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Building Occupancy Behavior and Prediction Methods: A Critical Review and Challenging Locks

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ABSTRACT Energy use in buildings is increasing to provide optimal comfort for the occupants. People spend 90% of their lifetime in buildings. Therefore, indoor environment quality and comfort management have a crucial role in maintaining occupants' health and productivity. Reducing energy consumption for optimal comfort management is important to minimize CO_2 emission and global warming by the building sector. According to the literature, it is possible to control and reduce energy consumption by monitoring occupants' behavior and estimating the number of occupants. A critical review is carried out in this paper to analyze the existing methodologies for modeling occupant behavior and prediction with respect to comfort and energy management. A comprehensive analysis is also performed on recent developments and challenges in modeling, along with recommendations and future perspectives.

INDEX TERMS Building comfort, energy consumption, occupancy prediction, occupant behavior, stochastic behavior, smart building.

I. INTRODUCTION

Life expectancy of modern life has increased and humans are spending most of their times in indoors due to the present-day life style. Researches show that around 90% of people spend their time indoors and 65% of time in offices [1]. Poor functioning buildings have adverse effects on occupants health. For example, cognitive performance of a person depends on the indoor environment; presence of high concentration air pollutants in indoor affects the respiratory health, lower ambient temperature can cause cardiovascular disease and chronic respiratory problems majorly in old occupants. Furthermore, low indoor air quality of the building is the reason for Sick Building Syndrome (SBS); feeling cold, headache, dizziness, confusion, nausea, fatigue, respiratory problems, irritation of eyes, throat, nose and skin. Even with the technological development, 23% of the office workers comment about indoor air quality [2], [3]. Therefore, significant attention is required towards maintaining a healthy and comfort ambience inside the building for occupants enhanced life style. Indoor environment quality is basically categorised as:

1) Thermal comfort
2) Visual comfort
3) Air quality
4) Acoustic comfort

These comfort factors are dependent on many physical and physiological factors such as geographical location, relative humidity, metabolism rate, air velocity, lighting, noise, human behavior, etc. [4]–[6]. Enhanced life style and attention towards indoor environment shows the necessity to maintain a healthy and comfort ambience inside the building.

Thus, the fundamental expectation of the occupant from a building is to achieve maximum indoor comfort, regardless the outdoor weather conditions. Buildings consume major factor of global energy and account for considerable CO_2 emission as shown in Fig. 1. In China, 84% of the total energy is consumed at the Urban areas and majorly responsible for CO_2 emissions [8], [9].

Statistics show that buildings consume 40% of total global energy demand (Fig. 2) and more than half of it is used

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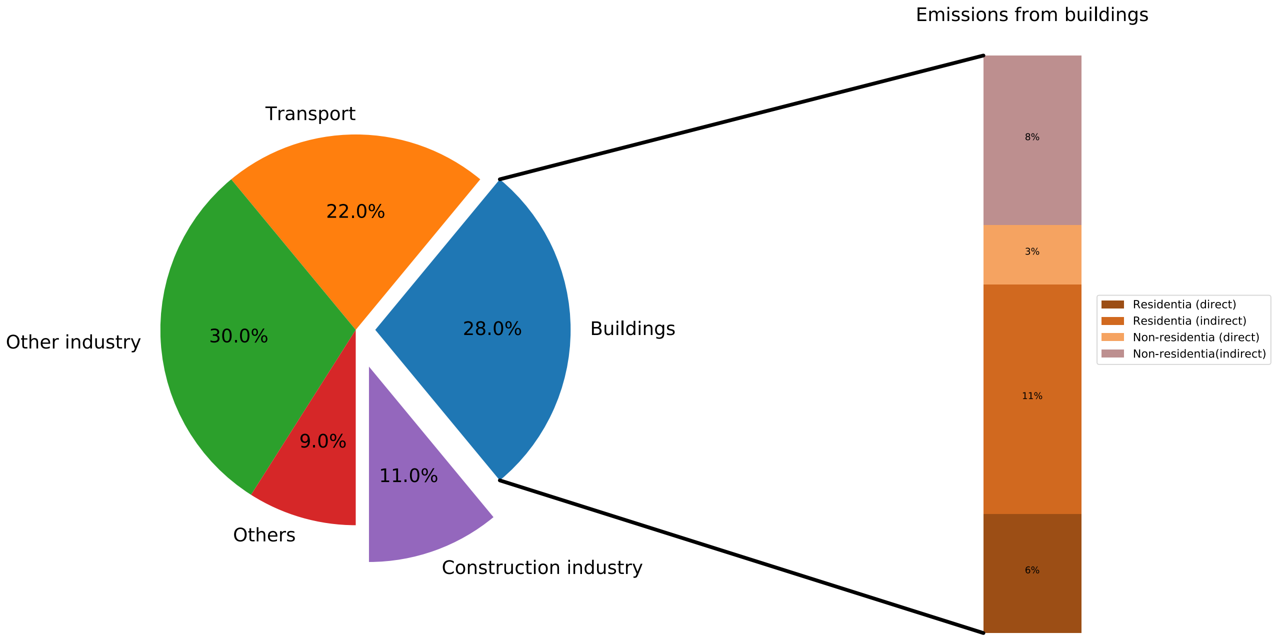

FIGURE 1. Share of CO_2 emission according to building sector in global level [7].

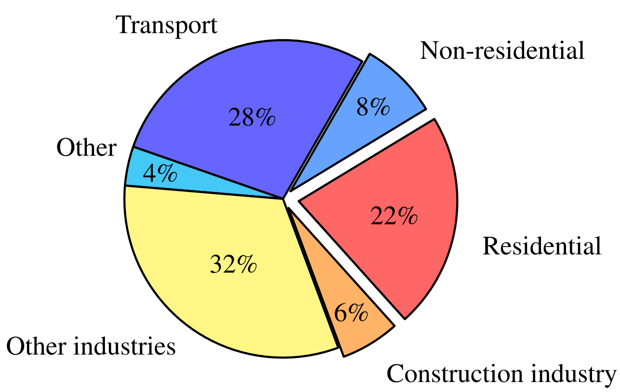

FIGURE 2. Global share of buildings and construction industry final energy consumption, 2018 [7].

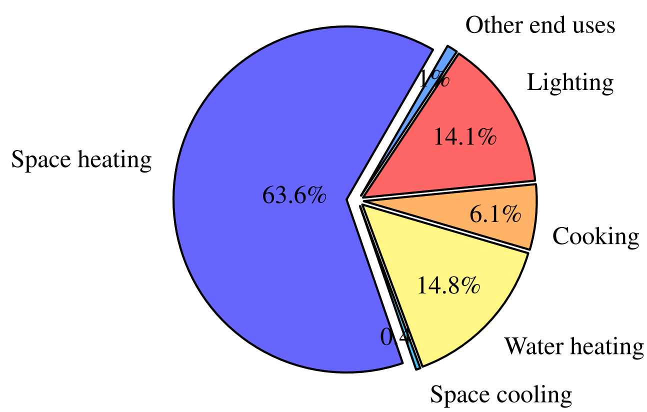

FIGURE 3. Final energy consumption in the residential sector by use in EU [10].

for thermal comfort. Likewise, buildings emit 33% of the total greenhouse gas. In USA, lighting (25.5%), heating (14.2%), and cooling (13.1%) of energy used in commercial buildings [4]. Energy consumption by the residential sector in European Union (EU) is as shown in Fig. 3. Heating, ventilation and air conditioning (HVAC) in the building is responsible for 40% of energy consumption in USA [11]. Furthermore, [12] projected an average increase of 1.5% per year in the energy consumption for HVAC in buildings for next 20 years. Therefore, reduction of building energy consumption is crucial for sustainable development, to minimize its impact on global warming and climate change. Nevertheless, the comfortability and energy consumption are directly proportional to each other [13]. Hence, a rational approach is required to minimize the energy consumption by providing maximum comfort. *"How human beings can better live in harmony with nature?"* has become the worrying factor for the society as global warming is in alarming situation. However, there have been increase in the research of occupant behavior and prediction. Especially after 2014, number of studies in the global level have reached a booming development as shown in Fig. 4. The EU Climate change adaptation strategy (2013) and the Paris Climate Agreement (2015) are legally trying to reduce global warming by global commitment [14], [15]. As buildings have huge part in global warming, researches on occupancy prediction and behavior analysis to reduce energy consumption are considerably increased. By the state-of-art, country wise researches are shown in Fig. 5.

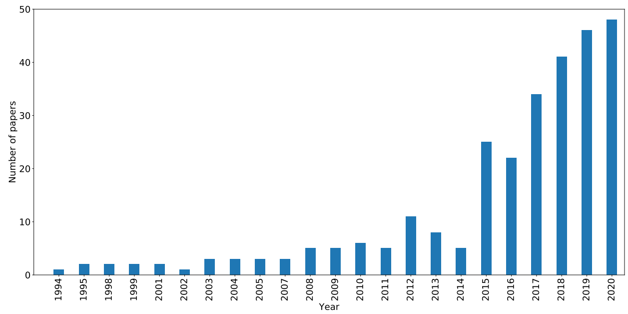

FIGURE 4. Global yearly researches on occupant behavior and prediction.

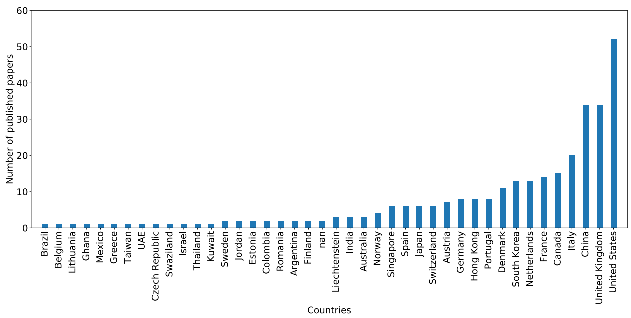

FIGURE 5. Country wise researches on occupant behavior and prediction.

Complex in nature and mutual relationship of environment and human behavior, it is required to understand the environmental aspects of a building from both natural and socio-environmental contexts [16]. To achieve this, myriad of researches have been done on smart building, occupant behavior and comfort analysis, renewable energy resources for buildings, green building, and net zero-energy building, etc.

Several review papers have addressed occupant estimation considering the behavior. Occupancy estimation and detection methodologies with sensor fusion are reviewed in [17]. Machine learning models for occupancy prediction and window opening behavior is reviewed in [18]. Detailed state-of-the art review is done on occupant behavior and energy consumption in [19]. Occupant comfort in high-rise multi-unit residential buildings were reviewed based on survey and measurement method considering thermal, visual and air quality in [20]. The effectiveness of green certification and comfortability are also analyzed in the same article. Recent approaches for occupant behavior analysis are studied in [21]. The difficulties for occupant behavior modeling are reviewed in [22]. The summary and main topics of above reviews are summarised in Table 1.

Unlike review papers mentioned above, this paper does a detailed review of building architecture, occupant comfort types, necessity of occupant behavior modeling, single and multi-occupant behavior analysis methodologies, occupant detection, estimation, prediction modeling and various occupant comfort influencing parameters for modeling and current research development. Number of occupants prediction methodology review is also covered by this review. The current review paper presents importance of occupant comfort and achieving it using occupant behavior analysis and prediction methodology by reducing energy consumption. Section 2 provides overview of occupant comfort types and its importance. Occupant behavior modeling methodologies, parameter considerations are discussed in detail in section 3. Critical analysis of existing occupant number prediction, detection and estimation are reviewed in section 4. Section 5 provides the discussion of the overall paper.

II. OCCUPANT COMFORT

Occupant comfort is the influential parameter that determines the well-being, overall satisfaction, productivity of the occupant. Occupant comfort is also a state of mind which refers to an inhabitant's overall satisfaction with the indoor environment. Overall indoor comfortability also reflects the occupant's quality of life. Many factors have a negative impact on the occupant's comfort level. A significant amount of energy can be saved by knowing the number of occupants present and understanding their behavior and preferences [22]. Occupant comfort is majorly categorised as thermal comfort, visual comfort, air quality, acoustic comfort and along with the consideration of psychosocial factors.

A. THERMAL COMFORT

Thermal comfort is the major factor in building for energy consumption due to heating and/or cooling. Thermal comfort definition according to Hensen states that *"A state in which there are no driving impulses to correct the environment by the behavior"* [23]. According to American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), thermal comfort definition is *"The condition of the mind in which satisfaction is expressed with the thermal environment"* [24]. Thermal comfort is basically a state of mind, which is influenced by many inputs such as geographical, physical and psychological characteristics, metabolism rate, age, gender, and other factors [25]–[27]. Thermal comfort is the crucial factor that is responsible for major energy consumption by buildings as shown in Fig. 3 [28]–[30].

Thermal comfort has been discussed since 1930s [31] and there have been many researches and reviews. Thermal comfort model approaches started with the analysis of thermal tolerance [32]. After that the first classical thermal comfort model; Fanger's Predictive Mean Vote (PMV) model was developed taking into account only the most important thermal parameters that influence human comfort for a large group of people [27]. Based on PMV, percentage of dissatisfaction (PPD) index is derived. PPD estimates number of people who feel "slightly warm" and "slightly cold" in Fanger's PMV model as shown in Fig. 6. The correlation between PMV and PPD is calculated using below equation 1 [33].

$$PPD(\%) = 100 - 95 \times e^{-(0.03353 \times PMV^4 + 0.2179 \times PMV^2)} \quad (1)$$

TABLE 1. State of the art reviews related to occupancy comfort, behavior, and prediction modeling.

Reference	Details
[17]	Recent solutions for occupancy detection and estimation with different sensors
[18]	Summary of parameters considered for modeling, performance analysis of existing machine learning algorithms
[20]	Occupant comfort review using measurement and survey-based studies in high-rise multi-unit residential buildings Review on existing methodologies for modeling occupant behavior analysis and its importance
[22]	Current methodologies for occupant behavior modeling

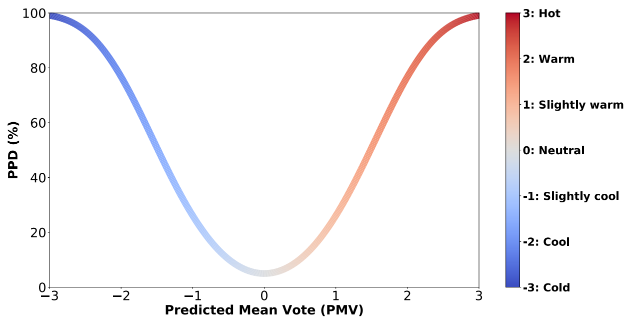

FIGURE 6. Predicted mean vote and percentage of dissatisfaction.

Fanger's model is the basis for standards like ASHRAE 55-1992 [34], ISO 7730 [35] that were developed to calculate the thermal comfort index and are widely used around the world. PMV measures thermal sensation in the scale of 7 points having central categories as 'slightly cool', 'neutral' and 'slightly warm'. People voting for these categories are considered as comfortable. Despite the difficulty to obtain the specific criterion like mean radiant temperature and air velocity [36], many studies tested the applicability and efficiency of Fanger's model and proved that Fanger's model is not suitable for outdoor climate, non-uniform habitat, elderly people, disables and children [36]–[39].

In recent decade, several new thermal scale models are developed to overcome the drawbacks of the Fanger's model [40]–[43]. Earlier, thermal properties of air inside a zone decided heating, ventilating, and air-conditioning details. In the future, occupant-specific and highly responsive frameworks will be the standard for heating, ventilating, and air-conditioning details [44].

Though thermal comfort is more researched area than other comforts, due to the inter-connectivity of different domains, complexity of human thinking; deepened research is required in the domain to analyze and accurately predict the thermal comfort. Existing models have many limitations and due to that, they are not yet completely accepted in international standards.

B. VISUAL COMFORT

Visual comfort is one of the most influencing factors for occupant productivity and visual well-being.

In EU, 14% of the total energy is used for artificial lighting [7], [10]. In Malaysia, artificial lighting accounts for 20% of the commercial electricity usage [45], South Korea uses around 30% of lighting energy among overall building energy [46]. Researches have shown that energy savings can be achieved to a significant extent by using artificial lights whose intensity can be varied based on occupancy. Lighting energy consumption is dependent on maximum acceptable window luminance threshold, occupants comfort threshold, and activities. By proper control of artificial light and daylight (using shades), indoor light can be regulated with minimum energy consumption [47], [48]. In the educational and office buildings, cognitive performance of occupants are important along with mental and physical state. As a result, a greater number of visual comfort studies have been conducted in conjunction with HVAC thermal comfort research [49].

Countries with more solar radiation have the added convenience to get more natural light and visual comfort. Natural light reduces the dependency on artificial light, thus minimizes energy consumption. Furthermore, natural light also proved to elevate the mood and well-being of the occupant. According to research studies, low-light environments have a negative impact on physiology, psychology, and cognitive performance. A pleasant visual environment is essential for healthier work and living places. Therefore analysing the illumination level required for the particular application and reducing the artificial light usage by utilizing the maximum available natural light are the main ways to enhance visual comfort [9], [50]–[53]. Application of shading devices such as blinds, façades, overhangs, are used to capture the sunlight coming into the building while reducing glare [49]. Similarly, by altering their geometry and configuration; the amount as well as direction of the light distribution can be altered.

1) SHADING

Natural light can be increased in the building using large and transparent windows. Windows are usually difficult for controlling heat gain and energy loss. To overcome this problem, solar shading is an efficient technique. Shadings are of two types:

- Fixed shadings
- Movable shadings

Fixed shades are used to block the unwanted glare in the summer that also blocks the required sunlight during winter. By using optimal hanging of the shades, the winter lights are generally let inside the buildings. Nevertheless, it's not the optimal way to control the sunlight in two seasons due to the diffused sun light. On the other hand, implementing the movable shades functions better by adjusting them according to the climate. Among the movable shading, external shading has better performance, and the cost is relatively high. Due to the mentioned reasons, movable internal shades are widely used. Effective blinding systems can save 30%-77% of the lighting energy. Rotation angle, shape, improved controlling, size, configuration, optimal slat angle, and colour of slats decide the amount of radiation that should be transmitted, reflected and absorbed [54]–[57].

Lee and Tavil [58] presented switchable electrochromic (EC) windows combined with overhead shades that reduce peak electricity demand while maintaining visual comfort in summer and winter. Yao [59] showed that 8% of the energy can be saved by movable solar shades compared to bare windows and improves visual comfort by 19.9%. Furthermore, [46] proposed a methodology using glare index to calculate the visual comfort and achieve it by blind slanting, and by lighting control. However, the control strategy depends on season, and priority. Fasi and Budaiwi [60] enhanced the energy efficiency of the building by using glare index and daylight factor. The analysis shows that using double-pane, clear-glass windows with daylight integration reduces total energy consumption by 14% compared to double-pane clear-glass windows without daylight integration. Furthermore, simulation results demonstrate that windows with automated Venetian blinds enhance visual comfort by reducing energy consumption. Similarly, the issue of blinds efficiency improvement using control techniques has been discussed in [61].

Façades are also used for shading purposes, their use maintains the desired level of the indoor and outdoor interaction; thus help to maintain warmth during winter, shading in summer, provide acoustic comfort and hence provides well indoor comfort for occupants. Their design depends on the geometry of window, environment, occupant, etc. There has been many advances in adaptive solar façades which have modular, dynamic, flexibility. However, there is still requirement for the façades that can adapt to the climate change, optimal visual comfort. Also to use maximum solar light without causing glare and thermal discomfort [62]–[65].

Switchable EC windows are used to control the indoor lighting that keeps the place warm during winter by passive heating [66], [67]. Visual comfort can be enhanced by proper orientation of the buildings, various shading and glazing strategies based on the solar radiation, and light dimming [49], [61], [68].

C. AIR QUALITY

To provide healthy and comfortable surrounding for the occupant, high indoor environment quality (IEQ) should be maintained. Air pollution inside the building can cause serious health problems. Despite the fact that individuals commonly spend over 90% of their time inside, in many countries no government law explicitly controls indoor air quality (IAQ). Toxin levels are commonly a few times to a few hundred times higher inside than outside, thus indoor air normally represents more than 90% of human exposed to toxins [69]. The subsequent social and financial effects are critical. For instance, more than 4.5 million instances of asthma result from openness to sudden exposure and the yearly financial expense due to the same reason is roughly \$3.5 billion [70].

Air temperature and relative dampness cause development of microorganisms, and several hundred varieties of fungi and bacteria species. Surface building materials are porous, rough and in the damped environment, will be favorable for the rapid increase of these micro-organisms. Due to the indoor moulds, IAQ degrades considerably. These moulds may produce spores, allergens, toxins, air born particles, and other metabolites. Indoor air humidity has major effects on respiratory system, eyes, work performance, sleep quality, voice disruptions, concentration, etc. [71]. Generally, health risk due to indoor air quality may depend upon different factors like exposure time, just as on individual characteristics like age, sex, genetics, and basic health condition.

Wargocki et *al.* [72] have shown that doubling the ventilation rate at a constant pollution load, or by doubling the contamination load at a constant ventilation rate can improve overall air-conditioning performance efficiency by 1.9%. Whereas [73] presented the relation between ventilation SBS and ventilation rate per healthy occupant. Experimental results for one day show that poor ventilation caused 12% for headache, 19% each for eye, nasal side effects, and 31% for exhaustion affecting the occupants' performance.

Most of the indoor air quality researches have been done at schools as children are more vulnerable for some pollutants than adults and they spend more time indoors. Moreover, adverse effect of this will have immediate and long-term issues. Outdoor air quality also plays major role in determining the IAQ. Especially particulate matter (PM) which can cause respiratory problems, CO produced by vehicles can add to hemoglobin in human blood to create carboxy-hemoglobin, which disrupts oxygen exchange to human tissues. Researches have proved outdoor traffic pollution has severe effects on IAQ of nearby schools. Avoiding exposure to toxic environments such as microbiologic and chemical substances, controlling moisture, and providing adequate outdoor ventilation will mitigate and prevent adverse effects of poor environmental quality [74]–[76].

Due to occupants breathing, CO_2 concentration is an indoor specific issue. The concentration of it increases as the ventilation rate per person decreases. CO_2 has serious health consequences, including deep breathing, visual disturbances, while 25% indoor concentration will cause death. When the concentration is above 5000 ppm, it affects the decision making, this shows the importance of keeping CO_2 level below in the admissible rage in the indoors [77], [78]. The HVAC based controlling system has majorly focused on CO_2 concentration while calculating the indoor air quality as it's the main waste produced in the system. The CO_2 based comfort optimization reduces a lot of energy consumption [79], [80].

It is difficult to quantify indoor air quality and understand occupant comfort by survey for the following reasons:

- The absence of steady measurements, principles, agreement on what comprises good IAQ,
- The variety, intricacy of pollutants discovered indoor that can influence human well-being and prosperity,
- The lacking comprehension of connections between toxin levels, risk of those toxins, and their consequences (both intense and continuous),
- The reach of health impacts identified with indoor impurities exposure, and that the same exposure can influence various people in different ways,
- Whether or not the toxins being estimated are the ones that truly matter
- The absence of necessities to measure and screen IAQ, prompting an absence of attention to potential issues and cures [81].

Volatile compounds, carbon dioxide, microbes, carbon monoxide, formaldehyde are the typically considered air pollutants inside the buildings. Indoor air quality is generally managed by following three steps:

- Emission source control: can be done using low emitting source materials such as paints and interior furnitures during construction and renovation.
- Ventilation: the objective is to provide exchange between indoor/outdoor air to maintain high IAQ.
- Indoor air measurement: verify if indoor concentrations are consistent with the given thresholds and therefore to monitor the efficiency of emission source control methods and ventilation [82].

Among the three, ventilation is the easiest and effective way. Natural ventilation is preferred over mechanical ventilation because it consumes less energy, costs less, and requires less maintenance [44]. While constructing new building, low carbon emitting buildings can be constructed. To improve air quality, Knudstrup et *al.* [83] proposed a passive design strategy and hybrid ventilation system as an alternative to integrating renewable energy sources. Environmental emissions can be significantly minimized by integrating renewable energy sources.

D. ACOUSTIC COMFORT

Providing isolation from the disturbing noise is called acoustic comfort. This can be achieved by stopping noise source or by isolating the indoor from noise. To determine the acoustic comfort, noise level reduction is calculated for indoor envelope and determined. However, due to the multidisciplinary nature of both the problem and solution methods, ensuring indoor comfort is a complex procedure. Although there are many regulations to maintain the IEQ, the idea and meaning of a healthy building is as yet advancing due to complexity to analyze and involves many factors [84], [85].

III. OCCUPANT BEHAVIOR

Building occupants' direct interaction with the building, such as adjusting temperature, shades, lighting, and ventilation and so on, has a significant impact on building energy consumption. A detailed research and understanding of occupants behavior is essential to maintain comfort and better control the building energy.

Modeling of the occupant behavior involves following steps:

1) Data collection: in data collection, required data to access the condition and/or to build algorithms are collected. Data collection is the base for many modern predictive techniques.
2) Data preparation: after collecting the raw data, it is rearranged as per the requirement and this process is called data preparation. Here, collected raw data are prepared for modeling by averaging, cleaning the redundancy and missing data, and scaling or by merging according to the need.
3) Model selection, development and evaluation: after having the processed data, modeling type such as statistical, categorical or numerical. According to the data, complexity to execute the algorithm, resources, runtime, efficiency, and error factor; the type of algorithm is selected and executed.
4) Model evaluation: model convergence is evaluated after executing the model, runtime, efficiency, error factor, and prediction accuracy to determine the performance of the model.
5) Continuous learning: after establishing the model and evaluation, new data has to be continuously fed, removing the old and irrelevant data to update the model to make it adaptive.

To model occupant behavior, researches have majorly adopted sensors and survey methods to collect the daily information of the occupant. Occupants behavior is influenced by many parameters as shown Fig. 7. Although, considering all the parameters make the model extremely complex and difficult to analyze. Hence, only the most important environmental and non-environmental parameters influencing occupant behavior are considered for modeling. Using sensors an intelligent environment is created to observe the occupant closely and collected data is saved in the database. Sensors are used to automatically detect the number of occupants using different parameters like temperature, IR radiation, humidity, and CO_2 detector. Sensors are also used to comprehend dweller behavior, environmental aspects, occupant interaction with devices, and to model and predict occupant behavior. As the collected data set increases, it will be easier to train the model or to understand the behavior. Along with the size of the dataset, relevance of collected data determines the effectiveness of the model. However, some of the missing data can be handled using artificial intelligence techniques. More references on data recovery can be found in [87].

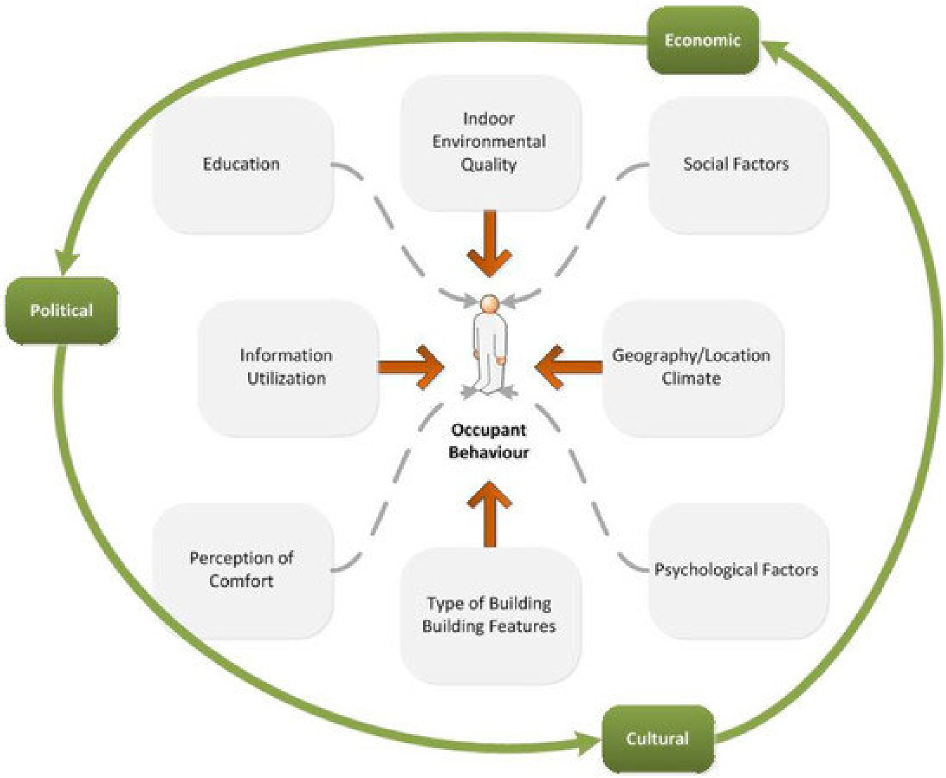

FIGURE 7. **Influential factors on occupant behavior [86].**

Sensors are more convenient to collect data as they do not interrupt the daily life of the occupant. However, some sensors may intrude on the inhabitant privacy while collecting data and may also necessitate the interface of other electronic devices. Whereas, surveying gives direct interaction with the occupant. This helps to understand the occupant better and may give additional data as well. However, determining frequency of data surveying determines the quality of data. This is because often inspecting decreases the error but disturbs the occupant. Sensors are preferred on this matter as the data resolution can be as less than 1 min [88]. Collecting data using sensors is majorly categorised as "direct approach" and "indirect approach". Direct approach is using sensors straightforward and direct detection of occupants such as Passive Infrared radiation (PIR) sensors, video cameras, radio-frequency identification (RFID). These approaches are effective and direct, maintaining the privacy is difficult. Therefore, researchers are preferring to use indirect approach and environmental data for occupant behavior analysis and prediction. Indirect approach involves calculating CO_2 concentration, monitoring motion sensor, using other indirect measurements to predict the occupants [89]. In the indirect set of sensors, occupants are monitored without disturbing their privacy. Temperature, relative humidity, CO_2 level, electric meter reading, water consumption in a building, etc. are used to in this category. Table 2 summarizes a commonly used list of sensors, along with their applications and problems.

Literature studies show that combination of sensors are used to model occupancy behavior and prediction. Easy, effective and instant data collection of occupant feeling and behavior is not yet practical due to the complex nature of the human being. Individual occupant behavior modeling is easier than a cumulative one as modeling parameters gets complex.

A. GENERAL APPROACHES

Yun *et al.* [102] presents a survey results of lighting in 4 offices. The results showed that occupants behavior pattern is significantly related to reduce energy consumption. Optimal utilization of indoor light can save up to 30% of lighting energy. However, the model performance can be better analyzed by implementing it to other types of buildings.

Using window operation status, occupant behavior modeling is presented in [98]. Stochastic nature of window operation behavior based on temperature is analyzed by implementing probability model.

Dynamic thermal sensation-based model predictive control is proposed in [103] to control the centralized HVAC. This methodology determines optimum supply of air temperature for HVAC chamber. Dynamic thermal sensation (DTS) based controller proved to perform better than PMV based Model predictive control (MPC) in terms of better energy consumption (25%) energy saving.

In [11] presented MPC for HVAC controlling considering occupant consideration to obtain thermal comfort. Analysis

TABLE 2. List of sensors used for occupant data collection.

Sensors	Specific application	Comments
Camera [90]	Detects number of occupants and their behavior	Complex processing and less privacy
Passive Infra red [91], [92]	Identifies occupant motion, ideal for single person office	False working is possible
Motion sensor [18], [93]	Helps to identify number of occupants	Complex to analyze occupant behavior monitoring
Illuminance sensor [94]	To detect the light intensity	Must be used with other sensors to analyze occupant behavior
Weather report [95]	Temperature and weather data	Dependent on local weather stations
CO_2 concentration sensor [18], [96]	CO_2 concentration level	Gives delayed response and ventilation of the building will malfunction the data
Pressure sensors [97]	Identifies presence and usage of a place by occupant	No privacy but high accuracy of data
Temperature sensor [93], [98]	Provides temperature variation and window status	Gives delayed response and must be used with other sensors to analyze occupant behavior
Humidity [93]	Detects humidity in the environment	Must be used with other sensors to analyze occupant behavior
Plug load sensors [99], [100]	Plug load consumption by the occupants	Sensor should be connected for each socket
Acoustic sensor [93]	Detects the sound level	Available on the market at low cost, but must be used with other sensors to analyze occupant behavior
Wi-Fi [101]	Occupant data collection	Easy and effective method, everyone should be connected to Wi-Fi

showed that 8% of the electricity consumption is reduced with enhanced occupant comfort. However, the model is focused on thermal comfort and has only simulated results.

Jia *et al*. [95] modeled occupant behavior considering interaction with window, light, door, and environmental conditions. Sensors are used to detect indoor environment and survey is used for understanding occupant behavior. Proposed method is systematically developed and analyzed changes in occupant behavior individually and collectively for a given situation. However, detailed study of stochastic nature of occupants and affectivity of the model for different building types and environment is not analyzed.

Li *et al*. [104] tested personalized occupant behavior model with cost sensitivity analysis (POBM–CSA) using many advanced algorithms. Though it is complex to design, modeling is focused on the single occupant behavior. Cost analysis helps to consider the varied opinion of the occupants while modeling. Further validation on different and mixed occupant behavior and testing in different environment will be definitely interesting to know the applicability.

Tabak and Vries [105] presented the probabilistic and S-curve prediction models to understand the occupant behavior in intermittent break times. Experimental data sources were used for prediction and accuracy of the model depends on the input data that is very uncertain. They concluded that accurate data will help to better predict the occupant behavior and increase the efficiency of work place, provide better comfort and to utilize the energy effectively.

Linear and logistic regression models are developed to manage the missing data and to understand occupant detection as well as to know the occupant activity level. Methodologies are experimentally implemented. Accuracy of the model is calculated using R^2 and mean absolute percentage error in [106].

Piselli and Piselli [107] developed data driven occupant behavior model to monitor, analyze and reduce energy consumption. They analyzed 2 years of data collected from sensors and energy consumption profile. The analysis showed that generalisation of the occupant behavior model is not feasible as humans are stochastic and occupants' attitudes, emotions changes which influences the comfort.

Currently used automatic light can save lot of energy while occupant is absent. Although, data survey showed that there are occupants who are not happy due to the malfunctioning of the sensors. Also if the building is intelligent and high performance, effective energy saving is possible by training the occupant to better understand the building features [108].

B. MACHINE LEARNING ALGORITHMS

Li and Yao [109] considered occupant behavior to determine heating and cooling loads in a building. Linear regression, State vector regression (SVR) and Artificial neural network (ANN) are the three machine learning techniques were used to predict the energy usage depending on the user behavior. Data for heating and cooling load intensities were generated in EnergyPlus. Gaussian radial basis function kernel SVR model performs better than other models by providing less than 4% normalised root mean square error (RMSE) for cooling and heating load estimations.

Khosrowpoura *et al*. [110] modelled to predict occupants' short term energy-use patterns using support vector machine, K-means clustering method is implemented for the means of classification to increase the effectiveness of energy efficiency programs. Predictions showed that 50% of low efficient occupants are highly predictable and another 36.6% are predictable in average. The modeling of occupant behavior is done by taking survey that can be improved by using sensor fusion.

Mahmoud *et al*. [111] presented the necessity to predict the occupant behavior by experimenting on elderly people having dementia. Data were collected using sensors and modeling is done using nonlinear autoregressive exogenous model (NARX) and Elman neural algorithms. Comparison with other existing methods and predicting the behavior will help to improvise the model.

Penga *et al*. [112] presented short detection of occupants using sensors development of behavioral model using K means clustering methodology. Occupancy prediction is modeled using k-nearest neighbour (kNN). Monitoring occupant behavior related to energy consumption and using demand driven control strategy to maintain comfort and to save energy. Using 11 case studies and model saved 7%- 52% of energy during cooling. Applicability of complicated algorithm may be difficult for the local controllers.

To increase the efficiency of the system, paper [113] presents how to extract occupant schedules from the data and if data is missed out, how to extract it from normally logged parameters. Combination of k-Shape clustering and change-point detection method is used to derive the occupant schedule from data. The proposition considered temporal variation of occupants behavior.

Spataru *et al*. [89] analyzed occupant behavior in relation with domestic house to reduce energy consumption. Occupancy profiles from data driven models generated diverse and non-diverse occupant presence models. The results show that assumptions about occupants are conservative in nature and it cannot provide accurate results. For estimating district energy demand, occupant profile and density are very impressionable aspects. They showed, 30% of the cooling demand and 20% of greenhouse gases can be reduced by controlling occupant behavior.

Virote and Neves-Silva [114] proposed Markov chain model for occupant behavior modeling. The occupants behavior is further utilized for the energy consumption modeling. The presented occupant behavior model including assumptions and hidden Markov model (HMM) is applied only on occupant behavior towards lighting system. The modeling will get complex as the building size increases. However, proposed energy consumption model predicts accurately with less than 2% error.

HMM has established temporal relation between the occupants and environmental parameters in each step. Using HMM, the Markov model and log-logistic survival model are used in [94] to determine and control of lighting and shading in offices. The maximum error rate for predicting lighting energy consumption was 13.04%. The model is also capable of predicting the occupant behavior.

Ding *et al*. [94] compared log-logistic and Markov model with general methods such as considering the classification of occupants, the average statistical data. The model did not consider the coupling relationship between the two systems, ignoring coupling relationship and diversity between occupants. Proposed method performed well than mentioned conventional methods by providing 13.04% of error rate while estimating lighting energy usage. The experiment proved that coupling had greater positive impact for the prediction.

Yan *et al*. [116] proposed Markov chain-based Monte Carlo method for occupants behavior for energy usage. Data were collected using electric meters. User behavior towards energy action, energy working hours model, and air-conditioner energy use behavior were modelled and experimentally tested. The methodology is applicable for statistical patterns of users' behavior. The modeling is adaptive for different buildings that can be implemented on other buildings, and data collection method can also be varied. Further improvement is possible to increase accuracy and to do analysis with large data set.

Ryu and Moon [90] used indirect data collection to know about occupant behavior. Decision tree and HMM algorithms are used to predict the occupants arrival time on next day. Occupancy profile, CO_2 concentration, and electricity consumption are three majorly collected data for behavioral analysis and prediction. They concluded that proposed model is well suited for controlling application in buildings maintaining the privacy of the occupants.

Occupant behavior studies show that occupants' light sensitivity and preferences have a greater influence on controlling the lighting in a building. Different occupancy patterns have different effects on the building and use energy in different ways. Age, gender, psychological state, location, comfort level, schedule, and environmental factors all have an impact on occupant behavior. In a building, occupancy behavior cannot be analyzed solely using sensors because humans behave differently in different situations. A personalised model or survey methodology provides a more accurate insight of occupant behavior inside a building. The survey and questionnaire methods provide a quick and easy way to understand the status of building behavior. The voting results can be used to determine the building's operational and comfort status.

Baird and Dykes [121] conducted a large survey in 45 buildings and discovered that negative comments outweighed positive comments, and if 10 are negative comments and 1 is positive, the building's performance is considered poor.

Existing research has primarily analyzed occupant behavior with respect to thermal comfort, focusing on heating and cooling systems, and visual comfort regarding sunlight, glare, and artificial light. Summary of occupant behavior methodologies with their pros and cons are listed in Table 3. The analysis shows that majorly machine learning approaches have been utilized for modeling. SVM, Markov chain and neural networks have been utilized for occupant behavior modeling. Without large database and detailed analysis, the generalisation of the existing approaches cannot be done. Listed methodologies provide around $\pm 15\%$ of the error factor for the behavior modeling in different error calculating matrices. The adaptability of the presented technologies has not been thoroughly examined.

TABLE 3. Critical analysis of occupant behavior methodologies.

Reference	Methodology	Outcomes	Constraints
[98]	Building physics algorithm with a stochastic occupant model	Without night ventilation, window position changed 61%-76%, includes occupant interaction with a window control in summer	Security measures to open window during night are not considered
[94]	Prediction model, Markov model and log-logistic survival mode	Lighting and shading coupling control behavior	Frequent survey will disturb the occupant
[115]	Kernel ridge regression and k-means	Detect the changes in behaviors based on energy consumption data	Model is not yet robust
[114]	Stochastic Markov model	Model learns occupants behavioral patterns and it does not behave as a behavior recognition model	Behavior of the occupants are based on assumptions
[110]	State vector model (SVM) and occupants short-term energy usage behavior	Modeling and predicting individual energy usage behavior	Predicting for short term and limited for work station
[95]	Agent-based model: Performance Moderator Functions server (PMFserv)	Occupant behavior analysis and behavior prediction	Presented individual level results cannot be generalised
[111]	Comparison of Non-linear autoregressive exogenous model (NARX) and Elman network	NARX network performs better than the Elman network by providing 6% error rate	Difficult to identify daily movement pattern of the occupant
[104]	Personalized behavior identification cost-sensitive problem model evaluation	Model can improve identification performance considering personalized preferences and attitudes of occupants	Complexity in designing
[105]	Probabilistic and S-curve	Using experimental data, intermittent activity of the occupants were predicted	Sensitivity analysis could be interesting
[116]	Markov chain Monte Carlo (MCMC)	Adaptable to any type building, works quickly, and predicts occupant behavior rapidly	Method could not predict the energy use behavior rules with a high resolution
[117]	Survey method	Gives clear idea about occupant personal behavior towards thermal comfort	Clothing level is approximately modelled as it varies continuously
[112]	K-means clustering; Occupancy prediction: k-nearest neighbor	Proposed methodology can be used for controlling space thermal and ventilation control, to infer humidity and CO_2 concentration set points	Proper occupancy information can reduce more energy consumption
[90]	The Classification and Regression Tree (CART) algorithm and HMM algorithms	Predictive control applicable for simulation and real building, can predict the occupant arrival time using indirect approach	Energy consumption maintaining the comfort is yet to be developed
[118]	Survey and decision methodology	Higher resolution level in modeling	Model cannot be generalised
[119]	Poisson process model with two different exponential distributions	Statistical properties of occupancy are analyzed	Difficult to understand the transient nature of occupancy during occupied periods
[120]	Linear data analysis	Results proved marginal shift in electricity usage correlates with an increase in occupancy	Practically saving energy by asking consumers is difficult
[89]	Data analysis	Adaptable to other houses and minimises energy consumption	Complete analysis has not been done
[102]	Data analysis of lighting and occupant behavior	Upto 30% energy can be saved if indoor light is utilized wisely	Occupants are negligent to save energy
[113]	K-Shape clustering, change point detection method, Linear and logistic regression models	Methodology can be applied to any number and type of building at the same type	Data availability, requirement for installing sensors, PIR sensor result in big building with lot of movement is not reliable
[107]	Conduction transfer function (CTF) algorithm	Capability of different static and stochastic occupancy models can be evaluated	Observed key factors such as light usage is inconsistent
[106]	Rule-based algorithms	Detailed occupant behavior in urban buildings is analyzed	Weather influence is not considered during the case study

IV. OCCUPANT PREDICTION METHODOLOGIES

The ability to detect the occupants presence and estimate the number of occupants inside the building at any given point of time provides more advantage for optimal building energy management. Detection of occupancy presence means detecting the existence of occupant in given controlled environment. Whereas, occupancy prediction is estimating the number of people in the particular building. When compared between detection and prediction, detection can be done through multiple sensors, however predicting the occupancy is a difficult task due to the heterogeneity of occupancy behavior. Prediction is done by monitoring occupants using sensors and studying their behavior. Different types of sensors are used to monitor various characteristic of occupants and their behavior for the current state. The occupants behavior and prediction modeling architecture is as shown in Fig. 8. The strong and sensitive relation between the occupant, comfort and energy consumption are the main hindrance to set standard scale of energy usage per person.

Variation of the energy demand is mainly due to the occupancy interaction with the building to keep indoor conditions comfortable to them. External environmental conditions and building itself are main influential parameters for change in indoor conditions. Using building energy management system (BEMS) based on occupancy behavioral data, overall comfort can be regulated optimally while saving significant amount of energy. BEMS considerably increases the overall building performance and efficiency. Recreation of various schedules and practices inside business structures has shown energy use changes from 30%-150% [97], [122]–[124]. Despite the fact that occupancy behavioral analysis is critical for energy optimization, prediction of exact occupant behavior is still a difficult task. Lack of understanding of human behavior, complex interaction with buildings,

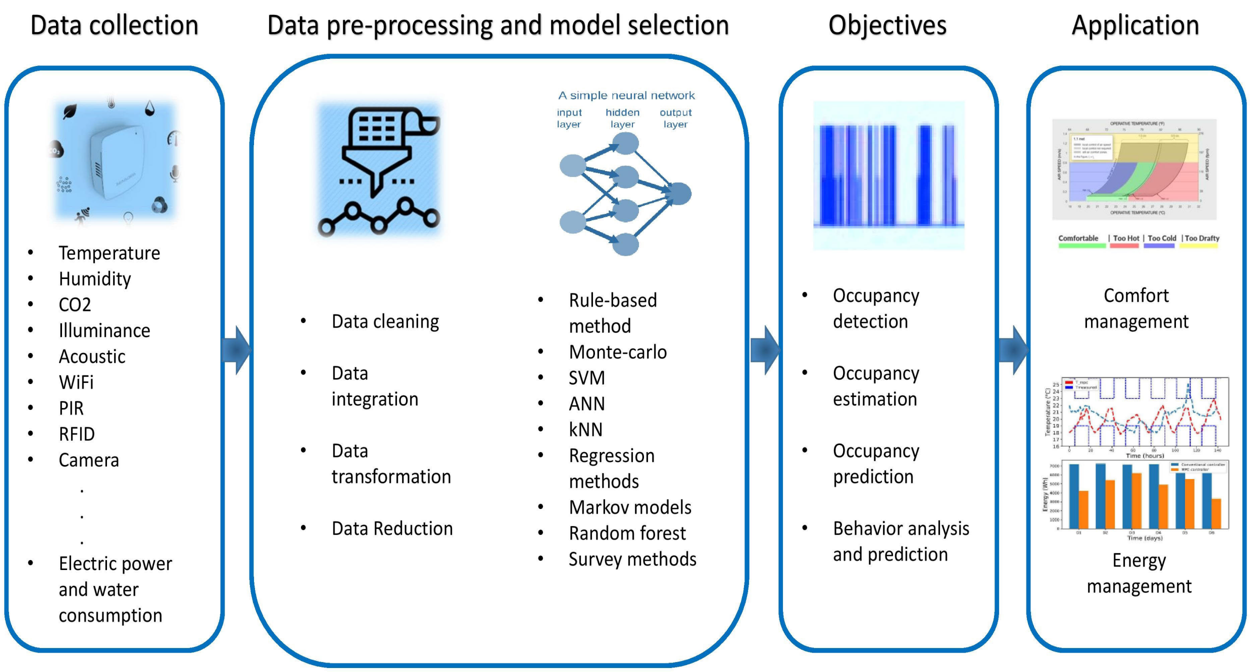

FIGURE 8. Occupancy behavior and prediction modeling process in buildings.

and relation between environmental condition; occupancy behavior and prediction have limited the application of such controllers in the building.

A. ANALYSIS OF OCCUPANT PREDICTION MODELING

Many researches have tried to detect and predict the occupant in conditioned environment and thus to control and optimization the energy consumption.

Tachikawa *et al.* [125] proposed estimating the number of occupants using CO_2 concentration. The CO_2 sensor is used at the Keio University Network oriented Intelligent and Versatile Energy saving System (KNIVES) that controls the power demand and supply. The advantage of this methodology is only CO_2 sensor data and low pass filter are used for occupancy estimation. The low computational time (15 sec) is the added advantage. Although, ventilation has huge impact on CO_2 concentration and estimation accuracy. Measurement of estimated and measured number of occupants' error would have added value for the research.

Lawrence and Braun [96] presented estimation CO_2 generation, flow rate evaluation, and influence of ventilation using quasi-static model and parameter estimation methods. Short-term experiment in a controlled environment proved that error in the estimation of CO_2 concentration is 4%-15%, which is within the acceptable accuracy range. However, the patterns were distinct for various building structures such as restaurant, schools, and homes.

Zikos *et al.* [122] worked on detecting, estimating the density and predicting number of occupant by using conditional random fields-based approach. Data was collected using multi sensors like CO_2, motion and acoustic sensors. Experiment was carried out at 4 different places with separate characteristics to compare the results and for model validation. Minimum occupant prediction accuracy of the methodology is 75%. The proposed model performed better than HMM in different places, number of occupants and short period data set. By reducing the time consumption for building and training model may improve performance of the proposed technique.

Liang *et al.* [126] used data mining technique for occupant prediction in offices. Occupancy schedules pattern is observed using cluster analysis, learning the behavior rules using decision trees and prediction is done based on the scheduled rules. Hidden patterns and characteristics can be identified in this method. To model the proposed method, simple data set is enough and experimental result at an office building at Philadelphia proves that a simple algorithm provides 8.5% of mean absolute error (MAE).

B. MACHINE LEARNING APPROACHES

Qolomany *et al.* [101] proposed replacing existing sensors by available Wi-Fi database and to estimate the occupancy in the building by using Auto Regression Integrating Moving Average (ARIMA) models and Long Short-Term Memory (LSTM) time series models. LSTM performed better than ARIMA by decreasing the RMSE error around 88.2-93.4%. Computational efficiency of LSTM is also better than ARIMA.

Ding *et al.* [127] presented occupancy modeling using Gaussian distribution, and used this model in the controller to minimize energy consumption. The experiment carried out in dormitory, educational, and office building using the monitoring system (cameras) and survey methods. The model performance error showed 15% RMSE.

Vafeiadis *et al*. [100] utilized water consumption and electric meters to detect the occupancy. The estimation model is developed using Monte-Carlo simulation and machine learning algorithms. Among them, Random forest method resulted in 80% accuracy and F-measure showed 84% of accuracy. Larger data set and verification on various buildings would help for the further improvisation of the proposed model.

Wang *et al*. [128] compared three modeling techniques: k-nearest neighbours, support vector machine, and artificial neural network, to predict the number of occupants inside an institutional building. Data was collected using environmental sensors (CO_2, temperature and humidity level detector), Wi-Fi probe and camera for verification. Data were tested in different ways; environmental data, Wi-Fi data, and fused data to understand the better way to utilize the sensors. Short-term experiment and analysis proved that artificial neural network performs better for fused data and SVM functions well with Wi-Fi data. However, the error is always above 20% measured in mean absolute percentage error (MAPE) in all the cases. By including more environmental sensors, the accuracy of estimation of the proposed model may be elevated.

Amayri *et al*. [129] proposed sensor combinations to determine the number of occupants inside a room. Motion detector, power consumption, CO_2 concentration and window/door position detector are utilized in this research work. Decision tree algorithm is used for occupant prediction and C45 as well as random forest algorithms are applied to execute recognition tests. The performance error of proposed methodology is around 19%.

Meyn *et al*. [130] presented sensor-utility-network (SUN) for data collection in office buildings. Occupancy behavior is modelled using HMM method and Bayesian network for the prediction utilizing the collected data. The error of estimating occupants reduced from 70% to 11% after applying SUN for collecting data. The SUN performance is also compared in the research with CO_2 estimator, video cameras and PIR sensors.

Sangogboye *et al*. [131] evaluated the performance of occupant predictive models using multi-label classification (MLC) methodology. In the research, performance of SVM and Preheat methodologies were compared. Results show that MLC has increased the accuracy of prediction for each predictive model by 6%. SVM is preferred to work better than PreHeat method during high occupancy frequency and proposed modeling conditions.

Liao and Barooah [132] developed Mixed Agent-based Rules Model (MARM), to simulate the occupant behavior and Monte-Carlo method to extract the models to detect the occupant in a room. Simulations were carried out to evaluate the performance of proposed methodology and results showed that estimated results were almost accurate with real occupancy number. The mean error of estimated and real value was 0.1 and a standard deviation of 2.1 that was within acceptable range. Simulation and experimentation verification and multi-occupant in multi-room condition testing may improve performance of the model. Complexity to model each occupant graphical model is one of the major drawbacks of the methodology.

Wang *et al*. [133] presented predicting reliable occupancy using Dynamic Markov Time-Window Inference (DMTWI) model considering stochastic and time dependent nature of the occupant. Performance of the presented model is determined by comparing presented model with Auto- Regressive Moving Average (ARMA) and Support Vector Regression (SVR) methodologies. DMTWI model performed better than SVM and ARMA by providing performance accuracy above 80%. Some limitations of the model are reliability of Wi Fi probes along with privacy of data.

Wang *et al*. [134] presented using Markov based feedback recurrent neural network (M-FRNN) algorithm to model and predict the occupant profiles. Wi-Fi probes are used for data collection and collected data was verified using cameras. Proposed methodology performs better than Markov model for shorter days and smaller number of people. Privacy concern, verification of the methodology on different buildings and different occupant conditions have not been included in the modeling. Though minimum accuracy of the model is above 80%, data reliability is less as only one sensor is used, over the time if the signal is weakened or the Wi-Fi router gets technical problems, data update to the model will not be possible.

Ryu and Moon [90] developed occupant prediction model using decision tree and HMM algorithms. Data for the modeling are collected using electricity consumption by lighting, CO_2 concentration in indoor and outdoor for every 1 min interval in the Building Integrated Control Test-bed (BICT) at Dankook University. Maintaining privacy of the occupants, present as well future prediction of occupant's arrival time are the added advantages of the proposed methodology along with its adaptive nature. Proposed model performs better when occupant number is high.

Flett and Kelly [135] modeled Markov based occupancy profile considering their interactions with related individuals and occupancy prediction duration. Data for modeling are collected using survey method from United Kingdom Time-Use Survey and the model has considered occupant profile with corresponding characteristics. Enhancements of the model may be done by improving the model consistency, and status duration prediction. The model provides idea of occupant variation in communities that is difficult to apply for single houses. The error percentage of HMM model were ranging from 1.4%- 22%, which were within acceptable range.

Andersena *et al*. [92] presented occupancy presence sequence modeling using inhomogeneous and homogeneous Markov chain models for an office building. The data was collected using 57 sensors for every 2 mins intervals. The results show that inhomogeneous method improved one step predictions. Model clearly distinguishes the occupants status as ''present'' or ''absent''. However, correlations between occupants and days are not considered in the model.

Whereas, [136] presented an approach to estimate occupancy presence in the provided zone using the inhomogeneous Markov chain model. Motion sensor data collected over 5 years for 20 zones, the model is simple and effective that is flexible to use in all types of buildings with any type of occupancy pattern. The accuracy of the proposed model, error in the prediction has to be evaluated yet and movements of occupant between the zones have not been considered.

Salimi *et al.* [137] presented modeling the status of the occupant continuously for individual, zone and room levels using inhomogeneous Markov model. The model updates, adapts and improves as the time progress is the added value. Performance of the model is analyzed using R^2 prediction model. As the model can capture various resolution levels and self-adaptive; frequent update of occupant behavior will enhance the performance of the model. Privacy issue of the data collection is still a concerning factor.

Li and Dong [138] presented occupant existence estimation using inhomogeneous Markov model. The data was collected from 4 houses using passive infrared sensors for 5 min intervals. The occupant prediction is short term, i.e., the prediction horizon is 24-hours. experiment is tested for 15 min, 30 min, and 60 min prediction window for houses. They observed a behavior pattern that occupants were mostly in kitchen during afternoons and evenings, and in bedroom during night. The results of the model show that for short term forecast the Markov model performs better with more than 80% accuracy whereas ANN and SVR outperformed the proposed model in 24 hour predictions. The proposed model is able to adapt to the changes in occupancy of the house.

Occupancy prediction is important to control the energy consumption by maintaining the comfort for the residing occupants. Occupant predictions are of various types; occupancy detection which refers identifying the presence of the occupant at the moment in the controlled environment, occupancy estimation which refers measuring the density of people at a given moment inside the building, number of occupancy detection which predicts the number of people inside the building. Estimating the number of occupants by preserving their privacy is challenging due to the complexity of the influencing parameters and stochastic nature of human. Summary of existing occupant prediction methodologies is listed in Table 4. Occupants number prediction again can be categorised as short term prediction and long term prediction based on the prediction horizon. However, the analysis clearly shows that occupant number prediction for future is not yet well established.

V. DISCUSSION

Providing comfortability for all occupants in the controlled indoor environment with optimised energy consumption is the objective of intelligent buildings [141]. Studies show that 30%-42% of energy can be saved by accurate occupancy prediction even after maintaining comfort [93], [142], [143]. Researches show that huge amount of energy is wasted during non-occupant hours. Miscellaneous energy loads (MEL) contribute 20% total building energy consumption [144], [145]. Although, there are researches and optimized solutions for energy usage and reliability considering buildings as distributed nanogrids, user behavior analysis and occupant prediction are necessary because they are an integral part of buildings [146]. Nevertheless, there are only few studies that have been conducted to understand energy consumption when occupant is absent and to provide comfort when occupant returns back [139]. Though by improving the technology, efficiency of the system can be enhanced; occupants role and their interaction with the building is crucial to save the energy because amount of energy consumption in any building is closely related to occupant habits, their living style, income, and their preference. For these reasons, prediction of occupancy and understanding their behavior are essential. Since the human nature is very stochastic, it is difficult to predict the exact behavior and reaction in every state. Here the research on occupant presence, behavior, and prediction stands out.

Collecting data and computational time are time consuming while modeling occupant behavior and prediction model. The quality of building indoor environment comfort such as thermal, visual, acoustic, indoor air quality along with occupant behavior and prediction are analyzed and determined by data mining techniques. Occupant data collection using fusion of unobtrusive sensors and questionnaire provides accurate modeling of occupant behavior. Humidity and temperature sensor with local weather forecast is utilized to collect data related to thermal aspect of the occupant modeling. Using illuminance sensor and weather report, indoor lighting requirement is analyzed. Related to air quality of the building and to determine the number of occupants, CO_2 level is commonly adapted method. However, CO_2 concentration in indoor may vary due to the status of window, door and ventilators. Furthermore, energy waste by non-human produces CO_2, which may affect the data. Motion sensors, pressure sensors, electricity consumption are also used to model the occupant behavior and prediction. Researches are also using on Wi-Fi probes as sensors. In the modern era, almost all the buildings are using Wi-Fi. It does not need extra infrastructure and miscellaneous products. The main concern with Wi-Fi is privacy of the occupant as address is related with occupant information. Applying dynamic Media Access Control Address (MAC) masks, a universally unique identifier (UUID) hashes or aggregated results are solutions proposed in [134]. Sensitivity and dynamics of data recognition of sensor are factors techniques advanced the data accuracy. However, As there is no sensor that can measure all indoor parameters together, methodologies like sensor fusion, artificial intelligence, and data mining are commonly used to collect and deal with missing data along with collected data. [147] Eliminating risk of cyber-physical attacks,

TABLE 4. Critical analysis of occupant prediction methodologies.

Reference	Building Type	Methodology	Advantages	Comments	Error(%)
[126]	Residential home	Recurrent neural networks: NARX and Elman	NARX works better than Elan network	Tested on short term data (only for 14 days)	5%-9%
[90]	Test bed	Decision tree and HMM	Indirect modeling approach to predict occupants number for present and future (next morning)	The model is adaptive in real-time	Error in measurement of indoor CO_2 concentration: 10.5%, Indoor CO_2 moving average (15 min): 15.0%, CO_2 I/O ratio: 6.8%, Total electric power consumption of the lighting system and appliances: 13.8%
[138]	Residential house	Inhomogeneous Markov model	Proposed model compared with Probability Sampling, ANN, and SVR; the method allow prediction for 15min-24hour window	High computational cost, inadequacy of data to understand seasonal factors and generality of the model is not tested	Average 5% correctness ; 11% maximum difference in 15-min ahead prediction of occupant in the room and home; less than 20% of error
[133]	Offices	Dynamic Markov Time-Window Inference (DMTWI) model	Time-window is flexible, and the collected data is real time, online and frequency of data collection is customizable	Occupant needs to connect with Wi-Fi; data resolution and time frame have not been well decided	15%
[135]	Residential house	Higher-order Markov Chain	High resolution model stays stable for small number of occupant	Performs better than higher order event-based approach; Limited by lack of large, multi-day occupancy datasets	Less than 5%
[131]	Commercial buildings	Multi-label classification (MLC), compared PreHeat and SVM	Performs well for higher occupancy	Prediction is poor for lower occupancy	Less than 6%
[139]	Office	Frequentist maximum likelihood algorithm, Bayesian estimation, feed-forward neural network, extreme learning machine	Energy and occupant predictions are done	Only one CO_2 sensor is used and modeled only during summer	Around 10%; for further values refer the paper
[96]	Commercial buildings	Quasi-static model and Parameter estimation methods estimation	Good prediction accuracy and uses only one sensor	CO_2 takes time for building up and minute changes are difficult to notice	4%-15%
[137]	Office	Inhomogeneous Markov chain prediction	Self updating model	Privacy issue	14%: for lighting control and 32%: HVAC system control
[101]	University campus	Train Auto Regression Integrating Moving Average (ARIMA) models and Long Short-Term Memory (LSTM) time series models	LSTM is more accurate	LSTM needs inputs, more data, slow to train and run	19.1% by ARIMA and 6.6% by LSTM
[136]	Offices	Inhomogeneous Markov chain	Senses the occupant presence, capable of reproducing	Zone movement cannot be modelled, single occupant is considered	-
[134]	Office	Markov based feedback recurrent neural network (M-FRNN) algorithm using Wi-Fi	Better and reliable than conventional CO_2 based approach	Short term validation	around 20%
[92]	Offices	Inhomogeneous Markov chains compared to homogeneous Markov chains	Significantly improved one step predictions	Correlation of occupants and/or between days is not studied	-
[128]	Office	Compared machine learning techniques: k-nearest neighbors , SVM, and ANN	Error measures such as MAE, MAPE and RMSE showed that SVM was well performing with Wi-Fi data and NN-based model with fused data has best performance	Complex space with longer duration has to be analyzed	For kNN : 44.4%, SVM: 36.6% and ANN: 37.3% ; for further error values refer the paper.
[127]	Any	Gaussian distribution model	Both occupancy and energy consumption data were considered	Results showed that surveyed and clustered occupancy pattern was not comprehensive	$\pm 15\%$
[140]	Hospitals	Statistical predictions for individual; predictive occupancy models	Enormous number of data sources, proved model data is vulnerable to time and season	Privacy issue, short time data collection	All 3 days RMSE value and add a sentence saying for further error values refer the paper
[100]	Residential house	Comparison of Random Forest learning technique with other techniques	Simple classification modeling using smart meter(water and electricity) data collection	Not a robust predictive model	Around 20%
[129]	Offices	C45 and random forest algorithms	Less error, better performance	Short term validation	19%–18%
[130]	Offices	Sensor-utility-network (SUN)	Less error, computationally efficient, scalable method	Privacy issue	11%
[125]	Classroom	CO_2 sensor	Simple, and proves CO_2 based occupant prediction can be done	Difficult to install in existing building, trade off between measurement and accuracy	Occupant prediction error is not calculated. CO_2 measurement error is 83.3%
[132]	Commercial building	Monte-Carlo	Agent based model, fused sensor data with model prediction	Single room and single occupant are considered	Less than 10%
[122]	Offices	Based on Conditional Random Field probabilistic models	Performs better than HMMl	Training the model is time-consuming.	For HMM: 11.5% and for CRF: 11.3%; for further error values refer the paper.

providing privacy are the focusing area for further research. Comfortability of occupants to monitor their behavior is also concerning aspect while collecting data.

Individual and cumulative occupant behavior are the two types of modeling focused on thermal and visual comfort. Furthermore, stochastic, deterministic and combination of both (agent-based) approaches are available for occupant behavior models. Occupant interaction with building, series of events and predicting the socio-economic and emotional behavior which affect the building energy consumptions are difficult to monitor and model. Occupant behavior is majorly modeled using combination of various types of algorithms. ANN [148], regression models, MPC [149]–[151], Gaussian distribution model, Markov chain models, clustering algorithm, are to name a few. Different energy related platforms, open plat forms are utilized to simulate the modeling such as MATLAB, EnergyPlus [152], GridLab [153], Python [154], etc. With recent developments in wearable sensors, which can measure heart rate, skin temperature, metabolism rate, heath status, neural reactions, there are various improvements in the modeling by better understanding physiological and psychological effects of occupant with the building. Detailed analysis of individual and group occupants behavior related to energy consumption and intelligent environment can be expected in near future [22].

Accurate occupant prediction is important for the efficiency and facility control of buildings along with occupant behavior modeling. Improved sensor technology and intelligent building provide greater opportunity to detect and predict the occupants more accurately. Occupant prediction can be categorised as follows: occupant detection to know if the occupant is present inside the building or not, occupant estimation for huge commercial buildings to evaluate the density of occupants. Occupant estimation is generally categorised as low, medium and high density. The last one is predicting the accurate number of occupants using sensor fusion, data mining and prediction technologies. In addition, occupant prediction is done for current time, short term and long term prediction. Due to the unpredictable nature and various parameter inclusion, estimating exact number of occupants is still difficult. Self-adaptive models using machine learning models, considerably Markov chain derived models are used for accurate occupant prediction.

The main technique used for occupant behavior modeling and prediction is machine learning technology. Modeling with general methods is time-consuming, and generalizing the concept to every building is difficult. Machine learning models are developed on the basis of collected data. Furthermore, using machine learning techniques, behavioral and prediction models can be implemented with the same set of input data. Especially, advanced techniques from Markov model such as HMM, inhomogeneous hidden Markov method, SVM, etc. are majorly used algorithms as they can better handle stochastic nature of humans. Various artificial neural network algorithms are also used to understand occupant behavior and predictions. Neural network algorithms generally take time to train the model. Algorithms for behavior and prediction modeling are selected considering flexibility to adapt for diverse set of data and conditions, computational time, efficiency, complexity of modeling.

If the data is reliable and self-adaptable, the prediction models are capable of self-updating and improvising their performance as the time progresses. Various input parameters influence the efficiency of the model. Unreliable and wrong assumptions will affect the performance of models. Predicting the exact number of occupants and behavior in a building is difficult and generalised, simple technique is not yet established due to complexity of input parameters and more research is required in this domain.

VI. CONCLUSION

Reducing energy consumption, carbon footprint while maintaining optimal comfort is the major objective of energy efficient buildings. By integrating advanced technologies, efficiency of the system can be enhanced. However, occupants' role and their interaction with the building has significant influence on the building performance. Hence, prediction of number of occupants present in the building and understanding their behavior is essential to reduce considerable amount of energy while maintaining the comfort level.

Thermal, lighting, IAQ, and acoustic comfort are major comfort factors considered with respect to the inhabitant. These comfort levels are mainly influenced by architecture, age, health, gender, culture, environment factors, and emotions. Furthermore, collecting data from the building and occupants is easier with the development of IoT and wearable sensors, but it is still difficult to analyze and predict exact human behavior. Difficulty is also due to the research gap between human behavioral science and the building industry. Strong interconnection of emotions and cognitive behavior, the time-varying nature, the difficulty in quantifying, the influencing parameters have made future and current prediction of occupant behavior are complicated.

Advancements in machine learning have made it possible to model occupant behavior and prediction to a large extent. Different types of Markov chain models and artificial neural networks are mainly used to model occupant behavior and predictions. As of now, if the occupants are following routine and pattern, the developed models can predict effectively. Thus, in the future more research is needed on behavioral analysis for single and multi-occupancy prediction.

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