploring the application of “archetype” in buildings, it is necessary to learn the fundamental meaning of the term. It will help to establish the need for using “archetype” to study buildings. The origin of the word “*Archetype*” comes from the Greek Philosophy of “*pure form*” coined by Plato (Bloom and Kirsch 2016). The term is meant to represent the fundamental characteristics of a large group of things. Later, the term was part of various academic discourses that included Psychology, behavioral economics, demographic studies, anthropology, biology, and literary analysis. In modern times Archetype is used as a scientific method of population classification, clinical science, Nanotechnology market research and behavioral finance. At a fundamental level the “Archetype” can be defined as a collection of reoccurring characters and phenomena sharing similar traits across different unconnected samples. Carl Jung defines it as a derivative of a collective unconscious in the Jungian Archetypical theory (Papadopoulos 2006). Several studies in comparative anthropology later ratified the concept. Hence, irrespective of its domain, "archetypes" is a theoretical representation of reoccurring characteristics that occurs unconsciously and collectively by a population. It is a critical point for researchers to understand while using the term in any research investigation.

1. **Application of "archetype" as a concept in building sciences**

A wide range of social, economic, cultural, and technological factors (Omer 2009) governs the energy consumption of buildings. Buildings with identical layouts and architecture vary wildly in terms of energy consumption (Kohler, Steadman, Hassler 2009). It is critical to understand that archetypes can be an effective way to classify buildings based on the consumption behaviour of their users. Buildings do not consume energy rather the people inside it do (Delzendeh et al. 2017). Hence developing "Archetype" representing a large group of buildings can help in understanding the consumption pattern of various user groups. The user within these groups unconsciously behaves in a certain way and evolves a collective consumption pattern. "Archetype" is one of the most relevant concepts to study the behavior related to building energy consumption. "Archetypes" can also be relevant in the absence of large datasets. In building sciences, these "Archetypes" are often referred to as "Reference Models" (Moner, Maldonado, and Robles 2018).

A generic approach used for characterizing residential building archetypes mainly comprises five steps as illustrated in Figure 2. The first step is the collection of data from the existing residential building stock distributed over a large scale using both primary and secondary data collection methods. Following this, the segmentation step deals with splitting data to identify the volume of archetypes represented by the existing building stock. After segmentation, the characterization step further describes the residential archetypes based on data-driven approaches. In the next step, the quantification approach ascertains the distribution of residential archetypes based on national statistics data available for buildings. Lastly, dynamic building energy simulations are performed to analyse and validate results (Ali et al. 2019). Every step of the methodology for describing residential archetypes is discussed in detail in the following sections.

3.1 Data collection

It is a very crucial step in the development of building archetypes. It requires detailed geometric and non-geometric information about any building. Geometric information covers building envelope, building type, building shape, building area and no. of floors, walls and windows. Non-geometric information on the other hand covers building envelope U-values, building construction details and HVAC systems. The relevant building information is often extracted from the existing building stock. The collection of geometric and non-geometric data can be of different scales and usually decides the granularity of data available for the existing building stocks. Data collection is generally made at four different scales i.e. nation scale, city scale, regional scale and district scale. The national scale represents the building stock for the whole country. The city scale covers the building stock group of local authorities' buildings. Regional scale deals with the geographical division of a city into various areas where local authority creates different districts. On a district scale, a district is set up as a group of small areas or neighbourhoods (Ali et al. 2019).

3.2 Data segmentation

The segmentation process examines the number of archetype buildings needed to represent the residential building stock of any nation. Segmentation criteria help in facilitating data compilation and generally provide a good representation of energy demand in residential and non-residential buildings. Various criteria of data segmentation (dwelling type, age of building, dwelling type clustering, HVAC system and climate zone) used to obtain the number of residential archetypes buildings are depicted in Figure 1.

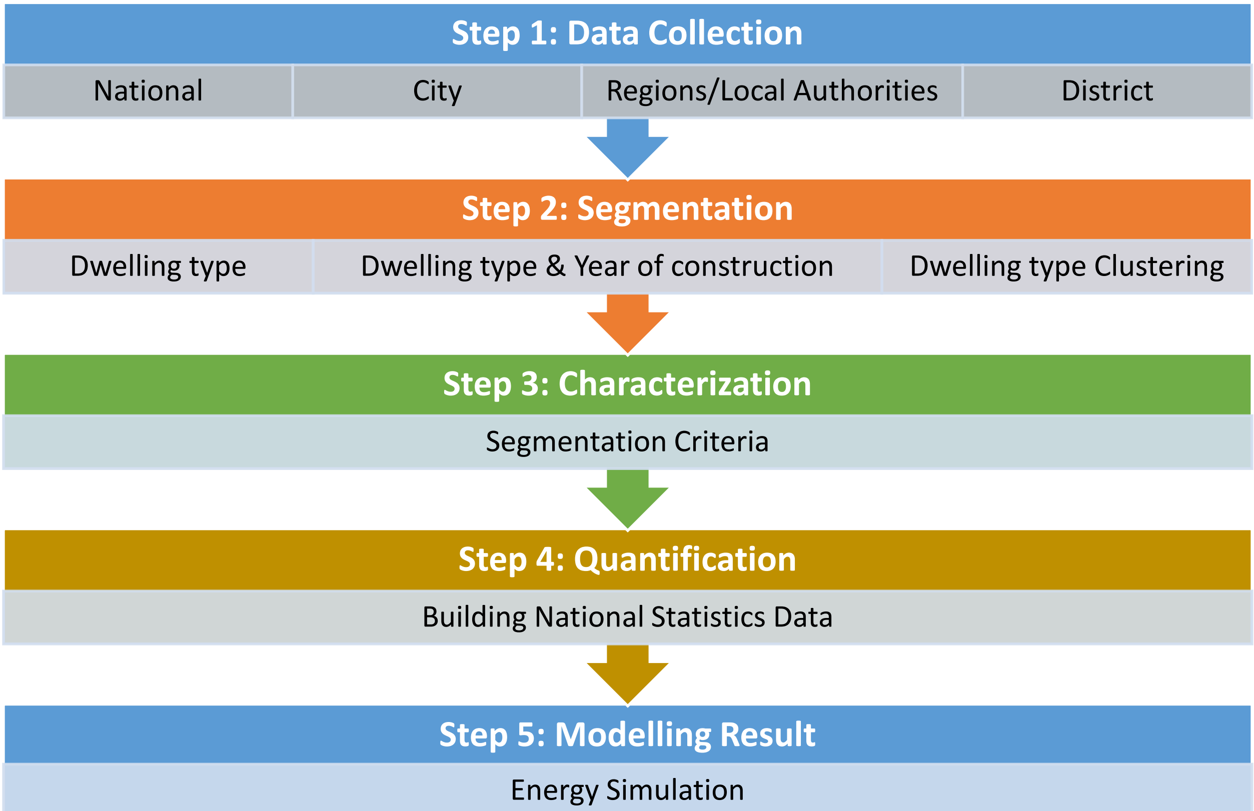

Figure 2. Methodology steps for multi-scale building archetypes development (Ali et al. 2019).

Details of various criteria used for segmentation are given in the following subsections:

- Dwelling type: It is usually specified from the use of dwelling, dwelling layout (i.e. number of floors) and how the dwelling is attached to neighboring dwellings (such as detached, semi-detached and terrace houses). Classifying buildings plays a critical role in building energy modeling as the energy usage in buildings differs according to the topology. For example, detached, semi-detached and terrace houses might have different cooling and heating requirements and energy usage (Ali et al. 2019; Mata, Kalagasidis, and Johnsson 2014).
- Age of dwelling: It can be identified from the building regulation codes, historical events and updates in construction technologies. The year of the building's construction can significantly impact the building's energy performance. Older buildings usually consume more energy than newer buildings as the latter have used advanced construction technology focusing on energy savings. According to European Commission, the age of building construction of more than 35% of the buildings in Europe is above 50 years, and

about 75% of the building stock is energy inefficient. So, the age of a building is the crucial parameter in defining the building archetypes.

- Dwelling type clustering: Clustering of dwellings is an unsupervised machine learning technique that deals with assigning specific dwellings to the same group called cluster so that all the cluster dwellings possess similar characteristics (Mata, Kalagasidis, and Johnsson 2014).
- Cooling and heating system: It is defined from the details of heating, ventilation and air-conditioning unit.
- Climate zone: It is defined according to the climatic conditions specified by the national building regulation codes specified within a country. Meteorological data obtained for the dwellings located in the highly densely cities existing in the particular climate zone can be considered representative of that climate zone (Meteotest 2009).

In the segregation stage (step 2), dwellings are divided into groups based on selected parameters. At this stage, detailed properties of the selected parameters are not measured. The values associated with the parameter are measured in the characterization stage (step 3).

3.3 Data characterization

Based on selected segmentation criteria, the relevant information is extracted from the characterization process using a data-driven approach instead of a simple statistical approach. The characterization process investigates each building archetype's thermal properties and technical characteristics. Geometrical and non-geometrical information is generally required to characterize building archetypes in each building stock. This information is also a prerequisite in urban building energy modeling that considers various parameters like construction details, glazing, internal loads, HVAC systems and occupancy profiles. Methodology details used to characterize building archetypes are described here (Ali et al. 2019).

3.3.1 Data pre-processing

Data on building stock is generally collected through statistical surveys; however, this type of data is often subjected to various inconsistencies (like data incompleteness, data duplication and missing data). Therefore, before using this data in algorithms, the pre-processing of data is required to remove all possible data inconsistencies. Various methods used for pre-processing data include cleaning, integration, transformation and discretization (Ali, Buccella, and Cecati 2016). Data cleaning deals with removing data inconsistencies such as outliers, missing values and noisy data from the master database. Several imputation methods like; mean imputation, cold deck imputation, regression imputation and stochastic regression imputation are also used by researcher while dealing with larger datasets. The robustness of imputation generally relies on how much data is missing relative to the available dataset size. If the amount of missing data is sizeable relative to the available dataset, and the latter is relatively small, then this method is generally not recommended. Data integration amalgamates various sources of data. Data transformation converts nominal data into numeric data required for clustering in the development and implementation of algorithms. Data discretization transforms the data on construction years to age bands. The historical databases often consist of redundant variables that might not impact the archetypes development process. Thereby, the most representative and valuable variables can be extracted to improve the quality of data using the feature extraction method, which involves engineering and statistical methods (Fan, Xiao, and Zhao 2017; Zhang, Cao, and Romagnoli 2018; Kapetanakis, Mangina, and Finn 2017). Engineering methods utilizes experts' interpretations and findings from the literature. While the statistical methods use inferential tools and data mining approaches (i.e. regression analysis, discriminant analysis and neural network) for data preparation and analysis. Building stock data particularly collected through surveys often comprises high volume of inconsistencies and anomalies, which should be removed before implementing the database into the analytical technique. These data outliers and extreme data points can be detected through data outlier techniques such as distance and density-based methods and local outlier factor technique. However, it is critical to understand the rationale behind removal of such data extreme points. The group of outliers and extreme data points must be carefully examined before exclusion from the datasets. In certain cases, the outliers represent a minority group within the dataset. Such attempts must be avoided to keep the model representative of the whole study group.

3.3.2 Selection of algorithm

The algorithm's selection shall be based on segmentation criteria; for instance, when building stock is segmented by dwelling type. The data will be grouped based on dwelling types before implementing the database into the aggregation process involving geometric or arithmetic mathematical functions. Likewise, when building stock is segmented by dwelling type and year of construction, the data will be grouped accordingly before implementing the database into the aggregation process. Generally, the mathematical functions used for finding mean and standard deviation for grouping of data are given below (Ali et al. 2019):

$$\bar{x} = \frac{\sum x_i f_i}{n}$$

$$\mathrm{S} = \frac{\sqrt{\sum (x_i)^2 f_i - \frac{\sum (x_i f_i)^2}{n}}}{n-1}$$

Where $\bar{x}$ is the mean; "s" the standard deviation, "n" the sample size, "x_i" the group mid-point and f_i the frequency of each group.

Among various clustering algorithms, the k-means algorithm is widely used for clustering building stock in the segmentation process. In this algorithm, each cluster is the mean of the cluster aimed at dividing the observations into k clusters (where each observation is associated with a respective cluster) (Tardioli et al. 2018). The objective function of the k-means algorithm is to reduce the sum of distances of the observations to their corresponding centroid. A mathematical function known as Euclidean distance is commonly used for it and is given by the following equation (Ali et al. 2019):

$$\mathrm{C} = \sum_{i=1}^{K} \sum_{X \in C_i} \left| \left| x - c_i \right| \right|^2$$

Where c_i is the mean of the n data points in cluster C_i.

Compared to other algorithms, the k-means algorithm has high scalability and simplicity. However, it has significant limitations when the building stock data contains outliers and different-sized clusters. Validation and calculation of resulting clusters (having characteristics like compactness, roundness and separation) can be made using internal validity indices, i.e. Silhouette Index (Rousseeuw 1987), Davies Bouldin Index (Davies and Bouldin 1979) and Gini Index (Liao 2006). Moreover, archetypes are characterised based on the interpretation of results obtained for aggregation and clustering of building stock data. Every aggregated value and cluster centroid value depicts the features of a specific building archetype. All parameters considered in the feature extraction phase exhibit the building archetype's physical properties (i.e. construction materials, HVAC systems and glazing).

3.4 Quantification Process (Classification of Buildings in National Statistical database)

Distribution or classification of building archetypes is determined through quantification process. Quantification of building stock decides the representativeness of building stock (Number of buildings represented by each archetype in the building stock). The 'weighting coefficient' parameter can be assigned to each building archetype to aggregate the results. Generally, the national statistics or census data are sufficient to quantify the building archetypes involving the number of buildings and their floor areas (Benejam 2010). In case, this information is available for a particular year, it can be extracted from information related to construction and demolition rates for the specific year. Regarding heated floor areas, the sources generally need to detail if total or net areas are included. Arababadi (2012) utilized building research establishment fact files of domestic and non-domestic buildings for energy studies in the UK. Mata, Kalagasidis, and Johnsson (2014) performed building stock aggregation for building archetypes using national stock data of the UK, France, Spain, and Germany. Likewise, the Irish Census (Census of Population 2016) provided information on Irish building stock data (such as type of dwellings, year of construction, occupancy levels, fuel for heating or cooling units and energy rating of buildings) of 2,003,645 buildings. Once the building stock data is collected, segmented, characterized and quantified (as specified in the preceding steps), it is fed as input information to energy simulation models for energy modeling and obtaining energy performance indicators.

3.5 Energy modeling

It is the last step of devised methodology for developing building archetypes. Energy simulation software (i.e. EnergyPlus or IES VE) is generally used to model building archetypes to determine the gross building energy consumption and building demand profiles. Thus, the results will be examined to study the influence of energy modeling on a large scale. Depending upon the modeling levels, building energy modeling (BEM) can be classified into two types, namely, Building Energy Performance Simulation (BEPS) and

Urban Building Energy Modeling (UBEM). The BEPS need information on building geometry (such as building shape and proportions) from the existing building stock data like DOE and TABULA. National building stock data is the only source of building information at the most significant scale. The BEPS is suitable for implementing individual building scale whereas the UBEM is suitable for implementing district or urban building scale. At individual building scale, the errors are higher than aggregate level in bottom-up energy modeling (Ali et al. 2019). EnergyPlus is a widely used BEPS engine for simulation dwellings using a limited number of variables. It is quite suitable for energy modeling of a large scale and performing classic parametric simulations. More details of building energy modeling and approaches are discussed in section 5.

2. Building archetypes and building energy consumption

The relevance of energy in buildings has been studied globally in various contexts. In 1967, Sir Leslie Martin and his fellow researcher tried to find suitable built forms for different land use, where they emphasized energy in buildings (Martin 1967). Though the prime focus was to find an appropriate built form, the study prepared the base for a new research vertical in "building energy". Since several studies were done in different parts of the world to understand energy in buildings in a different context. However, some studies (Gupta 1984; Blowers 1993; Steemers et al. 1997) have discussed energy consumption in buildings while addressing thermal and lighting comfort. Most studies (until the late 80's) for residential energy consumption have used a top-down approach. These studies were enough to provide a volumetric understanding of consumption on a regional scale. However, they had minimal insight into the granular details and qualitative factors contributing to energy consumption at the household level. Hence, MacGregor, Hamdullahpur, and Ugursal (1993) did a techno-economic evaluation of space heating systems by monitoring their performance in different dwellings. Later in 1997, a group of researchers from Karlsruhe University (German) monitored the energy consumption in buildings while analyzing German building stock (Kohler et al. 1997). Huang and Broderick (2000) used the DOE building simulation program to determine the conservation potential of a building envelop component (walls, roof, window, etc.) in residential and commercial buildings. The study done by Shimoda et al. (2004) included different archetypes of residential buildings at an urban scale in Osaka to study their energy consumption pattern to find the explanation for the gap between actual consumption and estimated consumption levels.

4.1 Archetype based studies for building energy consumption.

The table below is a consolidated list of journal papers, which have made some significant contribution in this domain of research (2004 to 2021).

Sl. No.	Publication details	Inferences	Region/ Country	Sample size	Approach	Building Type	Archetypes Considered
1	Larsen and Nesbakken (2004)	The authors used ERA D simulation engine and have concluded that 42% of the energy contributed for space heating and 24% for domestic hot water.	Norway	1453	Engineering Model	Residential	Not Available
2	Swan, Ugursal, and Beausoleil-Morrison (2008)	The paper provides detailed models with high resolution data inputs. These help in finding the changes in consumption pattern of residential buildings due to new technology integration.	Canada	17000	Engineering Model	Residential	Not Available
3	MacGregor, Hamdullahpur, and Ugursal (1993)	The study shows that energy saving and other financial gains in residential buildings can be well estimated.	Canada	244748	Engineering Model	Residential	27
4	Kohler et al. (1997)	The authors have used bottom-up engineering methods to estimate the energy consumption at the building level and their results closely match with other studies and estimates.	German	160	Statistical Model	Residential and Non-residential Both	Not Available
5	Jones, Lannon, and Williams (2001)	Using GIS helps to feed in more accurate spatial and geographic data in unique layers. The authors suggest using historic data sets like, building age, material specifications, etc for estimating energy consumption in buildings.	UK	4516	Engineering Model and GIS	Residential and Non-residential Both	Not Available
6	Shipley, Todesco, and Adelaar (2002)	The paper suggests use of 'Archetype technique', for simulating the building energy demand, by using reference building types to represents a large group of buildings.	Canada	3500	Engineering model	Residential	Not Available
7	Carlo, Ghisi, and Lamberts (2003)	The paper considers roof area ratio, façade area ratio, load density, and a few more variables to formulate the archetype for parametric simulation.	Brazil	695	Engineering Model	Non-residential Buildings	12
8	Shimoda et al. (2004)	Paper concludes that, variation between statistical and actual values of energy consumption is due to exceptionally inefficient energy usage by end-users or due to selection of samples with significantly larger household size.	Japan	1058000	Engineering Model	Residential Buildings	23
9	Wan and Yik (2004)	The paper suggests that, making changes in the equipment ownership levels and their usage the margin between the estimated and actual values of energy consumption can be reduced effectively.	Hong Kong	68	Engineering Model	Residential Buildings	1
10	Yao and Steemers (2005)	The study has developed four typologies of residential building in UK, by adopting thermal resistance method proposed by Martin Centre.	UK	100	Engineering Model	Residential Buildings	4

11	Palmer et al. (2006)	The authors have used BREDEM-8 (monthly heat flux simulation engine) tool for estimating energy demand for space heating and domestic hot water.	UK	Not Available	Engineering Model	Residential Buildings	431
12	Petersdorff, Boermans, and Harnisch (2006)	The study examines 5 standard buildings with 8 insulation types for modelling the EU-15 housing stock. The study has also built different options of retrofitting, even applicable for small buildings.	EU Region	Not Available	Engineering Model	Residential Buildings	5
13	Nishio and Asano (2006)	The authors have developed a tool for generating archetype, using Monte – Carlo technique, to understand the distribution range of building variables.	Japan	10000	Engineering Model and Monte – Carlo technique	Residential Buildings	3
14	Kadian, Dahiya, and Garg (2007)	The paper simplifies the equation to accommodate penetration and all domestic energy uses (lighting, heating etc.).	India	2554000	Statistical Model	Residential Buildings	Not Available
15	Saidur, Masjuki, and Jamaluddin (2007)	The authors have developed the model for Malaysian household using estimates made by different researchers about equipment ownership, energy rating, and efficiency.	Malaysia	Not Available	Statistical Model	Residential Buildings	Not Available
16	Clarke et al. (2008)	The authors have used envelope insulation, wall to floor ratio, window sizes as some of the key variables for residential building classification.	Scotland	22,78,000	Engineering Model	Residential Buildings	3
17	Isaac and Van Vuuren (2009)	The paper predicts a 34% reduction in heating demand and 72% rise in energy demand for space cooling by 2100 at dwelling unit level across the globe.	Global	Not Available	Statistical Model	Residential Buildings	Not Available
18	Kavgic et al. (2010)	The authors have proposed models as effective tools for finding the potential areas of saving in the buildings.	UK, Finland, Canada, US, Belgium	Not Available	Comparative Analysis	Residential Buildings	Not Available
19	Famuyibo, Duffy, and Strachan (2012)	The authors have used multi linear regression and clustering techniques to develop more models that are accurate.	Ireland	Not Available	Statistical Model	Residential Buildings	13
20	(McKenna, et al. 2013)	The study investigates the importance of refurbishment and modification in the building envelop for better energy performance.	German	Not available	Statistical Model	Residential Buildings	Not available
21	Pisello et al. (2014)	The study explores the effectiveness of modelling studies to understand the impact of external urban factors on building level energy consumption.	US	2	Engineering Model	Residential and Non-residential Both	Not Available
22	Aksoezen et al. (2015)	The authors have used gas consumption (especially used for heating) for energy modelling and classified the buildings based on their age.	Switzerland	20,802	Statistical Model	Residential Buildings	Not Available
23	(A. Fonseca and Schlueter 2015)	The paper explores the spatiotemporal energy consumption patterns in the buildings of Switzerland.	Switzerland	1392	Engineering models and GIS	Residential Buildings	172
24	Loga, Stein, and Diefenbach (2016)	The paper highlights the major modification in data structure and processing that helped several countries to adopt it and develop region specific residential archetypes.	EU Region	Not Available	Comparative Analysis	Residential Buildings	Not Available

25	(Braulio-Gonzalo, Dolores Bovea, et al. 2016)	The paper highlighted the role of intrinsic parameter for improving energy performance of residential buildings at the urban scale.	Spain	Not Available	Statistical Model and GIS	Residential Buildings	3
26	Pasichnyi, Wallin, and Kordas (2019)	The authors have adopted the archetype technique to prepare urban scale model and suggested a transition from single logic to multi-purpose data intelligence service.	Sweden	5532	Statistical Model	Residential and Non-residential Both	5
27	(Molina, et al. 2020)	The authors have proposed 496 archetypes to represent the 100% of the housing stock and whereas 90 of them represent 95% of the housing stock.	Chile	Not available	Statistical Model	Residential Buildings	496
28	(Braulio-Gonzalo, D. Bovea, et al. 2021)	The study has investigated the role of socio-demographic aspects of occupants in the variation of energy consumption pattern.	Spain	113	Statistical Model	Residential Buildings	Not available

Table 2: Key inferences from refereed journals (2004 – 2021). Prepared by the author.

Unlike developed economies like UK and US, housing stock is not regulated in developing economies. With rising income levels people prefer to upgrade their existing appliances to uplift their standard of living in these parts on the world (Nayak & Rajan, 2021). Hence only building geometry may not be sufficient to predict the consumption levels. Moreover, collecting and compiling reliable data sets are also tricky. Hence, developing archetypes at the national may need help to address the problem. An urban or regional-level archetype may be a good option. Clustering techniques can be deployed to develop these models with various levels of detailed building attributes. The classification parameters may vary from region to region due to socio-economic diversities.

5. Discussion on findings

So far, the present research scenario on building stock information and its association with building energy consumption has been reviewed. This review indicates that there is increasing recognition of the need to understand the dynamics of different scaled national building stocks. Significant efforts have been made towards this direction, and it is observed that these efforts are driven mainly by the need to understand the present and future energy needs and growing trends. Besides, the climate change issues attributed towards achieving sustainable development goals have also encouraged researchers to focus more particularly on the classification of building stock in the form of building typology. Such classifications are essential to understand the structural and architectural configurations required for creating the structural model and analyzing the dynamic performance of buildings. Typology classification is essential to understand the building's behavior, which assists in long-term planning for sustainable building development. Building typology dramatically depends on the local climatic conditions, geography, socio-economic aspects and construction skills and materials. The prevalence of building typologies for a specific region can be examined by introducing new design codes and bylaws. Detailed building stock data of multi-scale is needed to develop the building typologies; however, specifying building typology at a regional scale is challenging.

In recent years, advanced techniques (such as remote sensing and spatial investigation) and social and cultural analyses have been widely used to classify building stocks. The geographical information system is another favored application tool that allows data sharing for different motives and outlooks. Towards the policy strategies, there is increasing recognition that public policies related to building stock should be tested and evaluated based on the evidence. Classification of building stock into a small sample of buildings and archetype buildings could help analyze the building databases. Such classifications have numerous implications for building energy use, comfortable indoor environment, construction, life cycle assessment and quantity surveying. However, considering building stock as a research object can only present partial information about building stock. However, the collected data relating to interests cannot be generalized. The phenomena relating to energy savings and actual building costs are generally precluded in the partial models. Some countries, mainly European countries, recognize more reliable models representing the dynamic of building stock; however, the need for more sufficient statistical data upon which these models are based is also observed. Thereby, more advancement in research related to building stock is needed.

The new methods are rendering new and exciting insights and knowledge in the domain area of building stock and energy performance. It leads to a multidisciplinary or trans-disciplinary format of research. The issues related to building stock do not arise within a single domain (such as history or physics) or two domains of common interests (like computational biology or biochemistry). Many issues are societal and have come from outside traditional domains or disciplines. The critical societal issues are reduction in materials and energy consumption to achieve sustainable development goals. It involves capital and social values, which might result in more complexity in building stock. Thus, multiple decision-making theories are required for different timeframes relevant to building stock.

Further, a reliable energy consumption database for residential buildings is unavailable in a large part of the developing world, making the new research validation process difficult. A critical transition in user behavior is also easier to identify with a reference database. In addition, there is a strong possibility of bias that can compromise minute details of user behavior in the archetypical model. Hence generalization of standard variables needs to verify. A sensitivity analysis of criteria can be a good choice in such cases. The accuracy of archetypical modeling depends on suitability of the classification criteria of the building stock. In diverse environments like India and china, developing suitable criteria for classification is extremely critical, as a wide range of users and building type constitutes the building stock. It makes data collection and segregation furthermore complicated.

As discussed in the previous sections, several large-scale projects were initiated to classify buildings stock in the US and EU regions. These typology-based classification models are usually based on various physical and thermal characteristics of a building structure, such as building area or size, occupancy, roof type, building age, insulation type, etc. These attributes of building form have proven impact on energy consumption. Hence, these typology-based models were widely adopted in building energy studies. These “Reference Models”, as they are referred to in literature, are representative of a few building attributes, commonly found in most buildings of that kind. However, there are no standard definitions of these models, yet they can be considered “building archetypes”.

These buildings collectively consume energy within a particular range following a fixed pattern due to similar physical and thermal attributes. Despite the wide application of these models by researchers and policy makers, consensus for a standard definition and methodology of development is yet to be formalized. It affects the process of peer-learning among the researchers in the domain. With standardization the effectiveness of energy efficiency policies from various regions of the world can be compared, which can provide critical insights about significant transitions in user preferences and behavior. Moreover, the “Archetypical Models” can also be a very effective tool for training energy auditors and simulation professionals.

6. Conclusion

Proper classification and modeling of the building stock are needed to characterize residential buildings. The development of building archetypes can significantly reduce the modeling efforts and computation time. This paper reviews building stock and its applications towards estimating building energy consumption. The generalized methodology describing the classification of the national building stock in the form of archetypes has been presented.

The following concluding remarks can be drawn from this review:

a. Such studies provide a more comprehensive picture of energy consumption in the residential building stock both at a micro and macro scale. It also brings better insights into the factors that influence the energy consumption pattern in these building stocks. In addition, it represents the methodological diversity in these kinds of studies.
b. The need to develop new archetypes depends on the variability of parameters upon which the buildings are divided in the most representativeness.
c. There is a need to understand the robustness of crucial data as the development of archetypes dramatically depends on it. Using national and regional scale data can yield different results than district-level data.
d. Defining building typology using local scale data is a daunting task; however, multi-scale typologies can be used as reference buildings to analyze energy savings and efficiency measures. Moreover, these typologies can also bring more profound insights into the consumption behaviour of the end-users.
e. Capturing the diversity of the representative stock through measurable physical and thermal attributes can be challenging for the researcher in the developing world due to the lack of a reliable energy consumption database. Minimal research is available discussing the impacts of socio-demographic diversity on energy consumption, especially in developing economies.
f. The bottom-up approach has a high potential for improvement in the segmentation process of archetypes at a large scale. It will help the local authorities analyze building energy performance at a granular level and improve sustainable energy policy decisions.

Acknowledgment

This work is supported by a Joint Indo-UK research project called "Residential building energy demand reduction in India (RESIDE)," funded by the Department of Science and Technology (DST/TMD/UK-BEE/2017/07), Government of India, and the Engineering and Physical Sciences Research Council (EP/R008434/1), United Kingdom.

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