Sustainable Computing: Informatics and Systems 39 (2023) 100898

Contents lists available at ScienceDirect

Sustainable Computing: Informatics and Systems

journal homepage: www.elsevier.com/locate/suscom

Energy management of smart homes over fog-based IoT architecture

Muhammad Umair [a,b,*], Muhammad Aamir Cheema [c], Bilal Afzal [d], Ghalib Shah [e]

[a] School of Computer Science, The University of Sydney, Camperdown NSW 2006, Australia
[b] Department of Electrical, Electronics and Telecommunication Engineering, New Campus, University of Engineering and Technology, Lahore, Pakistan
[c] Faculty of Information Technology, MONASH University, Wellington Rd, Clayton VIC 3800, Australia
[d] National Centre for Cyber Security, Air University, Islamabad, Pakistan
[e] Sultan Qaboos IT Chair, University of Engineering and Technology, Lahore, Pakistan

ARTICLE INFO

Keywords:
Smart home
IoT
Home automation system
Energy optimization
Energy modeling
Fog-based architectures
Markov chain

ABSTRACT

Existing research studies on home automation systems mostly conserve energy by modeling the occupancy of users within home. Some others apply statistical approaches on the survey data about usage of appliances. Consequently, these research works either reduce wastage of electricity through automation or achieve energy efficiency based on appliances' usage estimations. However, they do not provide energy consumption modeling which is human comfort centric and also validated through practical implementation in real-world smart homes. We present a Markov-chain-based probabilistic model to obtain users stochastic activity patterns which are used to forecast the energy consumption in a smart home environment. These predictions are then leveraged by our novel comfort aware energy saving mechanism named as *prediction- and feedback-based proactive energy conservation (PF-PEC)* algorithm. The PF-PEC algorithm reduces the total energy consumption while ensuring standard human comfort. Furthermore, a fog-based Internet of Things (IoT) architecture is implemented and deployed in a smart home to efficiently incorporate the proposed algorithm in real-world scenarios. Experimental results show up to 36% energy conservation, marking substantial reduction in daily electricity usage.

1. Introduction

In the last decade, the proliferation of smart devices has remarkably improved and reshaped the lifestyles of their users [1]. A home automation system (HAS) introduces smartness and intelligence within home appliances to automate various household operations. The primal objective is to reduce the tiresome decision-making process thus making the user's life hassle-free and providing them with flexibility of control [2]. An Internet of Things (IoT) enabled smart home is a smart place where the appliances are connected to the Internet so that every appliance is identifiable, accessible and thus controllable across the globe [3]. IoT takes the conventional HAS systems to next step, to improve the services of various sub-systems and expand their outreach. The appliances are controlled based on the user activity patterns, user preferences, and/or according to the changes in dynamic environmental conditions. Major benefits include more rational use of energy and other resources which in turn results in superior energy management as well as significant time and cost savings [4].

Particularly, the energy management of smart homes has been a focus of the research community in recent years [5]. For instance, the significance of optimizing demand side management is discussed in [6,7]. Several research works leverage different statistical approaches to determine user activity patterns [8–10]. Some others have conducted user surveys to obtain energy demand and to predict energy consumption of households operations [11,12]. However, these energy management techniques are error-prone as they rely upon appliances data acquired through user surveys. They may under-perform when appliances' usage routines are changed due to variations in environment over a period of time.

Similarly, state-of-the-art Markov-chain-based solutions determine user state probabilities to compute user activity states and their resulting impact on energy demand [13–15]. However, one of the limitations in these approaches is that they do not consider the shared nature of appliances' usage for estimating the user activities and corresponding states. In other words, the proposed models in these research works do not determine the cumulative users' activity patterns. Research papers on computing household activities and predicting energy consumption also exist in literature [16,17]. In fact, many state-of-the-art predictive

* Corresponding author at: School of Computer Science, The University of Sydney, Camperdown NSW 2006, Australia.
E-mail address: m.umair@uet.edu.pk (M. Umair).

https://doi.org/10.1016/j.suscom.2023.100898
Received 19 March 2020; Received in revised form 30 May 2022; Accepted 14 July 2023
Available online 20 July 2023

algorithms investigated for smart homes are described in [18]. Nevertheless, the results obtained from these algorithms and prior works in this research area are not experimentally validated in real-world smart home environments.

In our research, a novel fog-based IoT-enabled HAS system is designed and implemented to take practical results in real-world scenarios. Therein, user surveys only serve as an initial knowledge to the system, which will be then updated by providing a continuous feedback about the real-time data reported from the appliances themselves. Hence, compared to traditional prediction based algorithms that use user surveys, real-time appliances data usage will provide better estimates of energy consumption. To the best of our knowledge, there exists no comprehensive work on IoT-enabled smart homes that gives thorough explanation of getting user activity patterns, and computes state transition probabilities along with stochastic state probabilities in order to estimate energy consumption; and in a further step, that applies optimization algorithm on the predicted energy consumption to reduce electricity usage in smart homes while ensuring user comfort.

This paper proposes a Markov-chain-based stochastic model to calculate user state transition probabilities which are then used to predict the energy demand in next few time slots. Initially, user daily life routines are acquired by conducting a survey. The survey is designed in a way to simplify the mapping of user data to four activity states which include *absent, sleep, active* and *hyper-active* state. The obtained data is then processed to calculate user state transition probabilities. These probabilities are provided as an input to the Markov chain model which gives user state probabilities in specified time slots. In this respect, we estimate power consumption ranges against user state probabilities that are updated later by real-time appliance usage through feedback mechanism. Experimental results are taken to validate that the actual energy consumption mostly stays within the range of maximum probability predicted from the model. Further, a *prediction- and feedback-based proactive energy conservation (PF-PEC)* algorithm is presented to minimize electricity cost by optimizing the operation of smart home appliances. To incorporate the proposed algorithms in real-world scenarios, a fog-based IoT architecture for smart homes is implemented and deployed which provides appliances control and local data processing closer to end-users. Finally, performance evaluation of proposed algorithms is conducted exhibiting significant reduction in the energy consumption of a smart home. Below, we summarize our contributions.

- We present novel algorithms that exploit human occupancy patterns for energy conservation in smart homes while ensuring human comfort.
- We present details of our general-purpose fog-based IoT architecture for smart homes discussing its functionalities and characteristics. We create a real-world testbed by implementing the proposed architecture in a real-world smart home system.
- We implement and deploy the proposed algorithms in our real-world testbed and conduct a detailed experimental study. The results demonstrate that our algorithms provide significant improvement compared to the existing algorithms in terms of smart home energy efficiency without compromising human comfort.

The rest of the paper is organized as follows. Related work is discussed in Section 2. Section 3 presents the details of our stochastic model and an algorithm that estimates the energy consumption in future timestamps. In Section 4, we introduce the proposed PF-PEC algorithm for energy conservation in smart homes. We present our fog-based IoT architecture for smart homes and the details of real-world testbed in Section 5. Section 6 presents the experimental evaluations and Section 7 concludes the paper.

2. Related work

2.1. Markov chain for energy optimization

Markov chain is a stochastic model in which the probability of each event in a sequence depends only on the state attained in the previous event [19]. We provide more details of Markov chain in Section 3.1 where we discuss how we apply Markov chain to obtain the user state probabilities for our work. Several research studies propose probabilistic methods to model user behaviors [8–10,20]. Authors in [8] established the user occupancy from sensors deployed in smart buildings. They proposed a Markov model to forecast the user occupancy. The model outperforms the existing techniques based on probability sampling, support vector regression and artificial neural networks for predicting short term user occupancy. A preliminary version of our work is presented in [21] that leverages Markov chain for energy consumption optimization. A building energy consumption model based on stochastic Markov models is proposed in [9]. Similarly, authors in [10] presented a four-state user occupancy model. They applied first order Markov chain on user activity data and presented significance of their method through correlation of occupancy states in multiple occupied dwellings. Similarly, a stochastic model of household activity patterns is presented in [20]. It investigates the empirical activity data and explores patterns in form of stochastic process with memory of variable length.

A Markov chain model is proposed in [22] to manage the power consumption prediction to prevent overload usage of electricity. It is a 3 state model including *normal*, *critical* and *emergency* states of the load. The predicted states are then utilized in a smart residential load management system. A Hidden Markov Model based algorithm is proposed in [23] to predict energy consumption in Korean residential buildings using data collected through smart meters. The model is validated on four buildings. The results show better root mean square error as compared to Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Classification and Regression Tree (CART). The above stated models although incorporate various factors which may directly or indirectly influence the energy consumption, but they do not provide the real world applications of their work in the context of energy conservation.

2.2. Smart home energy management

A smart home energy management solution is proposed in [24]. It considers a detailed set of attributes related to energy management in a smart home. These attributes are then linked to each other by meaningful and useful relationships. A fuzzy logic based smart home energy management is proposed in [25]. It classifies appliances based on their energy consumption patterns. In this respect, a fuzzy logic is then proposed to operate different classes of appliances. A bat algorithm (BA) based solution with exponential inertia weight is proposed in [26] to save energy in a smart home without deteriorating the user comfort. Temperature, illumination, and indoor air quality are considered to account for the user comfort. The proposed approach shows positive results due to improved convergence behavior.

A research study in [12] proposed an algorithm which manages household loads according to their predefined priorities and guarantees the total power consumption below certain levels. Another research in [14] identified several factors related to climate that can influence the energy utilization of a building and analyzed their contribution in energy consumption. A multi-agent model is proposed in [15] for simulating human activities for achieving energy efficiency. Authors in [16] developed a novel household resource allocation model which incorporates multiple interactions (such as interaction between time of use and energy consumption, the intra household interaction) based on multi-linear utility functions. They endogenously represented zero consumption for both time and energy within the group decision-making modeling framework. Likewise, a statistical method is presented in [17] for modeling the behavior of home occupants to estimate residential energy consumption. A behavioral artificial neural network model is proposed in [27] for simulating energy consumption in smart dwellings. A methodological framework is presented in [28] for validation of domestic lightening model. The metrics affecting lightening behavior are identified and lightening model according to different scenarios are statistically evaluated. However, these models do not consider and predict overall energy consumption of a home as they focus on limited factors such as users' occupancy and/or lightening demand within a home.

2.3. Feedback mechanism and new approaches for energy optimization

The research in [29] highlights the importance of information feedback for households' daily activities to improve the accuracy of energy consumption computations. This method gives direct feedback to households and the information is relevant since it emanates from their own reported activities. Authors in [30] investigated the complexity of existing models for occupancy behavior. Some of the concepts presented in these papers [29,30] are leveraged in our model such as the application of feedback to the system. Several models specific to certain cultures and geography are also available in literature. For example, in [11], a tool for predicting the total energy consumption and associated greenhouse gas (GHG) emissions of Australian households is developed. It integrates the thermal efficiency of building envelope, installed equipment, and different occupancy profiles with energy end-use modules for space and water heating, cooling, lighting, and plug-in appliances. However, these research works deal with specific use cases and are not generic enough to the energy demand of every geographical region. Nowadays, homes typically have multiple power sources such as solar, battery bank, and grid [31]. Due to COVID-19, daily routines of people have changed and they spend more time at home. So, domestic energy consumption has increased significantly. In this respect, a list of new approaches towards energy management is provided in [32].

2.4. Fog-based architectures and human-comfort-based energy optimization

Many fog-based and federated-learning-based architectures have been proposed and utilized in many applications in the past few years due to the increasing interest in fog and edge computing [33–37]. A novel four-tier architecture for load optimization in fog environments is proposed in [38]. A fog computing structure is proposed for tier-3. The proposed architecture helps in reducing fog node failures. A machine learning classifier is proposed in [39] to reduce the energy and latency at the fog nodes. It investigates the performance of different machine learning classifiers on a fog node. An energy consumption model is then proposed for the fog nodes. In [36], a fog platform termed as EHOPES is proposed which comprises different hardware and software capabilities. Therein, authors investigated the network requirements of various smart living applications of IoT and presented the performance of their proposed platform in terms of latency and throughput. The simulation results reported in [36] showed considerable improvement in reducing the latency. However, our proposed fog based architecture achieves better latency results in comparison to EHOPES fog platform. A context-aware energy saving algorithm (namely M-CHESS) is proposed in [37] which reduces energy consumption in smart home environment considering human comfort constraints. Our proposed solution human-centric as it also considers human comfort constraints as per ANSI/ASHRAE standard while improving energy conservation. Another design approach to operate HVAC in a smart home environment is proposed in [40]. It also considers the human comfort threshold in energy consumption management. It combines the values of humidity and temperature to define comfort zones. We compare our PF-PEC algorithm performance with that of E-HOPES and M-CHESS algorithms in performance evaluation Section.

3. Probabilistic model

We propose a Markov-Chain-based stochastic model which gives probabilities of user activities in a smart home. Moreover, the proposed model results in probabilities of consuming certain amount of power in specified time slots. This probability versus wattage dataset will then be used to propose an algorithm to minimize the cost of electricity considering different electricity tariffs. The user activities are categorized into four different states. These states are named as *absent, sleep, active* and *hyper-active*. A user can only be in one state at a given time. The description of these user activity states is given in Table 1. User states are defined in such a manner that each and every appliance to be used at home is covered.

3.1. Computing user states probabilities

Initially, we conduct a survey to receive user activity patterns throughout the day. This survey acquires information about the number of shared and personal appliances at home. It serves as an initial knowledge to the model and is used to calculate user activities in specified time slots. These activity patterns constitute a state transition matrix of a single user. It is important to mention that the user activities will be continuously updated using feedback mechanism by our proposed algorithm. In the next step, Markov chain is applied on the state transition matrix to compute stochastic user state probabilities. Every user has its own state probability matrix as there is a separate Markov process for each user. The user activity states are taken as the Markov states. The Markov set of states are: $\{\delta_n : 0 \le n \le 3\}$ where 0 means absent; 1 represents sleep state; 2 is active; and 3 is hyper-active state. Whereas, δ_n represents the nth state. Let $N_{i,j}$ denote the number of transitions from ith state to jth which is obtained from the survey of activity patterns of each user. Probability of transiting to jth state from ith state is denoted as $P_{i,j}$ and is computed as:

$$P_{i,j} = \frac{N_{i,j}}{\sum_{k=0}^{3} N_{i,k}} \tag{1}$$

Note that $P_{i,j} \ge 0$ and, for every state i,

$$\sum_{j=0}^{3} P_{i,j} = 1 \tag{2}$$

The following 4×4 Markov state transition matrix is obtained from user activity patterns:

$$T_s = \begin{bmatrix} P_{0,0} & P_{0,1} & P_{0,2} & P_{0,3} \\ P_{1,0} & P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,0} & P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,0} & P_{3,1} & P_{3,2} & P_{3,3} \end{bmatrix}$$

where each row in T_s represents transition probability of transiting from one particular state to the other states. Fig. 1 shows the state diagram representing these activity states. It is clear from the diagram that each state is accessible from itself and all other states. Hereafter, unless clear from context, we use T_s^u to denote the transition matrix for a particular user u. We use $P_n^u(t)$ to denote the probability that a user u is in state n at time t where n is between 0 and 3. The state probability matrix of a user $s^u(t)$ at time t can then be obtained by using its state probability matrix at the previous time $t-1$ and its transition matrix T_s^u:

$$s^u(t) = [P_0^u(t) \quad P_1^u(t) \quad P_2^u(t) \quad P_3^u(t)] = s^u(t-1) \times T_s^u \tag{3}$$

The initial state matrix (at time 0) of a user u can be obtained using its known state at time 0, e.g., if a user is in state 1 at $t = 0$ then the initial state vector is $s^u(0) = [0 \quad 1 \quad 0 \quad 0]$. Let U be the set of all users living in a home. The sample space is a set of all possible outcomes (represented by U_n) for all users U living in home, i.e. $Sample\ Space = (U_n)^U$. The possible outcomes are the combinations

Table 1
Description of user activities.

States	Description
Absent	A user is in absent state, when he/she is outside the home.
Sleep	When a user is present in the house but not engaged in any activity. Power consumed due to his/her presence only comprises of cooling and heating of environment in corresponding room.
Active	When a user is using his/her personal gadgets and appliances, i.e. computer, video-gaming, chargers, etc. These appliances are other than the cooling or heating appliances.
Hyper-active	When a user is utilizing one of the shared appliances at home. Shared appliances are the ones which are in-use of every person at home, i.e. water pump, electric geyser, electric hearth, washing machine, etc. These appliances also do not include heating or cooling appliances.

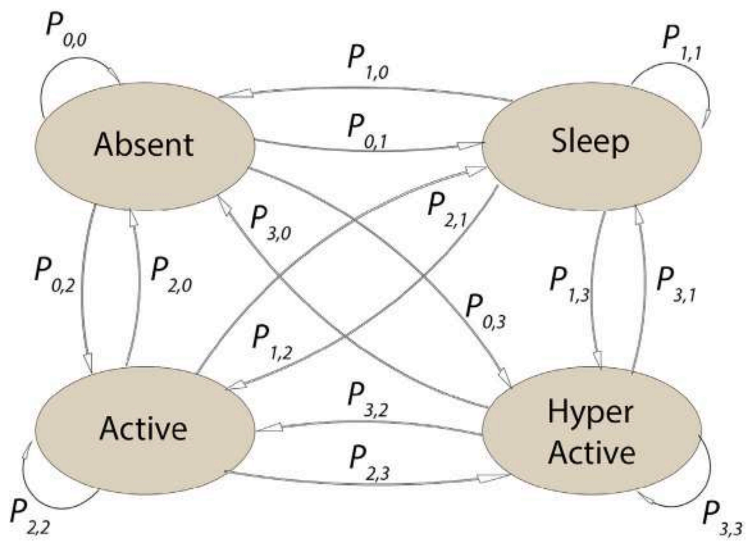


Fig. 1. User activities state diagram.

of different user activity states. Thus, an increase in number of users increases the sample space essentially. Power consumption depends on the activity states of the users in the house, e.g., if all users are absent, the power consumption is low. Several combinations may correspond to approximately same power consumption and considering all outcomes in the model will be redundant. Therefore, potential outcomes are identified and only their combinations are considered. For instance, one potential outcome is *all users are in absent state*; another possible outcome is *at least one user is in hyperactive state*, and so on. In essence, only those outcome combinations are selected that correspond to fairly different power consumption. Hence, our first outcome combination is *all users in absent state*. Reason to consider this combination in the model is because in most cases, it corresponds to minimum power consumption range in the house. Next, we consider several possible combinations of activity states of the users living in the house and show how to calculate their probabilities.

All users are absent. If all of the users are in state 0 (i.e., absent), the power consumption will be the lowest. The Markov state probability matrix in Eq. (3) is specific to one user. The activity states of all users are independent of each other. Therefore, to compute the probability of more than one user in a particular state, we simply need to find their joint probability i.e. probability that two users u and v are both in state 0 at tth time slot is $P_0^u(t).P_0^v(t)$. Probability of all users in absent state at time t can is obtained as:

$$P_{all-absent} = \prod_{u \in U} P_0^u(t) \tag{4}$$

All users are sleeping. If the users are present in home but are sleeping (i.e., in state 1), the power consumption will still be low but higher than when all users are absent. The probability that all users are sleeping at time t can be obtained as

$$P_{all-asleep} = \prod_{u \in U} P_1^u(t) \tag{5}$$

At least one user is hyper-active. The power consumption will be quite high when at least one user is hyper-active because, as noted in Table 1, the user will be using the shared appliances (which are usually the high load appliances) in the home. Now, we show how to compute the probability that at least one user is in state 3, the hyper-active state. The probability that a user u is *not* in hyper-active state at time t is $(1 - P_3^u(t))$. The probability that all user are in non-hyper-active state can be computed as $\prod_{u \in U}(1 - P_3^u(t))$. Thus, the probability that at least one user is in hyper-active state can be obtained as

$$P_{1+hyperactive} = 1 - \prod_{u \in U}(1 - P_3^u(t)) \tag{6}$$

At least one user is active. When at least one user is active (i.e., state 2), the power consumption will be lower than the case when at least one user is hyper-active but will be higher than when all users are asleep or absent. Similar to Eq. (6), the probability that at least one user is active can be computed as

$$P_{1+active} = 1 - \prod_{u \in U}(1 - P_2^u(t)) \tag{7}$$

Equations (4) to (7) provide the probabilities of different important combinations of user states that can be used to estimate energy consumption level. Hence, the principle defined for grouping of user activities into states and state probability data set along with current state of appliances (provided by feedback mechanism) help to estimate probability of consuming a certain amount of energy at a particular time slot. This data set is converted into a table as shown in Table 3a and Table 3b. These tables are specific to a use case described in Section 6. The values in these tables represent different probabilities of all users cumulatively consuming a certain power. Next, we present an algorithm that uses these probabilities to estimate probability of consuming high power at a certain timeslot.

Algorithm 1 : Energy Consumption Modeling Algorithm

Input: User Activity Patterns
Output: P_c, the probability of power consumption

1: Update T_a^u for every user ▷ where T_a^u= Activity Pattern
2: Compute T_s^u for every user ▷ where T_s^u= State Transition Matrix for user u
3: **while** $t \in \tau$ **do** ▷ where τ = peak hours duration
4: **for** each user u in U **do**
5: $s^u(t) = s^u(t-1) \times T_s^u$; ▷ Eq. (3)
6: **end for**
7: $P_{all-absent} = \prod_{u \in U} P_0^u(t)$ ▷ Eq. (4)
8: $P_{all-asleep} = \prod_{u \in U} P_1^u(t)$ ▷ Eq. (5)
9: $P_{1+hyperactive} = 1 - \prod_{u \in U}(1 - P_3^u(t))$ ▷ Eq. (6)
10: $P_{1+active} = 1 - \prod_{u \in U}(1 - P_2^u(t))$ ▷ Eq. (7)
11: $t++$
12: **end while**
13: Compute average probability of each combination over all timeslots considering the probabilities computed in lines 7-10
14: Using the average probabilities, estimate the probability of power consumption P_c at each level
15: return P_c

3.2. Energy consumption modeling algorithm

In this section, we present our energy consumption modeling algorithm (see Algorithm 1) which leverages the model proposed in Section 3.1. The algorithm employs the probabilities computed in Eqs. (4)–(7) to estimate the energy consumption. This estimated consumption can then be used to operate appliances in an optimal way to save energy. The probabilities are only computed for peak load hours during which the electricity is relatively costly. Afterwards, the estimated probabilities of high power consumption are fed to another algorithm (Algorithm 2 to be presented in Section 4) which controls the operation of appliances. Next, we present the details of Algorithm 1.

Algorithm 1 takes the user state transitions as an input and returns the probability of power consumption at future timestamps. Specifically, given different ranges of power consumption (e.g., low, medium, high), the algorithm returns, for each range, the probability that the power consumption in future timeslots will be within this range. Firstly, the algorithm takes user activity pattern of each user u (denoted by T_a^u) and computes the state transition matrix of the user (denoted as T_s^u). It is worth mentioning that the feedback from Algorithm 2 continuously updates the vector T_a^u for each user (line 1) to take into consideration any update in the user activity pattern, thus, T_s^u is recomputed for every user accordingly (line 2). Then, the algorithm iterates through each time slot t in the desired duration for which energy consumption needs to be predicted (line 3). In our implementation, we use the algorithm to estimate energy consumption only during the peak hours τ. In each iteration, the algorithm first updates the user state probability matrix $s^u(t)$ for each user u using Eq. (3) (line 5). Then, the state probability matrices of the users are used to compute the probabilities of different combinations using Eqs. (4)–(7) as described earlier (lines 7 to 10). In each iteration, for each t, these probabilities are computed and stored in an array to be used when the while loop terminates. Specifically, the algorithm uses the stored probabilities for each t and computes the average probability of each combination over all timestamps (line 13). Based on these probabilities, the algorithm then estimates the probability of power consumption at each level P_c (line 14). For example, if $P_{1+hyperactive}$ is quite high for each timeslot t (there is at least one hyperactive user), then the algorithm will return a high probability of the power consumption to be within the high range. Finally, the algorithm returns P_c which is to be used by Algorithm 2 presented in the next section.

Tables 3a and 3b in Section 6 show the output of Algorithm 1 when deployed in our real-world testbed. This data can be used in predicting the user behavior and power consumption of a smart home in near future. Next, we present a novel algorithm which uses the output of Algorithm 1 to reduce electricity cost while ensuring appropriate user comfort.

Table 2
ANSI/ASHRAE Standard factors for thermal comfort.

Factors	Description
Metabolic rate (*met*)	The energy generated from human body
Clothing insulation (*clo*)	The amount of thermal insulation person is wearing
Radiant temperature	The weighted average of all temperatures from surfaces surrounding an occupant
Air velocity	Rate of air movement given distance over time
Relative humidity	Percentage of water vapor in the air

4. Prediction and feedback based proactive energy management algorithm

In this Section, we present our PF-PEC algorithm that ensures reduction of appliances over-usage in a smart home during peak load hours, i.e., when electricity cost is typically higher than the normal rates. Considering an appliance activity is schedulable, the proposed algorithm schedules the activity from peak load hours to non-peak hours without affecting the users' comfort level. It does so if there is a strong prediction of appliance(s) usage in a peak load hour. In a smart home, the above mentioned scheduling is achieved by scaling the various thresholds of appliances up and down. A threshold is the particular value of any environmental factor such as temperature, humidity, etc., which determines the switch-on or switch-off operation(s) of the corresponding appliance(s). Hence, a change in the threshold value implies that the operation of the appliance can be advanced or delayed. While, a change in threshold value of an appliance is dependent upon its current as well as future probabilities of certain amount of power-consumption. Some other parameters are also incorporated to avoid any compromise on user comfort.

4.1. Calibration of threshold ranges on a common scale

To propose a single energy saving algorithm for all home appliances, it is necessary to calibrate environmental parameters on a common scale. These parameters are measured in frequently used units, i.e. temperature is measured in degree Celsius (°C), luminance is measured in *lux* and humidity is measured in percentage. To calibrate the temperature thresholds, ANSI/ASHRAE Standard 55 [41] is considered. This standard provides minimum requirements for acceptable thermal indoor environment conditions. It establishes the acceptable ranges of environmental parameters to achieve optimal comfort for smart homes users. The thermal comfort is achieved by controlling the factors mentioned in Table 2.

According to ANSI/ASHRAE Standard 55, the range of Predicted Mean Vote (PMV) for thermal comfort is −0.5 to 0.5 [42]. To make the computations easy, some factors are assumed constant for particular environmental conditions. A constant value of 1 is assumed for clothing level, which considers that the user is wearing a light business suit. Similarly, relative humidity is assumed to be 25% while the radiant temperature is 25 °C.

4.2. PF-PEC algorithm operations

Algorithm 2 outlines the pseudocode of PF-PEC algorithm which is executed in peak load hours. Peak load hours are denoted using τ, and P_c represents the probability of power consumption obtained from Algorithm 1. The parameter PMV_x is initialized to 0, which represents the Predicted Mean Vote (PMV) of user comfort for an appliance x

Table 3a
Probabilities of specified energy consumption obtained from Algorithm (1).

	KWh ranges	Time slots							
		8am–9am	9am–10am	10am–11am	11am–12pm	12pm–1pm	1pm–2pm	2pm–3pm	3pm–4pm
Probability of power consumption in KWh ranges	0.01–0.02	0	0.0003	0.0006	0.0007	0.0007	0.0007	0.0007	0.0007
	0.05–3.025	0.11	**0.1639**	0.1878	0.1983	0.2029	0.2048	0.2057	0.2060
	0.01–0.03	**0.6875**	0.5673	**0.5143**	0.4880	**0.4741**	0.4664	**0.4620**	**0.4595**
	0.02–0.04	0.0391	0.0454	0.0452	**0.0441**	0.0431	**0.0424**	0.0420	0.0417
	0.02–0.03	0.3129	0.3996	0.4308	0.4450	0.4525	0.4567	0.4590	0.4602
Actual Energy Consumed (KWh)	Practical	0.01	0.05	0.02	0.04	0.01	0.04	0.01	0.01

Table 3b
Probabilities of specified energy consumption obtained from Algorithm (1).

	KWh ranges	Time slots							
		4pm–5pm	5pm–6pm	6pm–7pm	7pm–8pm	8pm–9pm	9pm–10pm	10pm–11pm	11pm–12am
Probability of power consumption in KWh ranges	0.01–0.02	0	0.0012	0.0011	0.0009	0.0008	0.0007	0.0007	0.0007
	0.05–3.025	0.6	0.3819	**0.2838**	**0.2405**	0.2215	0.2130	0.2093	0.2076
	0.01–0.03	**0.8250**	**0.6693**	0.5702	0.5148	0.4895	0.4713	**0.4640**	**0.4603**
	0.02–0.04	0.1250	0.0935	0.0677	0.0540	**0.0473**	0.0441	0.0426	0.0420
	0.02–0.03	0.1200	0.2620	0.3559	0.4087	0.4360	**0.4494**	0.4559	0.4589
Actual Energy Consumed (KWh)	Practical	0.027	0.03	0.06	0.05	0.04	0.03	0.01	0.01

(line 1). The algorithm iterates a while loop for the desired peak hours duration (line 2). In each iteration, the algorithm computes PMV_x for each appliance x (line 3) and its corresponding thresholds (i.e. T^x_{PMV}) in a given environment (line 4). Afterwards, it computes the overall load of appliances in on-state at time t (line 5) along with the user-state based on the computed load (line 6). Then, the algorithm passes the user-states to Algorithm 1 that returns P_C (line 7), which is used to get average probability of consuming maximum power in remaining peak load hours. Next, appliances in on-state are selected (line 8). For each selected appliance (line 9), the algorithm first obtains the user-defined on-off threshold T^x_u for the appliance (line 10). The subsequent steps (lines 11 to line 13), are executed for these appliances if the user defined threshold T^x_u is greater than the threshold of human comfort T^x_{PMV} for the appliance x. Therein, it computes the difference (denoted by Δ) between the user-defined threshold (T^x_u) and minimum threshold required for human comfort (T^x_{PMV}) (line 12). The threshold value T^x_u is updated based on this difference (Δ) (line 13).

Algorithm 2 : PF-PEC Algorithm

Input: Human comfort constraints and parameters, τ; peak hours duration
Output: PMV_x, T^x_u, T^x_{PMV}

```
1: PMV_x ← 0
2: while t ∈ τ do
3:     Compute PMV_x for all type of loads
4:     Compute T^x_PMV for all type of loads
5:     Compute load in on-state at t
6:     Find user state from computed load
7:     Invoke Algorithm 1 and save value of P_c
8:     A ← Appliances in on-state at t
9:     for each appliance x in A do
10:        Obtain user defined on-off thresholds (T^x_u) of the appliance
11:        if T^x_u > T^x_PMV then ;
12:            Δ = T^x_u − T^x_PMV
13:            T^x_u = T^x_u + P_c × Δ
14:        end if
15:    end for
16:    t++
17: end while
18: return
```

In this way, the algorithm iteratively changes the threshold set for different appliances in peak load hours without compromising on human comfort. Moving the threshold away actually delays the switch-on event of appliances based on the average probability (P_c) of energy usage in the house. The greater the probability, farther will be the new threshold. Algorithm 2 also takes into account the difference between user-defined threshold and minimum threshold required for human comfort. If this gap is greater, user threshold moves faster to minimum value (T^x_{PMV}). As this difference decreases, pace of threshold towards minimum value slows down. The reduction in user threshold eventually results in more energy saving.

It is noteworthy that Algorithm 1 is also invoked in Algorithm 2 by passing user-states at time slot t which actually works as a feedback to the Algorithm 1. This feedback is necessary because the user activity patterns may change with time according to change in environment or circumstances. Hence, there is a need to estimate user states for current timeslot t. This makes system adaptable to the changes in user activities. A user state is thus estimated at run time based on the type and number of appliances in on-state and their power consumption at a certain time slot. This user state is accurately determined using the real data obtained from the smart home. This estimated user state is then considered by Algorithm 1 which re-computes the probabilities according to this new data to achieve more precise results. One immediate benefit of this feedback is that it somewhat solves the convergence problem of Markov chain process. As the data set on which Markov chain process operates changes consistently due to feedback, the results produced by Markov chain process now converge after a longer period. Another advantage of enabling feedback in the system is achieving higher accuracy of the produced results. One drawback of this feedback however, is that the system has to perform more number of computations. A visual description of this feedback mechanism is shown in Fig. 2.

To carry out all the above stated operations efficiently as well as effectively, a fog-based architecture for IoT enabled HAS system is designed such that the data about usage of appliances is seamlessly fetched to the cloud. A database is maintained at the cloud to save various forms of data sent by the appliances of a smart home. An application running on the IoT cloud thereby computes appliance usage time for each user. Using this appliance-usage time, user states at different time slots are computed and fed back to the Markov chain process. Hence, analyzing appliance usage data at cloud helps in predicting user's current state in real-time which will then update the user activity data. Markov chain is then applied on this latest user activity data to arrive at new state transitions and this process repeats for every next time slot.

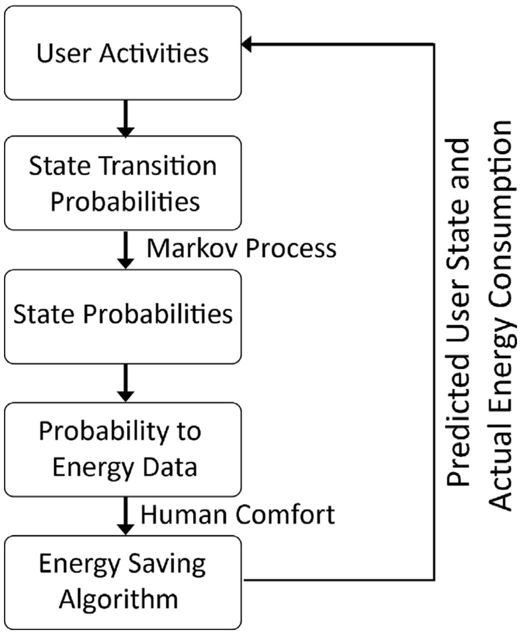


Fig. 2. Feedback mechanism of Algorithm 2.

5. Our proposed fog-based architecture and a real-world testbed for smart homes

In this section, we provide architectural details of the smart home that we use as a test bed. A fog based IoT architecture for smart homes is presented to realize the implementation of proposed energy optimization algorithms in a smart home environment. The efficacy of any smart home can get restrained depending upon its architecture. Traditionally, a HAS system may under-perform due to the limitations of underlying technology while the technology can itself under-achieve if the hardware and/or software platforms are not chosen appropriately. IoT offers various innovative features in HAS systems such as low complexity, power efficiency, small footprint and less communication intensive connections to the Internet. Another critical attribute that IoT brings to the table is data dissemination. However, this data dissemination is relatively weak in conventional smart home architectures and resultantly the useful data or its timely relevance gets lost usually. Hence, it is imperative to develop a fog based IoT architecture to incorporate favorable techniques such as data analytics and machine learning (ML) to enhance the capabilities of a smart home. A novel fog based IoT architecture for smart homes is therefore proposed to better utilize the algorithms for energy demand prediction and conservation as presented in previous Sections. There are four main building blocks of proposed architecture, i.e. Sensing and Data Acquisition, Actuations, Fog/Edge Node and Cloud. Each of these network entities have some predefined operating principles and standard protocols. This Section constitutes the functional and architectural details of these entities.

5.1. Sensing and data acquisition

Sensor modules are designed for data acquisition that resides multiple sensors. The microcontroller used in these modules contains 8kB of RAM and 16 channel 12 bit ADCs which makes it suitable for sensing modules. For wireless connectivity, state of the art Wi-Fi System-on-Chip (SoC) is used. To make the operation of sensor module energy efficient, they are equipped with 5 Volt batteries along with electrical power lines as the backup. To attain further energy efficiency, the sensor modules are also capable of duty cycling while their processor is capable of going into deep sleep mode. Some front-end intelligence is also provided within these modules to achieve better decision making while forwarding the sensed information. These features are incorporated with reasonably smaller footprint to fulfill the requirements of an intelligent sensor module for our fog based IoT architecture which is illustrated in Fig. 3 along with a snapshot of sensor module.

5.2. Actuation

To enable smart actuation of appliances, an actuation module is designed to replace existing switch outlets in conventional and smart homes. The specifications of microcontroller used in actuation module are similar to that of sensor modules. A Wi-Fi SoC is available for wireless connectivity. There can be multiple switches in a single actuation module. TRIACS are used as control switches and relays are included to cater for high load appliances. The major messages communicated through actuation modules are about the operation of appliances. These messages are translated into device on-off operations, fan(s) speed control, lamp dimmers, temperature settings of AC/heaters, etc. To ensure synchronization, devices respond with acknowledgment messages upon each actuation. The module constantly publishes its switches states via wireless link to local server to facilitate the ML and data analytics techniques. Actuation module snapshot is shown in Fig. 3.

5.3. IoT fog node

A large number of sensing and actuation modules are mostly installed in a smart home. To maintain the connectivity of each module with IoT cloud can be expensive in terms of resources. There is a need of IoT fog node that can maintain connection with the cloud while acting as an edge device for sensor and actuation modules. It enables these end-devices to log their data at local server and then to report it to the cloud. Some of the benefits of fog node include low latency, network scalability, and heterogeneity [43].

The functional architecture of our IoT fog node is depicted in Fig. 4. It operates in two distinct modes, i.e. an *online mode* and an *offline mode*. The *offline mode* ensures that appliances can be used within the local network when Internet connectivity is not available, and also synchronizes the appliances' states with the cloud when Internet connectivity is available again. The synchronization module periodically performs this synchronization and also ensures that the sync time is not much significant as compared to user lag faced, or latency introduced by removing the fog node. Whenever a user sets his/her preferences, it is made sure that those preferences are saved in both the local database on fog node and the database on the cloud. It makes the appliances directly controllable from fog node based on the defined user preferences. Moreover, fog node is equipped with various constrained protocols in its communication stack. At application layer, it communicates with sensors and actuators using Message Queuing Telemetry Transport (MQTT) protocol. To enable user defined intelligence in appliances, a local intelligence module is defined. In addition, a specific service is responsible for data dissemination among different application programming interfaces (APIs) running on IoT fog node. Device identification and device/user authentication services are also included. At transport layer, Transmission Control Protocol (TCP) is used along with Secure Socket Layer (SSL) for reliable and secure connectivity of devices with the cloud. Other services including Secure Shell (SSH), Secure File Transfer Protocol (SFTP), Web and Android APIs are implemented to access the fog node for configuration purposes.

The proposed fog node is implemented using Raspberry Pi 4, shown in Fig. 3, which has a quad core processor with 1 GB RAM, Ethernet, USB ports and Wi-Fi making it suitable for fog node. The proposed fog node has rich resources that have the capability to manage all the end nodes in a single smart home setup. It simplifies the management of data from multiple smart homes on the cloud i.e., single fog node per smart home setup. Moreover, it enables the smooth operation of fog nodes due to reduced network overloading. There are two limiting

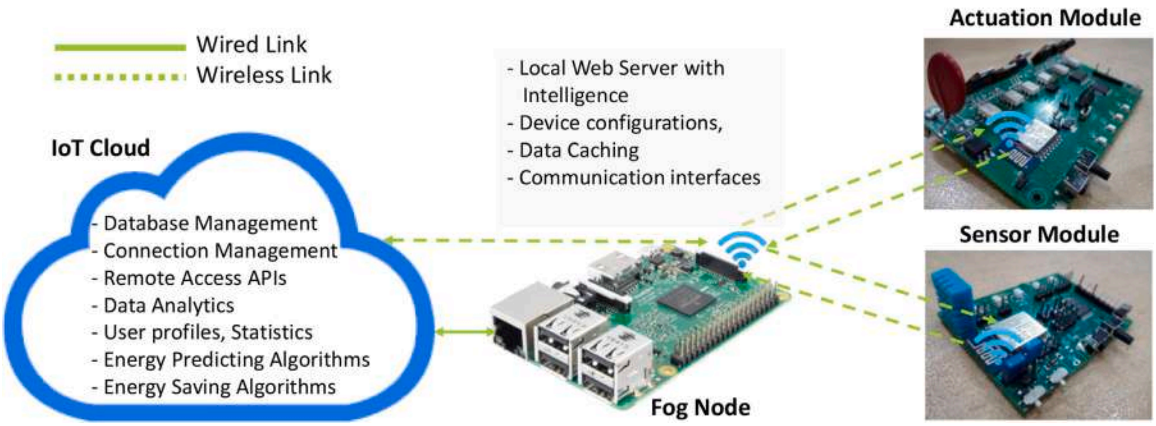


Fig. 3. Proposed fog based IoT architecture for smart home.

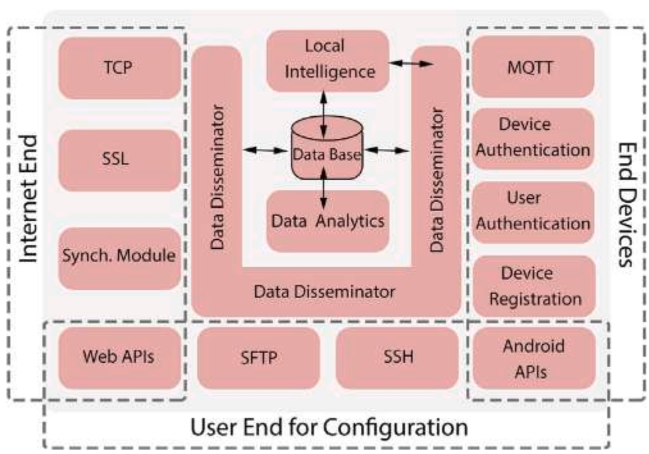


Fig. 4. Functional architecture of fog node.

factors in the operation of the proposed fog node: the range of the Wi-Fi and the number of requests that can be entertained simultaneously. Wi-Fi repeaters can be installed in relatively bigger and multi-story dwellings to enhance the range. Simultaneous requests in a fog node can be entertained by using threads. However, increasing the number of threads overload the fog node and creates a lag in fulfilling the requests. In the proposed fog node, a high number of requests can be entertained simultaneously because we are using a high-end device.

5.4. IoT cloud

Our smart home architecture includes customized implementation of IoT cloud whose functional diagram is shown in Fig. 5. The IoT cloud is equipped with multiple services and plug-ins to facilitate interaction with fog node, users and developers. TCP/IP stack is incorporated to provide connection oriented services together with SSL for secure communication. Our Algorithm 1 and Algorithm 2 are implemented in the cloud within Machine Learning module. Data dissemination layer is integrated to classify the data reported from appliances as well as sensor devices and to disseminate it to concerned services before saving into database. A copy of database is continuously replicated to another Virtual Machine (VM) in the cloud to incorporate ML and data analytics techniques without compromising the original data reported from appliances. Relaying service is responsible to entertain the service-accessibility requests for a specific device originated from users. Customized Android and Web APIs are designed to enable flexible control over appliances in a smart home. A monitoring module is responsible for generating alerts/warnings. FTP, SFTP and SSH protocols are also employed.

5.5. Real-world scenario to operate the test bed

The experiments are conducted on a real-world smart home system. We leverage the proposed system architecture presented in this section to implement a smart home system. A fog node, two sensor nodes and one actuation module is used in the test bed. The implemented smart home system is connected to the cloud being implemented using the architecture proposed in Fig. 5. It is worth mentioning that the deployed system have a centralized database in which the on-off thresholds of appliances are saved. These thresholds are set by the corresponding users. These thresholds are used by our proposed algorithms to operate the appliances accordingly. Algorithms 1 and 2 are deployed on the cloud. The outcome of Algorithm 2 is used to send commands to the fog node to operate the appliances accordingly.

The energy consumption model is validated by the experiments conducted in a 1125 square feet home with 3 occupants. It is a multi-story dwelling located in Lahore. Eight spots in the home are identified for system deployment. The experiments are conducted during spring season. All the occupants have different daily routines. First is a part-time worker, second is a housewife and third one is a retired person who normally stays at home. The results are taken from morning (8am) to midnight (12am).

6. Experiments and results

In this Section, the performance analysis of proposed algorithms is presented. Firstly, the prediction results of energy consumption estimation model (Algorithm 1) are discussed followed by the evaluation of proposed PF-PEC (Algorithm 2) which reduces the energy consumption of a smart home. The probability distribution of a particular user in different states at each time slot is shown in Fig. 6. It should be noted that our model includes all the appliances in use within a home.

The numerical results are illustrated in Table 3a and 3b. In that respect, different KWh ranges are specified that corresponds to the potential combination of outcomes considered by Algorithm 1. The predicted power consumption is provided in terms of the probability of consuming energy in a particular KWh range for different time slots. The values in Table 3a and 3b are not specific to a single user. These probabilistic values represent the likelihood of all users cumulatively consuming a certain power. The real energy consumed (KWh) at each

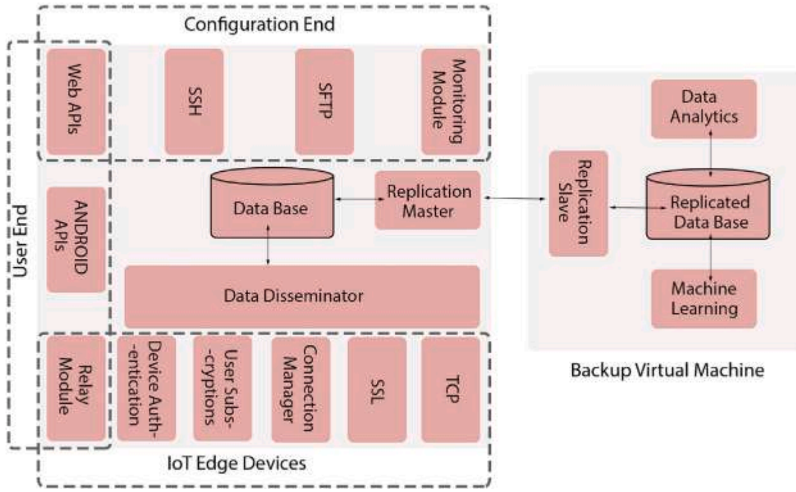
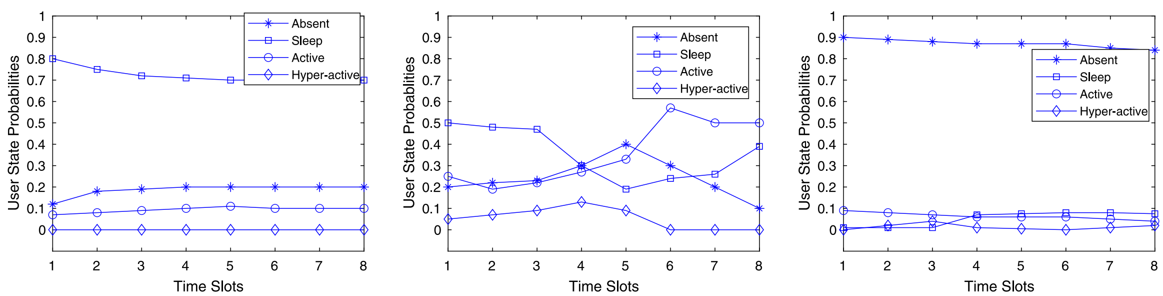


Fig. 5. Functional architecture of IoT cloud.



(a) Retired Person (b) Housewife (c) Part-time Worker

Fig. 6. Example of probability distribution of single user in four states.

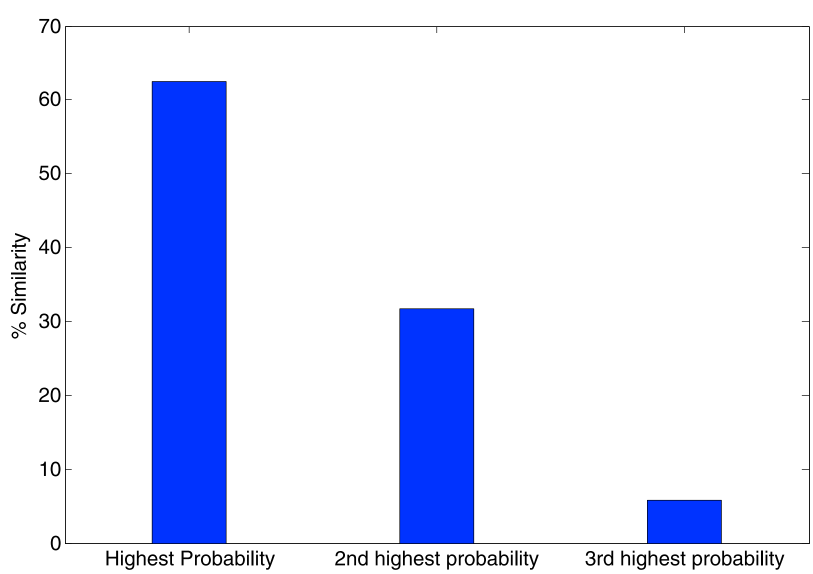


Fig. 7. Comparison between actual and predicted energy consumption.

time slot is also reported in the table and can be compared with the KWh range of highest probability event. For example, in 3a for time slot 8am–9am, the actual energy consumed is 0.01 KWh whereas the corresponding predicted KWh range, i.e. 0.01–0.03, has the highest probability. Similarly, for other time slots, the results obtained from our energy consumption prediction model in terms of KWh ranges and their corresponding probabilities fairly match with that of actual energy consumption of the smart home. In Fig. 7, the percentage similarity

Table 4
Results of PF-PEC Algorithm (2), lights and fan readings.

Days	Manual			Smart			Smart + PF-PEC Algorithm		
	Light 1	Light 2	Fan	Light 1	Light 2	Fan	Light 1	Light 2	Fan
Monday	6 h,3 m,9 s	6 h,3 m,9 s	6 h,3 m	5 h,49 m	5 h,49 m	5 h,58 m	4 h,54 m	4 h,54 m	5 h,45 m
Tuesday	6 h,42 m	6 h,42 m	6 h,42 m	6 h	6 h	6 h	4 h,1 m	3 h,51 m	5 h,46 m
Wednesday	7 h,32 m	7 h,32 m	7 h,32 m	5 h,50 m	5 h,50 m	6 h,1 m	3 h,18 m	1 h,18 m	5 h,37 m
Thursday	6 h,49 m	6 h,49 m	6 h,49 m	6 h,27 m	6 h,27 m	6 h,38 m	3 h,35 m	35 m	6 h,22 m
Friday	7 h,5 m	7 h,5 m	7 h,5 m	5 h,33 m	5 h,33 m	7 h,5 m	3 h56 m	6 m	6 h,48 m

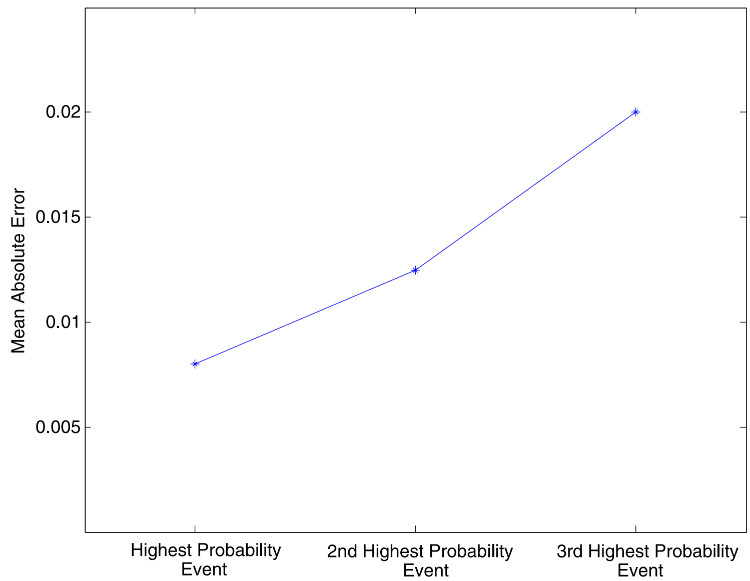


Fig. 8. Mean Absolute Error results to determine prediction accuracy.

of predicted energy consumption with that of actual is shown on *y*-axis and the events probabilities are shown on *x*-axis. This similarity measure is simply the percentage number of predictions matching with actual power consumption. It shows that the highest probability events in 3a and 3b have more chances to correctly predict the actual energy usage which in turn means that the actual energy consumed have more chances of falling in the KWh range of highest probability event. These chances gradually decrease if we move towards lower probability events. As the user states are defined on the basis of their appliances usage and number of appliances installed at home are pre-known, so KWh ranges are calculated using the information from feedback mechanism about user activity and the amount of load active at that time. So, user survey and feedback data helps to estimate the KWh range against each useful combination of user activity states which are aforementioned in Section 3. Thus, Fig. 7 demonstrates that actual energy consumption is very much closer to the highest probability event predicted by the model. Moreover, to validate the predicted results, Mean Absolute Error (MAE) is used as an evaluation criteria as shown in Fig. 8. It is evident that Mean Absolute Error for highest probability event (also mentioned in Fig. 7) is least whereas its value increases as we move towards lower probability events. More specifically, MAE for highest probability event is only 0.008 which shows the accuracy of prediction algorithm.

Algorithm 2 is tested in a different scenario as compared to Algorithm 1. The performance of PF-PEC algorithm is validated in an office equipped two lights, one fan and an AC, with a single occupant from 9:00am to 5:00pm for five working days. The light and temperature sensors are installed on the walls and accordingly PMVs for human comfort are calculated. Initially, Algorithm 1 is applied on user activity data and probabilities are generated against power consumption. Afterwards, Algorithm 2 is applied on this data to optimize the appliances' usage in peak load hours. The experimental results are considered for a duration of one week as shown in Table 4. It shows the daily time period for which both lights and a fan

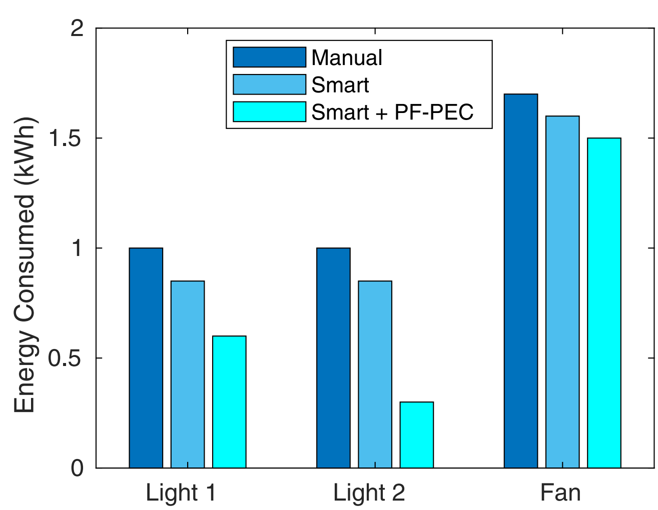


Fig. 9. Comparison of PF-PEC algorithm with baseline and simple smart home.

remained in on-state. These results validate that the PF-PEC algorithm further reduces energy consumption of a smart home. Fig. 9 graphically demonstrates these energy consumption in three different scenarios, i.e. manual home (normal operations with manual switches), smart home (occupancy, temperature and luminance based intelligence), and smart home with PF-PEC algorithm. It can be visualized that appliances usage decreases further when we simultaneously apply smartness and PF-PEC algorithm. Additional analysis determines that Light 2 and fan usage timings are reduced further after applying PF-PEC algorithm. This reduction in Light 2 usage is essentially due to the fact that only

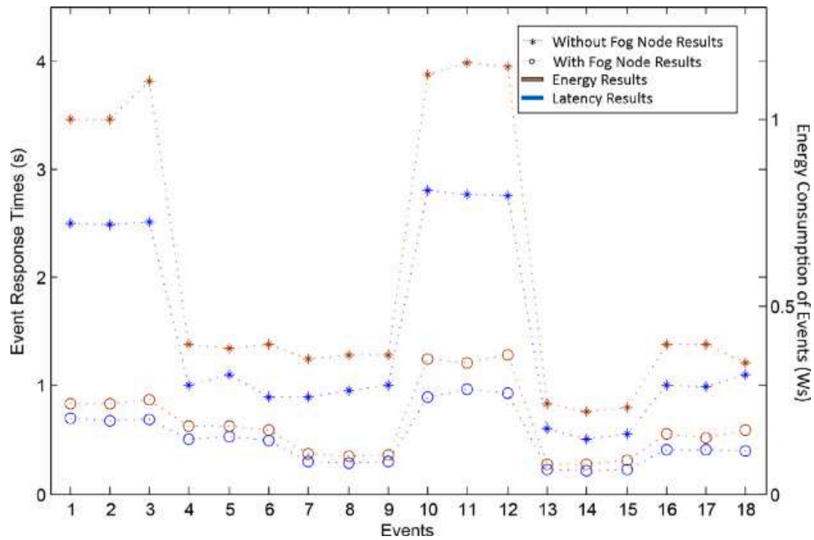


Fig. 10. Event response time results with and without fog node.

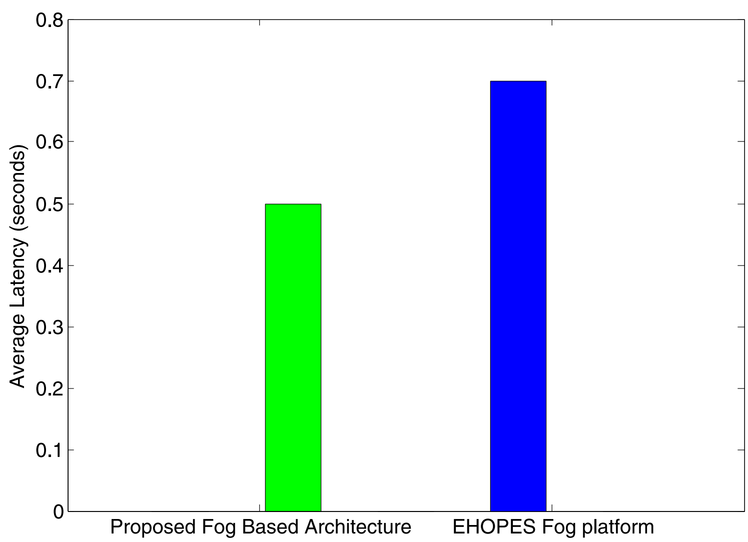


Fig. 11. Comparison of our architecture with EHOPES fog platform.

one light serves the purpose according to the visual comfort threshold of the user.

Fig. 10 shows the performance comparison of monitoring results with and without fog node in terms of average response time of different independent events along with their corresponding energy consumption. Therein, a single event is defined by 'a message communicated by sensor/actuation module to the cloud or fog node with a specific payload size, number of MYSQL queries executed and messages exchanged with other applications at the cloud or fog node, and finally sending back an acknowledgment (ACK) which completes an event cycle'. It can be visualized that the average event response time and corresponding energy consumption is remarkably reduced with the introduction of fog node in smart home architecture.

Similarly, in Fig. 11 we compare the latency results calculated with our proposed architecture with the average latency results achieved with another fog architecture based platform for smart environments, termed as EHOPES [36]. It can be seen that the average latency results in our case are reasonably better than the latency results attained with that of EHOPES platform. These improvements are achieved due to the modular implementation of architectural functionalities of fog node and its seamless interaction with cloud architecture.

Finally, the percentage energy conservation corresponding to different PMVs is shown in Fig. 12. It provides the comparison of PF-PEC algorithm with M-CHESS algorithm proposed recently [37]. Therein, the authors reduced the energy consumption of smart home considering various human comfort thresholds. In particular, the M-CHESS algorithm sacrifices the human comfort to attain higher energy savings. Thus, as shown in Fig. 12, the M-CHESS algorithm achieves energy conservation up to 33.7% with human comfort threshold of 1.0 which is increased to 38.6% by further compromising human comfort threshold to 1.5. On the contrary, PF-PEC provides the energy conservation up to 36% while achieving the human comfort threshold of 0.5 as per the ASHRAE standard. Therefore, the M-CHESS algorithm though flexibly change the human comfort range to attain more energy conservation. However, the average energy savings achieved by PF-PEC algorithm for a similar value of PMV is always higher than that of M-CHESS algorithm. Hence, our PF-PEC algorithm improves the human comfort as well as energy savings in a smart home.

7. Conclusion

The paper presents energy management and optimization techniques to minimize energy consumption in smart dwellings. A Markov

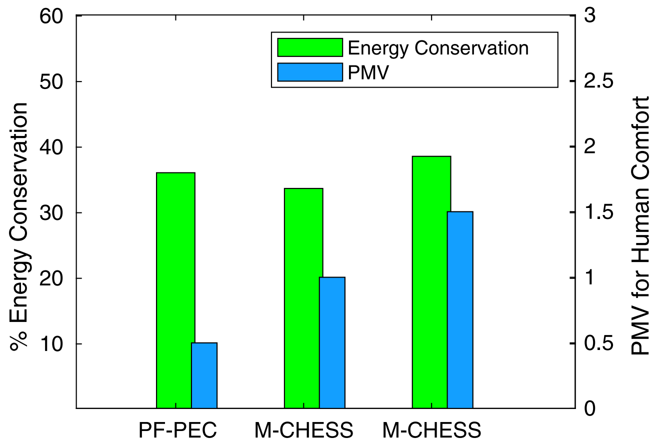


Fig. 12. PF-PEC algorithm comparison with an energy saving scheme (M-CHESS) that considers standard human comfort level.

chain model is proposed to compute probabilities of power consumption in different time slots. This data set is leveraged by our prediction and feedback based energy management algorithm which minimizes energy consumption during peak load hours. To efficiently incorporate the proposed algorithms in a real world scenario, a fog based IoT architecture is implemented. Experimental evaluations are conducted in a home having 3 occupants. Experiments reveal that the forecasted energy estimates are very close to actual energy consumed within home. Moreover, it is observed that the energy consumption and electricity costs are significantly reduced without degrading standard human comfort. We consider that this work can be instrumental for employing proactive and precise demand side management in future energy systems.

CRediT authorship contribution statement

Muhammad Umair: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization, Resources. **Muhammad Aamir Cheema:** Methodology, Data curation, Writing – review & editing, Supervision, Visualization, Investigation. **Bilal Afzal:** Writing – original draft, Writing – review & editing, Supervision, Visualization. **Ghalib Shah:** Writing - Review & Editing, Supervision, Visualization, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Bilal Afzal, Muhammad Umair, Ghalib Asadullah Shah, Ejaz Ahmed, Enabling iot platforms for social iot applications: vision, feature mapping, and challenges, Future Gener. Comput. Syst. 92 (2019) 718–731.
[2] Davit Marikyan, Savvas Papagiannidis, Eleftherios Alamanos, A systematic review of the smart home literature: A user perspective, Technol. Forecast. Soc. Change 138 (2019) 139–154.
[3] Zahrah A. Almusaylim, Noor Zaman, A review on smart home present state and challenges: linked to context-awareness Internet of Things (IoT), Wirel. Netw. 25 (6) (2019) 3193–3204.
[4] A.R. Al-Ali, Imran A. Zualkernan, Mohammed Rashid, Ragini Gupta, Mazin Alikarar, A smart home energy management system using IOT and big data analytics approach, IEEE Trans. Consum. Electron. 63 (4) (2017) 426–434.
[5] Jinsoo Han, Chang-Sic Choi, Wan-Ki Park, Ilwoo Lee, Sang-Ha Kim, Smart home energy management system including renewable energy based on ZigBee and PLC, IEEE Trans. Consum. Electron. 60 (2) (2014) 198–202.
[6] Adia Khalid, Nadeem Javaid, Mohsen Guizani, Musaed Alhussein, Khursheed Aurangzeb, Manzoor Ilahi, Towards dynamic coordination among home appliances using multi-objective energy optimization for demand side management in smart buildings, IEEE Access 6 (2018) 19509–19529.
[7] Minyoung Sung, Younghoo Ko, Machine-learning-integrated load scheduling for reduced peak power demand, IEEE Trans. Consum. Electron. 61 (2) (2015) 167–174.
[8] Zhaoxuan Li, Bing Dong, A new modeling approach for short-term prediction of occupancy in residential buildings, Build. Environ. 121 (2017) 277–290.
[9] João Virote, Rui Neves-Silva, Stochastic models for building energy prediction based on occupant behavior assessment, Energy Build. 53 (2012) 183–193.
[10] Eoghan McKenna, Michal Krawczynski, Murray Thomson, Four-state domestic building occupancy model for energy demand simulations, Energy Build. 96 (2015) 30–39.
[11] Zhengen Ren et al., A model for predicting household end-use energy consumption and greenhouse gas emissions in Australia, Int. J. Sustain. Build. Technol. Urban Dev. 4 (3) (2013) 210–228.
[12] Manisa Pipattanasomporn, Murat Kuzlu, Saifur Rahman, An algorithm for intelligent home energy management and demand response analysis, IEEE Trans. Smart Grid 3 (4) (2012) 2166–2173.
[13] A.D. Wills, Ian Beausoleil-Morrison, V.I. Ugursal, Adaptation and validation of an existing bottom-up model for simulating temporal and inter-dwelling variations of residential appliance and lighting demands, J. Build. Perform. Simul. 11 (3) (2018) 350–368.
[14] Zhun Yu, et al., A systematic procedure to study the influence of occupant behavior on building energy consumption, Energy Build. 43 (6) (2011) 1409–1417.
[15] Edouard Amouroux, Thomas Huraux, François Sempé, Nicolas Sabouret, Yvon Haradji, Simulating human activities to investigate household energy consumption, in: ICAART (2), 2013, pp. 71–80.
[16] Biying Yu, Junyi Zhang, Akimasa Fujiwara, A household time-use and energy-consumption model with multiple behavioral interactions and zero consumption, Environ. Plan. B: Plann. Des. 40 (2) (2013) 330–349.
[17] Brandon Johnson, et al., A method for modeling household occupant behavior to simulate residential energy consumption, in: Innovative Smart Grid Technologies Conference (ISGT), IEEE PES, IEEE, 2014, pp. 1–5.
[18] Shaoen Wu, et al., Survey on prediction algorithms in smart homes, IEEE Internet Things J. (2017).
[19] Paul A Gagniuc, Markov Chains: From Theory to Implementation and Experimentation, John Wiley & Sons, 2017.
[20] José Luis Ramírez-Mendiola, Philipp Grünewald, Nick Eyre, Residential activity pattern modelling through stochastic chains of variable memory length, Appl. Energy 237 (2019) 417–430.
[21] Muhammad Umair, Ghalib A. Shah, Energy management of smart homes, in: 2020 IEEE International Conference on Smart Computing, SMARTCOMP, IEEE, 2020, pp. 247–249.
[22] Cristian Chiñas-Palacios, Jesus Aguila-Leon, Carlos Vargas-Salgado, Edith X.M. Garcia, Julian Sotelo-Castañon, Elías Hurtado-Perez, A smart residential security assisted load management system using hybrid cryptography, Sustain. Comput. Inform. Syst. 32 (2021) 100611.
[23] Israr Ullah, Rashid Ahmad, DoHyeun Kim, A prediction mechanism of energy consumption in residential buildings using hidden markov model, Energies 11 (2) (2018) 358.
[24] Djamel Saba, Youcef Sahli, Abdelkader Hadidi, An ontology based energy management for smart home, Sustain. Comput. Inform. Syst. 31 (2021) 100591.
[25] Rabiya Khalid, Nadeem Javaid, Muhammad Hassan Rahim, Sheraz Aslam, Arshad Sher, Fuzzy energy management controller and scheduler for smart homes, Sustain. Comput. Inform. Syst. 21 (2019) 103–118.
[26] Mohamad Razwan Abdul Malek, Nor Azlina Ab Aziz, Salem Alelyani, Mohamed Mohana, Farah Nur Arina Baharudin, Zuwairie Ibrahim, Comfort and energy consumption optimization in smart homes using bat algorithm with inertia weight, J. Build. Eng. 47 (2022) 103848.
[27] Zhipeng Deng, Qingyan Chen, Simulating the impact of occupant behavior on energy use of HVAC systems by implementing a behavioral artificial neural network model, Energy Build. (2019).
[28] Da Yan, Xiaohang Feng, Yuan Jin, Chuang Wang, The evaluation of stochastic occupant behavior models from an application-oriented perspective: Using the lighting behavior model as a case study, Energy Build. 176 (2018) 151–162.
[29] Anders Nilsson, Misse Wester, David Lazarevic, Nils Brandt, Smart homes, home energy management systems and real-time feedback: Lessons for influencing household energy consumption from a Swedish field study, Energy Build. 179 (2018) 15–25.
[30] Isabella Gaetani, Pieter-Jan Hoes, Jan L.M. Hensen, Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy, Energy Build. 121 (2016) 188–204.
[31] Muhammad Umair, Bilal Afzal, Asad Khan, Atiq Ur Rehman, Y. Ahmet Sekercioglu, Ghalib A. Shah, Self-configurable hybrid energy management system for smart buildings, in: 2018 15th International Conference on Control, Automation, Robotics and Vision, ICARCV, IEEE, 2018, pp. 1241–1246.

[32] Muhammad Umair, Muhammad Aamir Cheema, Omer Cheema, Huan Li, Hua Lu, Impact of COVID-19 on IoT adoption in healthcare, smart homes, smart buildings, smart cities, transportation and industrial IoT, Sensors 21 (11) (2021) 3838.

[33] Mohammad Sadegh Aslanpour, Adel N. Toosi, Muhammad Aamir Cheema, Raj Gaire, Energy-aware resource scheduling for serverless edge computing, in: The 22nd IEEE/ACM International Symposium on Cluster, Cloud and Internet Computing, CCGrid, 2022.

[34] Mohammad S. Aslanpour, Adel N. Toosi, Raj Gaire, Muhammad Aamir Cheema, WattEdge: A holistic approach for empirical energy measurements in edge computing, in: International Conference on Service-Oriented Computing, ICSOC, 2021, pp. 531–547.

[35] Junaid Akram, Muhammad Umair, Rutvij H Jhaveri, Muhammad Naveed Riaz, Haoran Chi, Sharaf Malebary, Chained-drones: blockchain-based privacy-preserving framework for secure and intelligent service provisioning in internet of drone things, Comput. Electric. Engrg. 110 (2023) 108772.

[36] Jianhua Li, Jiong Jin, Dong Yuan, Marimuthu Palaniswami, Klaus Moessner, EHOPES: Data-centered fog platform for smart living, in: Telecommunication Networks and Applications Conference (ITNAC), 2015 International, IEEE, 2015, pp. 308–313.

[37] Ching-Hu Lu, et al., Context-aware energy saving system with multiple comfort-constrained optimization in M2M-based home environment, IEEE Trans. Autom. Sci. Eng. 14 (3) (2017) 1400–1414.

[38] Shivi Sharma, Hemraj Saini, A novel four-tier architecture for delay aware scheduling and load balancing in fog environment, Sustain. Comput. Inform. Syst. 24 (2019) 100355.

[39] Nagender Kumar Suryadevara, Energy and latency reductions at the fog gateway using a machine learning classifier, Sustain. Comput. Inform. Syst. 31 (2021) 100582.

[40] Daniel Fernando Espejel-Blanco, Jose Antonio Hoyo-Montano, Jaime Arau, Guillermo Valencia-Palomo, Abel Garcia-Barrientos, Hector Ricardo Hernandez-De-Leon, Jorge Luis Camas-Anzueto, HVAC control system using predicted mean vote index for energy savings in buildings, Buildings 12 (1) (2022) 38.

[41] Standard 55-Thermal Environmental Conditions for Human Occupancy, ASHRAE American Society of Heating, Refrigerating and Air-conditioning Engineers, (ISSN: 1041-2336) 2013, Available: https://www.ashrae.org/resources--publications/bookstore/standard-55-and-user-s-manual.

[42] Jermy Thomas, Tiffany Swenson, Amanda D Smith, Quantifying the importance of measured metabolic rates and clothing levels for effectively using a predicted mean vote model: A global sensitivity analysis, ASHRAE Trans. 125 (2019).

[43] Mohammad Aazam, Sherali Zeadally, Khaled A Harras, Deploying fog computing in industrial Internet of Things and Industry 4.0, IEEE Trans. Ind. Inform. (2018).

Muhammad Umair is a PhD student at the School of Computer Science, The University of Sydney. He is also a Lecturer at the Department of Electrical, Electronics and Telecommunication Engineering, New Campus, UET Lahore. He completed his B.Sc. Electrical Engineering and M.Sc. Electrical Engineering from University of Engineering and Technology (UET) Lahore in 2014 and 2017, respectively. He has worked as a Research Officer at Internet of Things (IoT) lab at Al-Khwarizmi Institute of Computer Sciences, UET Lahore. He has also worked at Sultan Qaboos IT Research lab as a Research Officer. His survey on Social IoT platforms is the most cited survey for SIoT applications. He has designed graduate level courses on IoT. His areas of interests include Internet of Things, Embedded Systems, Network Systems, Machine Learning, Algorithms Development, Pervasive Computing, Ubiquitous Computing, Cloud Based Systems, Data Analytics and working on application layer of any of the defined problems.

Muhammad Aamir Cheema is an ARC Future Fellow, an Associate Professor and Director of Research at the Department of Software Systems and Cybersecurity, Faculty of Information Technology, Monash University, Australia. He obtained his PhD from UNSW Australia in 2011. He is the recipient of 2012 Malcolm Chaikin Prize for Research Excellence in Engineering, 2013 Discovery Early Career Researcher Award, 2014 Dean's Award for Excellence in Research by an Early Career Researcher, 2018 Future Fellowship, 2018 Monash Student Association Teaching Award and 2019 Young Tall Poppy Science Award. He has also won two CiSRA best research paper of the year awards, two invited papers in the special issue of IEEE TKDE on the best papers of ICDE, and three best paper awards at ICAPS 2020, WISE 2013 and ADC 2010, respectively. He is the Associate Editor of IEEE TKDE and DAPD and served as PC co-chair for ADC 2015, ADC 2016, 8th ACM SIGSPATIAL Workshop ISA 2016 & 2018, IWSC 2017, proceedings chair for DASFAA 2015 & ICDE 2019.

Bilal Afzal is a graduate from National University of Science and Technology, Islamabad, Pakistan. He has worked as Research Officer and Senior Research Officer at KICS, UET Lahore, Pakistan. His research interests include Computer and Wireless Networks, Internet of Things (IoT), IoT Security, and 5G radio technology. He has served as the program committee member, co-chair and session manager in several IEEE conferences. He is regular reviewer of many impact factor journals including Elsevier FGCS, JNCA, COMPELECENG, SAGE JDSN, IEEE Network Magazine, and IEEE Consumer Electronics Magazine.

Dr. Ghalib A. Shah is an IEEE Senior Member, and Professor at the Department of Cyber Security, Air University Islamabad. He has worked as a Sultan Qaboos IT Co-Chair at UET Lahore. He joined Al-Khawarizmi Institute of Computer Science, UET Lahore in 2012 and established Internet of Things (IoT) Lab, where he received many research grants from HEC and ICT R & D Fund and several projects are in progress at this Lab. He also received a research grant for Cyber Security in IoT and is working on many projects. He actively works in the area of communication protocols and cyber security in IoT. Dr. Shah started his academic career at College of EME, National University of Sciences and Technology Islamabad as an Assistant Professor in 2007 and served for three years. He has been at the School of Computer Science, Australian National University as a visiting research fellow during 2009-10. He then joined the Next Generation Wireless Networks Lab, Koc University, Istanbul as a Research fellow and produced significant research publications in the area of cognitive radio sensor networks. Dr Shah received his B.Sc. major Math and M.Sc degree in Computer Science from Bahauddin Zakariya University Multan, Pakistan in 1997 and 2000 respectively and PhD degree in computer engineering from Middle East Technical University, Ankara Turkey in January 2007.