Estimation of Domestic Load Profile for Effective Demand-Side Management

MARYAM JALAL[1], ATTIQUE UR REHMAN[2], AZHAR UL HAQ[2], IHSAN ULLAH KHALIL[3]

[1]Department of Comupter Engineering National University of Technology Islamabad, PAKISTAN
[2] Department of Electircal Engineering National University of Sciences and Technology Islamabad, PAKISTAN
[3]Department of Electircal Engineering National University of Sciences and Technology Islamabad, PAKISTAN

Abstract: - In this article domestic base and shift based load profile are estimated for effective Demand Side Management (DSM). Domestic electricity consumption in Pakistan accounts for approximately 40% of total electricity sales. Effective DSM can reduce electricity consumption. Power generation companies are increasingly recognising the importance of analysing their customers' consumption patterns. This article proposes an agent-based modelling approach for forecasting household electricity consumption profile. AnyLogic software is used for establishing the model that uses variables and functions to estimate base and shiftable load of three hundred households. This article also estimates the weekly and 24-hour load profile for effective DSM operations by smart grid infrastructure. The results show that the agent-based simulation closely approximates real-time data, with a difference of only 2.4%.

Key-words: - Multi agent; Demand side management; Load profiling.

Received: August 27, 2023. Revised: August 11, 2024. Accepted: September 9, 2024. Published: October 8, 2024.

1. Introduction

Residential electricity consumption has gained significant attention due to its contribution to total electricity sales, particularly in Pakistan, where it accounts for about 40% [1]. Knowledge of household electricity consumption patterns is crucial for effective Demand Side Management (DSM) that potentially reduces overall electricity consumption [2]. Power generation companies are increasingly recognizing the value of analyzing their customers' consumption patterns to improve their services and manage resources effectively. This paper presents a detailed analysis of energy consumption patterns of 300 households, using an agent-based modelling approach to forecast household electricity consumption profiles. The AnyLogic software-based model uses variables and functions to estimate the households' base and shiftable loads. The study also explores the effectiveness of time of use electricity tariffs and co-location of energy-storage units with transformers as peak load management solutions. This research work discusses residential energy management strategies and emphasizes the need for innovative solutions to manage peak load and improve energy efficiency in residential settings. The findings of this study have significant implications for energy policymakers, providing a comprehensive understanding of household energy consumption patterns and potential strategies for effective DSM operations using smart grid infrastructure. The study also contributes to the ongoing discussion of demand profile forecasting techniques and heuristic optimization techniques used to implement DSM, citing several works in the field. Load profiling is considered an important factor for planning and regulating the expansion of existing capacity of the network [3]. It is difficult to approximate load profile of one household using another data of another household. Furthermore, many of these companies use the concept of smart grids, which optimize power generation and distribution to their clients [4]. By analyzing data from individual households, companies can tailor energy distribution to meet specific needs, ultimately leading to cost savings and reduced environmental impact. Overall, load profiling and smart grid technology work hand in hand to ensure a reliable and sustainable energy supply for consumers. Working capacity and efficiency of smart grids increase when the companies have load profile data from their customers. Energy management system collects load profile data from users by stimulating consumption patterns while considering varying loads and generation capabilities [5]. If these companies fail to estimate the electricity consumption profile of their clients, they may end up in situations where they may need to use alternative power generation measures. However, these sources usually require storage since they vary depending on environmental factors [6]. This reliance on alternative power sources can lead to higher costs for both companies and consumers, as well as increased strain on the overall power grid. By accurately predicting electricity consumption profiles and using smart grid technology, companies can better optimize energy distribution, reduce costs, and improve overall sustainability. It is crucial for companies to invest in energy management systems and leverage load profile data to ensure a reliable and efficient electricity supply for their customers.

This work proposes an agent-based domestic electricity consumption of 300 households' simulation and analysis. In this article base and shift load are analysed for forecasting weekly and 24-hours load profile. This article has six sections. Related research work is highlighted in second portion. System model based on formulation of proposed approach is discussed in third section. Fouth section presents simulations of proposed approach. Fifth section discusses results and analysis. Conclusion is drawn in the last section of the article.

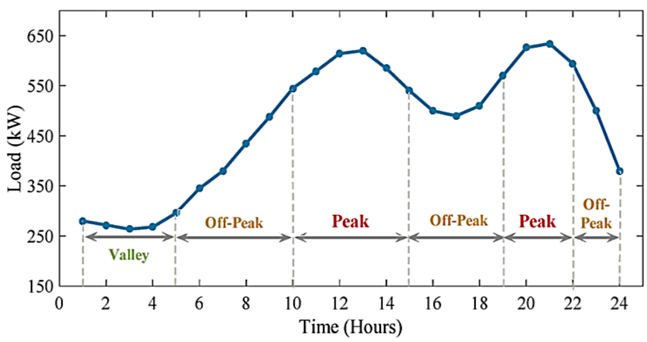

Figure 1: Example of Load curve [7]

2. Literature Review

This section discusses demand profile forecasting techniques as well as the heuristic optimization techniques employed for implementing DSM. Many researchers are focused to propose and devise mathematical and optimization techniques to schedule the peak load under optimal conditions. This enhances the capability of efficient use of available energy of smart grid. DSM is an effective mechanism to efficiently utilize available generated energy for increased reliability and productivity of overall system infrastructure [7]. It essentially modifies consumer demand for energy through various methods such as smart metering, indirect load control like incentive-based schemes and direct load control which include monetary incentive for turning off loads or rescheduling loads [8]. By implementing DSM strategies, utility companies can better manage peak demand periods and reduce the need for expensive backup power sources. Additionally, DSM can also help to reduce overall energy consumption and promote sustainability by encouraging more efficient use of electricity resources. An example of demand / load Profile curve over a specified time is shown in figure 1. Load and demand profiling means to accurately monitor and forecast electricity consumption patterns of users by implementing different techniques and optimization algorithms for achieving desired results [9]. Optimization algorithms such as particle swarm optimization, genetic algorithm, linear integer programming techniques are used to implement DSM by modifying user consumption pattern through demand response control strategies [10]. Agent base modelling is a relatively newer approach to forecast demand profiles which serve as prerequisite for DSM [11]. Emergence of distributed generations and smart grid framework has accentuated the importance of having an optimization technique to address the problems of peak load occurrence in distribution network [12]. Agent-based modelling has shown promising results in predicting demand profiles accurately and efficiently. By incorporating factors such as user behaviour and external influences, this approach offers a comprehensive understanding of energy consumption patterns. Furthermore, the integration of optimisation algorithms with demand response control strategies can effectively manage peak load occurrences in distribution networks, ultimately leading to a more reliable and efficient grid system. The combination of agent-based modelling and optimisation techniques is crucial to successfully implementing demand-side management strategies in the evolving energy landscape. In [13], latest DSM literature tilt towards stochastic modelling is presented. Credit based novel incentive scheme within stochastic planning environment is used. Figure 2 illustrates household smart energy management system including inflow of power from power utility to a home having energy management controller to implement control mechanism and thus enabling smart control on appliances connected. [14] proposed a Home Energy Management system for Distributed Energy Resources (DER) that includes scheduling for both electrical and thermal appliances, called HEMDAS. The main objective of this approach is to reduce energy expenses while ensuring user comfort. The system combines mixed-integer non-linear programming (MINLP) with a dynamic pricing (DP) scheme. In [15], Teacher learning based optimization (TLBO) is proposed in which load is classified into three classes: shift-able, shed-able and non-shed-able load. Cost efficiency is taken as the ratio of total energy consumption advantages to the total energy payments. Cost efficiency is considered as a signal for customers to adapt and alter their energy consumption pattern. Moreover, the fractional programming (FP) technique combining with day ahead pricing (DAP) is adopted in this scheme. The performance results show that cost efficiency is increased with large number of DERs [16]. In [17], for a system with an integration of PV to a windmill as RESs, and uncertainties arising by RESs integration, fuzzy logic technique is used. Agent-based Modelling and Simulation (ABMS) approach is used by researchers for complex socio-technical problems to serve as a pre-requisite for implementing DSM policies by forecasting electricity load profiles. [18] used the agent-based simulation approach by dividing the London urban area into zones using socio-demographic parameters. For each zone, a heterogeneous group of agents is created with an occupancy profile which simulates the hourly electricity consumption for heat-pumps, electric vehicles, and residential energy. The focus of the researcher was electric vehicles and residential use was represented as an aggregate in total electricity consumption. [19]used an agent-based model to study office building electricity consumption.

It has also been observed in the literature that mathematical models effectively model structure and environmental data better than probabilistic models. However, it is important to devise a strategy which can incorporate both the structural-environmental and socio-anthropologic aspects within the simulation element.

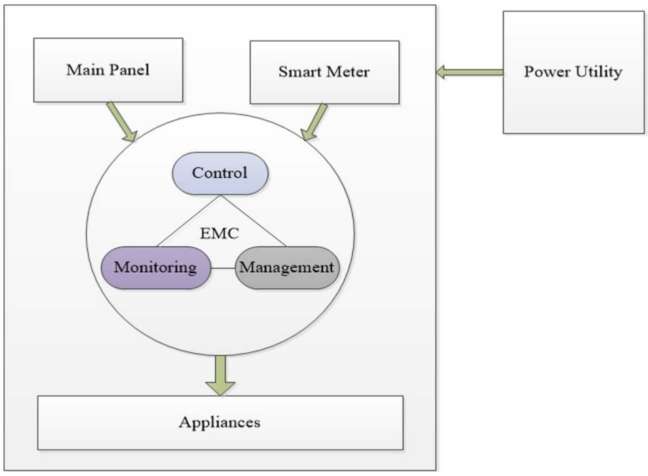

Figure 2: Flow chart of smart energy management

3. System Model

A house would typically have appliances that exert different power loads. For instance, the load of a water heater is different from that of lights. The usage of these appliances is typically independent of each other. It is possible to classify these loads according to their usage. Specifically, some of them will always be ON throughout the day, even when the houses are empty such as digital clocks, which are always ON throughout the day, even when they are not in the house [5]. Moreover, they run at constant power and therefore, in each household, they will always have similar loads per day.

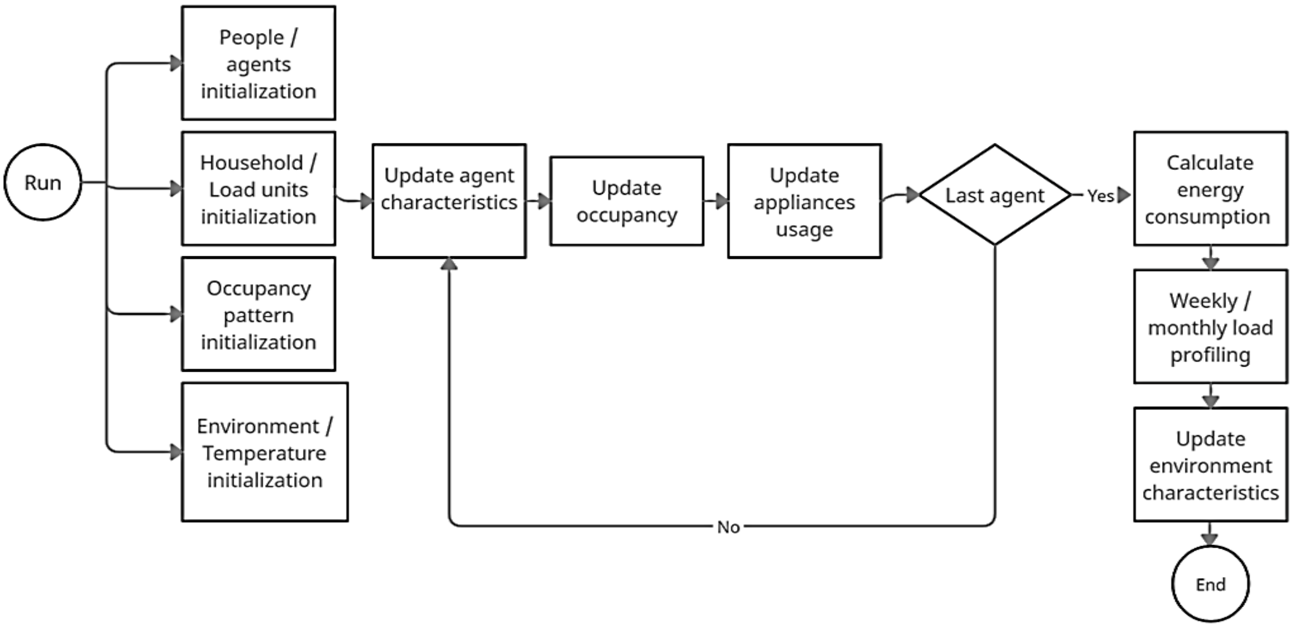

Figure 3: System model overview

This research work considers baseloads and shift load. Base load includes refrigerators, routers, digital clocks, and freezers. These loads run throughout the day for houses having them. Freezers have a rating of 80 W, the rating for routers is 4 W, that for digital clocks is 3 W, while for refrigerators is 50 W, and these values were obtained from [5]. There might be variation in base load always exists because some house holds do not have all these loads. Shift based loads have dependency on occupancy of the house or activity of the residents. For instance, a computer load will only be connected when a person is in the house and needs to use it. Same is the case of other shift-based loads, such as domestic hot water, televisions, and cooking. The usage patterns of these loads may not depend on their ratings. As shown, their power consumption is not constant in a house, and their usage has varying durations. This research work has also considered different usage patterns for these loads. When a power generation company intends to optimize their grids' power consumption, they may encourage people to shift these loads to low-consumption hours [6]. Such a step would improve the efficiency of the grid. Recommended actions may include charging an electric vehicle when sleeping to avoid straining the grid during peak hours. Figure 3 shows the overview of system model

System model depicts a step-by-step procedure for determining and estimating the amount of energy consumed. The process begins with identifying four crucial factors: people or agents, households or load units, occupancy patterns, and environment or temperature. Each of these parameters provides fundamental information needed for the next steps in determining energy usage. The process then updates the agent characteristics and the number of occupants regularly, which alters the usage of appliances. This update relies on the previously updated agent characteristics and occupancy data. After the update stage, there is a decision-making phase that verifies whether the last agent has been accounted for. If the last agent has been taken into consideration, the process proceeds to calculate the energy consumed. Before reaching a conclusion, this calculation also incorporates new information about the environment and load profiling every week or 24 hours. This flowchart presents a clear and systematic way to determine energy usage, considering several essential factors and their interdependence. Figure 4 shows the flow chart of opting shift load.

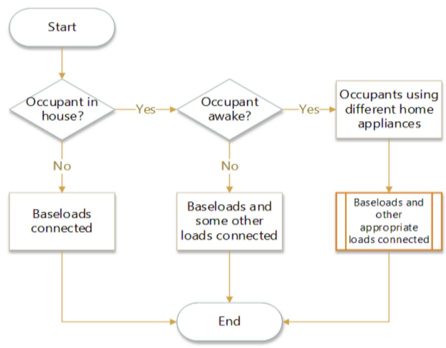

Figure 4: Flowchart of opting shift based load

4. Simulations

The developed domestic power consumption agent-based model was simulated using Any-Logic software with a small population of 300 households. The model considered various appliances such as light, television, computers, hot water, cooking, laundry, dishwashing, air conditioners, and electric vehicle charging. Each load was defined as a variable to monitor independently and facilitate plotting on time plots. The model also included phases representing time of use specially for shift-based load. Transitions between these phases were modelled to simulate realistic behaviours, such as going to work and returning home. Additionally, parameters for household appliances and load scheduling were listed, including service times and power ratings.

Another feature of this research work is that it shows a modelled average duration within which the occupants of the households were at work, at home, and awake. As described above, these factors affect some appliances' usage and the model's total load. As the simulation runs, it shows these variables' values, making it possible to follow them and see their effect.

Simulation also models the transition, that is time of returning to home or time of starting shift-based load. Just like the transition to work, this one also depends on a random function that makes the model simulate people returning to their homes. In this scenario, people tend to use their electric appliances at home during the evening hours. As a result, most of the electricity consumption occurs during this period. The duration of this state is determined by a modelled function that randomly allocates time. In the evening hours, people typically go to sleep, which reduces electricity usage in the final phase. So, the main running loads are the baseloads and others mentioned above. A 24-hour cycle illustrates the daily power usage of the occupants. Table I lists the parameters for household appliances and load scheduling according to four different categories of loads.

5. Results

In this research work, the load profiles of 300 households are examined to better understand their energy consumption patterns. Load profile is generally depicted graphically, which shows consumption of electricity in kWh at specific time. Hourly and weekly assessment is done using separate simulation with varying time duration.

Table I: Parameters for Appliance Agents

Load category	Appliances	Service time		Power rating
Baseload	Digital clocks	Continuous		3W
	Routers	Continuous		4W
	Refrigerators	Continuous		50W
	Freezers	Continuous		70W
Shiftable load	Washing machine	Cycle 1	20 min	1000W
		Cycle 2	40 min	400 W
	Dishwasher	Cycle 1	25 min	1800W
		Cycle 2	65 min	1200 W
	EV charging	*T* depending on *SoC & P*		5480 W

The figure 5 shows the load profile over a short time period. During this time, a gradual increase in energy consumption in the evenings and early mornings can be observed, which corresponds to occupant activities like meal preparation and morning routines. It is observed that the electric vehicle load has a maximum peak consumption of 460 kWh over a 24-hour period. When analysing load profiles over a week, the time axis has been changed to reflect seven days. The results show an interesting trend: before midnight, when all occupants are at home, total power consumption reaches 820 kWh. This period corresponds to evening activities such as lighting, entertainment, and housework. Furthermore, between 07:30 and 09:00 Hrs, there is a peak in energy consumption of 750 kWh which is consistent with occupants engaging various loads before leaving for work or other daily commitments. , Figure 6 depicts the individual load curves for each appliance modelled in proposed framework. These findings offer important insights for improving residential energy management strategies. All values are approximations which are based on simulation results.

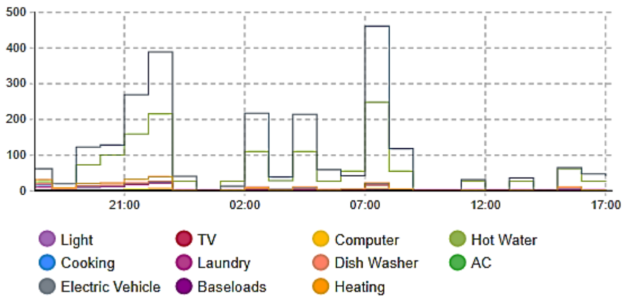

Figure 5: Different loads from evening to sleeping time

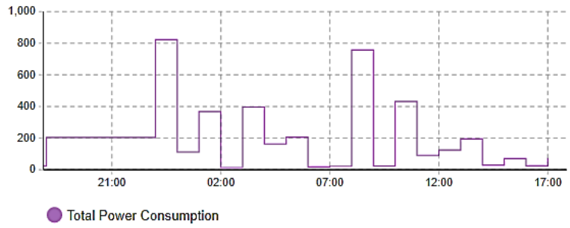

Figure 6: Plot of total power consumption

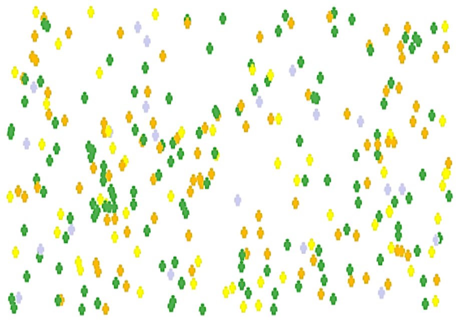

Figure 7: Any-logic graphical representation of the agents in different states

This study also looks at how shift-based loads are dependent on human/occupant requirements and how that affects their electricity consumption. Figure 7 shows the occupants' states, with the majority still at work (green), some already at home (yellow), and others in neither state (asleep, shown in grey). Figure 8 shows the monthly consumption data for 300 households. Electric vehicles, hot water systems, and air conditioning are the three largest consumers of electricity. Residents' daily use of electric vehicles necessitates daily charging, which contributes to high power consumption. Hot water systems consume a lot of energy due to their high-power rating. Policymakers in the energy sector have considered a variety of solutions to address these issues. One approach is to implement Time of Use (ToU) electricity tariffs, which can encourage EV owners to charge after midnight rather than in the early evening, potentially halving the increase in peak load.

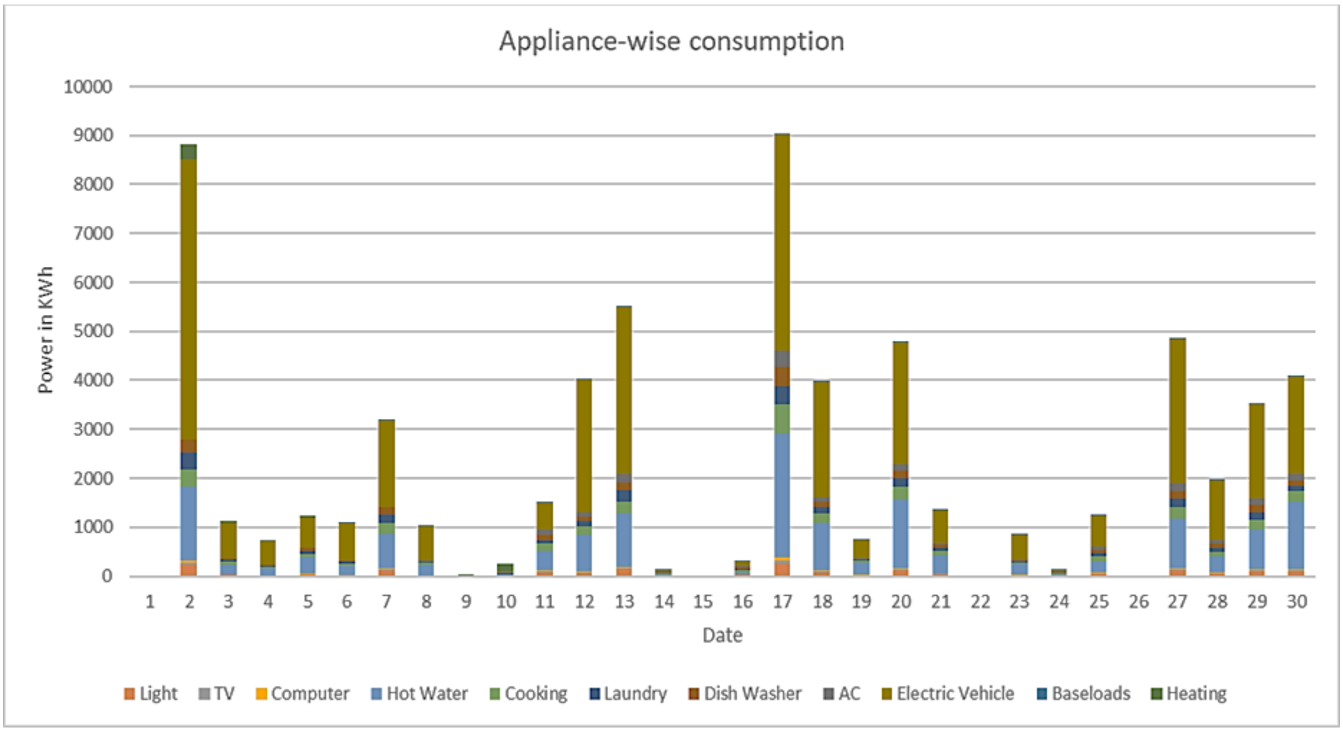

Figure 8: Appliance-wise consumption

However, ToU tariffs may cause "timer peaks" or "rebound peaks" if most people accidentally deploy their chargers for charging at the same time. Another solution is to co-locate energy-storage units with transformers, which can charge during low demand and discharge during peak demand, thereby reducing peak load. This study collects data on the usage statistics of approximately 14,000 homes for all months of 2020 and selects a sample of 300 households with specific characteristics from the collected data. The graph in figure 9 shows that the developed model closely approximates actual power consumption data. However, the two data sets have some noticeable differences. Specifically, most of the points for the simulated data are higher than the actual power consumption. These differences could have resulted from several causes. The first one could be the fact that the population that the validation data belongs to do not have electric vehicles while the simulation considered it. Electric vehicles have a high-power consumption, and therefore, their effect on the consumed power is significant. Another cause of the variation could result from the usage of power for other uses that either the validation or simulation data does not consider. The graph also shows that from May to October, the power consumed is much higher than other months of the year. This high consumption is the result of usage of air conditioners during the hot season. Graph also shows that lowest value of units consumed in respect of validated data are in the Month of March and value comes down to 23,685 kWh. Similarly lowest consumption units measured in respect of simulated consumption data is 23,675 kWh for the month of February. Furthermore, highest value of units consumed in respect of validated data are in the Month of July and value comes up to 76,365 kWh. The difference in percentage between the simulated kWh units and actual kWh consumption units is recorded in the month of December i.e. 25.1%. Similarly, the months in which simulated data closely approximates the real time data are May and September with value comes out to be 2.4 %.

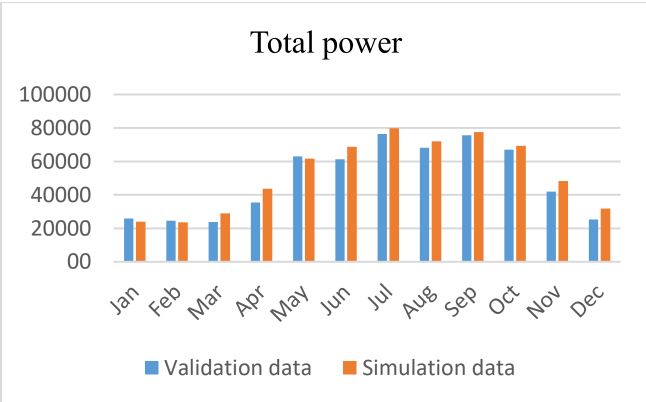

Figure 9: Validation of monthly estimated data

6. Conclusion

This article investigates the energy consumption patterns of 300 households to identify key insights for better management of residential energy. The study shows that the highest energy consumption typically happens during the evenings and early mornings when occupants engage in charging EVs and using hot water which highlights the potential of ToU electricity tariffs and the co-location of energy storage units with transformers as measures for managing peak loads. However, the study also raises concerns about "timer peaks" or "rebound peaks" when most people use chargers to charge at the same time as ToU tariffs. The study also finds some differences between the simulated and actual data on power use. The validated data shows that the lowest unit consumption is in

March, with a value of 23,685 kWh. The simulated data shows the lowest consumption in February, totalling 23,675 kWh. The highest consumption, according to the validated data, occurs in July, reaching 76,365 kWh. The most significant difference between simulated and actual kWh consumption units occurs in December, with a difference of 25.1%. However, the simulated data closely matches the real-time data in May and September, with a mere 2.4% difference. Overall, this study highlights the need for innovative solutions to manage peak loads and enhance energy efficiency in residential settings. Future research could focus on improving the simulation model and exploring alternative solutions for peak load management. The agent-based simulation closely matches the real-time data, with a mere 2.4% difference, demonstrating the effectiveness of the proposed model.

References

[1] "Buildings | Free Full-Text | Unlocking Household Electricity Consumption in Pakistan." Accessed: Mar. 13, 2024. [Online]. Available: https://www.mdpi.com/2075-5309/11/11/566
[2] "Engineering Proceedings | Free Full-Text | Demand Side Management for the Energy-Efficient Future of Pakistan Using a Low Emission Analysis Platform." Accessed: Mar. 13, 2024. [Online]. Available: https://www.mdpi.com/2673-4591/46/1/28
[3] F. V. Cerna, J. K. Coêlho, M. P. Fantesia, E. Naderi, M. Marzband, and J. Contreras, "Load Factor Improvement of the Electricity Grid Considering Distributed Energy Resources Operation and Regulation of Peak Load," *Sustainable Cities and Society*, vol. 98, p. 104802, Nov. 2023, doi: 10.1016/j.scs.2023.104802.
[4] "Energies | Free Full-Text | The Effect of Electric Load Profiles on the Performance of Off-Grid Residential Hybrid Renewable Energy Systems." Accessed: Mar. 12, 2024. [Online]. Available: https://www.mdpi.com/1996-1073/8/10/11120
[5] "Real-Time Energy Storage Management for Renewable Integration in Microgrid: An Off-Line Optimization Approach | IEEE Journals & Magazine | IEEE Xplore." Accessed: Mar. 12, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/6913531
[6] J. Jackson, "Improving energy efficiency and smart grid program analysis with agent-based end-use forecasting models," *Energy Policy*, vol. 38, no. 7, pp. 3771–3780, Jul. 2010, doi: 10.1016/j.enpol.2010.02.055.
[7] C. Hiroux and M. Saguan, "Large-scale wind power in European electricity markets: Time for revisiting support schemes and market designs?," *Energy Policy*, vol. 38, no. 7, pp. 3135–3145, Jul. 2010, doi: 10.1016/j.enpol.2009.07.030.
[8] "A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction | Energy Informatics | Full Text." Accessed: Mar. 12, 2024. [Online]. Available: https://energyinformatics.springeropen.com/articles/10.1186/s42162-023-00262-7
[9] A. Dogra, A. Anand, and J. Bedi, "Consumers profiling based federated learning approach for energy load forecasting," *Sustainable Cities and Society*, vol. 98, p. 104815, Nov. 2023, doi: 10.1016/j.scs.2023.104815.
[10] "Axioms | Free Full-Text | Efficient Optimization Algorithm-Based Demand-Side Management Program for Smart Grid Residential Load." Accessed: Mar. 12, 2024. [Online]. Available: https://www.mdpi.com/2075-1680/12/1/33
[11] "Agent based modeling - Scholarpedia." Accessed: Mar. 12, 2024. [Online]. Available: http://www.scholarpedia.org/article/Agent_based_modeling
[12] "Energies | Free Full-Text | Smart Grid, Demand Response and Optimization: A Critical Review of Computational Methods." Accessed: Mar. 12, 2024. [Online]. Available: https://www.mdpi.com/1996-1073/15/6/2003
[13] "Novel Incentive Mechanism for End-Users Enrolled in DLC-Based Demand Response Programs Within Stochastic Planning Context | IEEE Journals & Magazine | IEEE Xplore." Accessed: Mar. 12, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/8305654
[14] "Investigation of Market-Based Demand Response Impacts on Security-Constrained Preventive Maintenance Scheduling | IEEE Journals & Magazine | IEEE Xplore." Accessed: Mar. 12, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/6708454
[15] "A Distributed Direct Load Control Approach for Large-Scale Residential Demand Response | IEEE Journals & Magazine | IEEE Xplore." Accessed: Mar. 12, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/6766290
[16] M. Negnevitsky and K. Wong, "Demand-Side Management Evaluation Tool," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 212–222, Jan. 2015, doi: 10.1109/TPWRS.2014.2329323.
[17] A. Mnatsakanyan and S. W. Kennedy, "A Novel Demand Response Model with an Application for a Virtual Power Plant," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 230–237, Jan. 2015, doi: 10.1109/TSG.2014.2339213.
[18] G. Bustos-Turu, K. H. van Dam, S. Acha, C. N. Markides, and N. Shah, "Simulating residential electricity and heat demand in urban areas using an agent-based modelling approach," in *2016 IEEE International Energy Conference (ENERGYCON)*, Apr. 2016, pp. 1–6. doi: 10.1109/ENERGYCON.2016.7514077.
[19] T. Zhang, P.-O. Siebers, and U. Aickelin, "Modelling electricity consumption in office buildings: An agent based approach," *Energy and Buildings*, vol. 43, no. 10, pp. 2882–2892, Oct. 2011, doi: 10.1016/j.enbuild.2011.07.007.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.