Analyzing the Residential Electricity Consumption Under Varying Seasonal and Weather Conditions

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Abstract: - This article analyses the effects of seasonal variations and weather effects on the electricity consumption of residential consumers. To optimize energy usage, precise load profile forecasts are critical, and Demand Side Management (DSM) is a key strategy. DSM reduces the cost of energy acquisition and the associated penalties by continuously monitoring energy use and managing appliance schedules. The proposed approach utilizes DSM-assisted agent-based modeling to anticipate electricity usage patterns for 300 households. It also models inductive and non-inductive loads separately and selects specific loads to operate at specific times. This research work investigates the impact of climate on residential electricity usage, including air conditioning and heating demands and overall power consumption. Results are compared with a similar study to validate our approach.

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

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1. Introduction

In Pakistan, 40% of total electricity consumption comes from households, putting immense pressure on power generation companies to manage resources [1]. Understanding and improving energy usage patterns requires investigating seasonal fluctuations and climatic impacts on residential electricity demand. Seasonal variations, such as temperature changes from summer to winter, have a significant impact on the demand for heating, ventilation, and air conditioning systems, which account for a large portion of residential energy consumption [2]. Climate variables such as humidity and precipitation can influence energy usage patterns. DSM is considered promising strategy to address this challenge. It reduces overall power consumption by predicting and managing user's consumption patter [3]. Power generation companies are realising the importance of this information, leading to a demand for new methods to predict and control home electricity usage. By studying these variations and their effects, scholars and policymakers can develop better strategies for regulating demand, increasing energy efficiency, and promoting sustainable residential energy usage. This research work examines 300 households' energy usage pattern using an agent-based modelling approach to forecast electricity consumption patterns. Agent-based modelling is a potent technique that enables the calculation of base and shiftable loads of households using variables and functions [4]. It enables generation companies to make well-informed decisions and enhance energy utilisation capacity.

Smart grid technology uses load profile data from customers to increase operational capacity and efficiency [5]. The DSM of smart grid collects load profile data from users by simulating consumption patterns, taking into account fluctuating loads and generation capacities [6]. Energy policy makers through DSM 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 [7]. Figure 1 shows categories of DSM in respect of time required for implementation and subsequent impact generated on electricity utilization patterns. It carries out two approaches that are energy efficiency and demand response. Energy Efficiency is related to employing advanced efficient appliances to increase energy efficiency. Implementing energy efficiency program under demand side management umbrella is rather difficult as it needs a major overhaul of entire electrical power infrastructure.

Demand Response deals with behavioural change in consumer consumption patterns to increase efficiency by reducing peak demand of residential sector which constitutes major chunk of total cost incurred [8]. During demand response programs, users provide permission to electricity distribution companies to remotely turn off appliances using direct load control during peak demand times or power supply issues using a preset program on controllable devices [9]. This partnership enables the adjustment of load profiles, providing clients with advantages on their electricity bills.

Each household has a distinct load profile, making it difficult to predict one household's profile from another's data [10]. Shift base load rely on environmental conditions. Anticipating the trend of shiftable load by analyzing their usage pattern would result in better resource distribution and increased grid dependability [11]. To meet the capacity during peak demand hours, use of renewable energy sources such as solar and wind power can be helpful in terms of low carbon emissions and improved grid reliability.

This research work proposes a methodology to enhance prediction accuracy across different loads and weather situations. This research work utilises agent-based modelling for power profiling with real-world usage statistics from an electrical distribution provider. It also shows the impact of seasonal variation on electricity consumption. This article consists of five sections, related literature review is overviewed in 2nd section. Third section explains agent based modelling and proposed system model. Fourth section explains system model. Fifth section discusses results. Last section concludes the article.

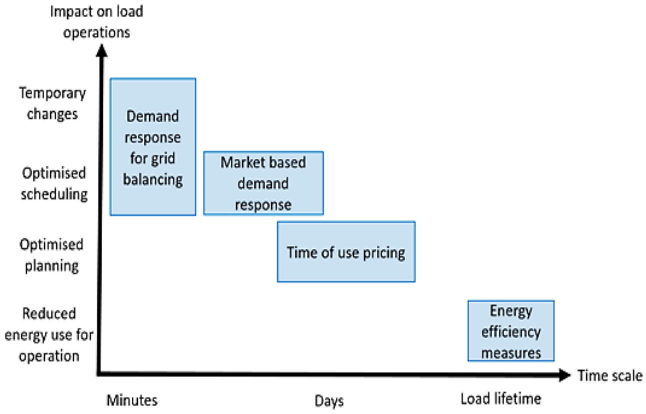

Fig 1: Categories of Demand side management [7]

2. Literature Review

Previous work carried out in the field of electricity load profiling and DSM can be classified as techniques followed on the basis of statistical / probabilistic / Time of use (TOU) models, agent base models, smart meters / home energy management systems / optimization algorithms such as particle swarm algorithm / genetic algorithms / neural networks / fuzzy logic and models based on effect of weather / occupancy on electricity consumption [12]. DSM employing heuristic optimization techniques is an effective tool for utilities to increase the flexibility of electrical distribution network and augment the efficiency of electrical system in the presence of distributed generation facilities in a smart grid environment [13]. DSM implementation in residential areas can improve the overall efficiency and reliability of the electrical system by minimising the demand for new power plants while increasing energy efficiency and power quality [14].

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 [15]. [16] 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. [4] used an agent-based model to study office building electricity consumption. Table I gives summarized previous literature work analysis.

Table I: Summary of the related work on DSM

Ref.	Description	Data Source
[17]	Energy credits are awarded for better contribution in DR which can be used in non-DR period	Power is nonzero and initially assumed to be 12 kW from the total of the 40 households.
[18]	A centralized DR selects an optimal combination of individual load profiles.	PV generation with a total rated power of 1MW.
[19]	The tool employs Monte Carlo simulations to generate hot water consumption profiles.	Energy metering data of 279 households across Tasmania.
[20]	Used survey for actual and forecasted demand considering different scenarios of growth rate.	96 households were surveyed.
[16]	Cost efficiency-based algorithm to optimize cost benefit per unit cost	Synthetic consumption patterns by clustering method.
[21]	The model considered the factors of land use, energy landscape, and customer inclination.	
[22]	Energy Management controller using Markov modelling	Detecting User behaviour pattern through preset reference models.
[23]	Non-Cooperative game theory, Day ahead energy market is considered and minimization of cost in robust situations with distributed algorithm is presented.	Synthetic, general framework
[18]	Implemented DCCM, TSCM using SQ (state queuing) approach for refrigerator load to achieve hybrid scheme for better regulation and load management capabilities.	Simulation of model uses Calgary city estimated 900,000 devices rated at 110W, resulting in 99 MW of power Capacity.
[24]	Produced structures by DLC are optimized by Integer Genetic Algorithm that is discussed in this paper.	In residential area, it is assumed that 210 equipment are controllable out of 1650 and in industrial area, 50 equipment are controllable
[25]	CPSDS (Cyber physical smart distribution system) in which RLAs are presented with various categories of incentives for event-based DSM mechanism.	The proposed DSM framework for CPSDS is examined using IEEE 37 bus test system residential, industrial and commercial loads.
[26]	The paper describes the modelling of DR using a fuzzy system approach which is typically a rational decision making model.	Two peak periods (6am-9am, 6pm-9pm) are considered with peak of 3.1 kw.
[27]	PSO is implemented, hour breakdown scheme is used to arrange appliances according to particular type.	14 different controllable types of appliances are considered.
[28]	GA and Binary PSO are utilized to build a hybrid algorithm. Peak and cost minimization with maximizing user comfort is considered.	14 types of appliances considered.

3. Agent Based Modelling

Agent-based modelling is a technique for determining household power consumption patterns by simulating the behaviour of various factors influencing electricity usage as separate agents. In this research work, agents are environmental temperature, occupancy patterns, load unit types, and household members. Each agent has unique characteristics and behaviours. The environmental temperature agent, for example, is important in determining the household's heating and cooling needs based on current weather conditions, whereas the occupancy pattern agent monitors the presence or absence of occupants and their activities. The load unit agent is responsible for the various appliances and devices used in the home, each with its own distinct power consumption pattern. All these agents interact with one another and the environment. Household occupancy patterns, for example, can have a significant impact on appliance usage, which then affects overall electricity consumption. Furthermore, external factors such as pricing schemes and energy-saving initiatives can influence these agents' decision-making processes. By simulating the interactions of these agents over time, the model estimates the household's total electricity consumption and generate a detailed power usage profile. ABM provides a thorough understanding of how various factors influence overall electricity consumption, which can be used to develop strategies for improving energy efficiency and demand-side management. Based on the benefits of using the agent-based approach to simulate the power usage profile, this work adopts technique. It uses *Any-Logic* software to develop and run the model. The software makes it possible to model and simulate all these households' power usage and provide a viable model and results. Given these advantages of agent-based modelling, it emerges as more superior to other methods used in such instances. Figure 2 shows an example of agents of the electricity consumption model taken from [29]

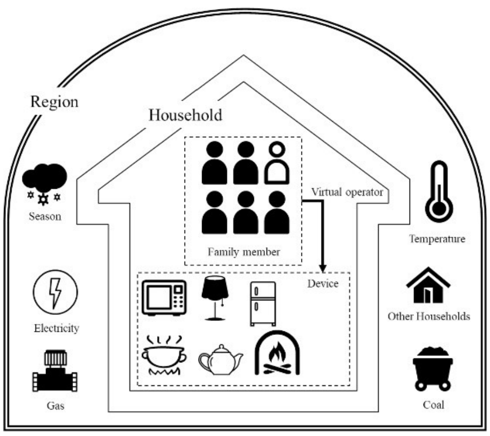

Fig. 2. Household energy consumption

4. System Model

This research work considers inductive loads which are used for cooling and heating. Impact of inductive heating and cooling load are different form that of lights. Climate and weather conditions influence the power consumption of these loads. High-temperature conditions bring discomfort to people, which causes them to use air conditioning appliances that bring their houses' temperatures to conducive conditions. Similarly, when the temperatures are too low, people use appliances that regulate it, making it comfortable for occupants of a house. These devices typically have high power ratings, which causes them to exert a large load on people's power consumption. For instance, air conditioners have a typical power rating of 1000 W. Such a rating has a significant impact on the total power consumption of a house. In extreme climatic conditions, such as during winter or summer, people are most likely to use fans and air conditioners more than in other periods. These loads may also be in use even when people are asleep. In such instances, they will not follow similar patterns as described above. When modelling people's power consumption profile, it is crucial to consider these loads since they can account for large consumption variations from other times. On community level the consumption of these adjustable loads becomes high. Additionally, these loads cause the variability of power consumption among households due to different operating conditions such as low cool/heat, high cool/heat, turbo mode etc. Therefore, this research work considers this dissimilarity and models it to better estimate these variations and its impact on the total load. Thermostats regulate the consumption of adjustable loads during unfavourable extreme temperature conditions. Proposed model checks the temperature before estimating the load profile of inductive heating or cooling load. If the temperature is high (greater than 28°C), then the model considers air conditioning loads, and when it is cold (i.e. temperature lower than 20°C), it considers heating loads. Process flow chart is shown in figure 3. Another crucial factor to consider when simulating domestic power consumption is the variability of occupancy based inductive loads such as air conditioner and heater. This research work models these variations differently. In the case of fixed loads, it only varied the usage patterns of users. Precisely, it gave the agents a different amount of time to use these fixed loads.

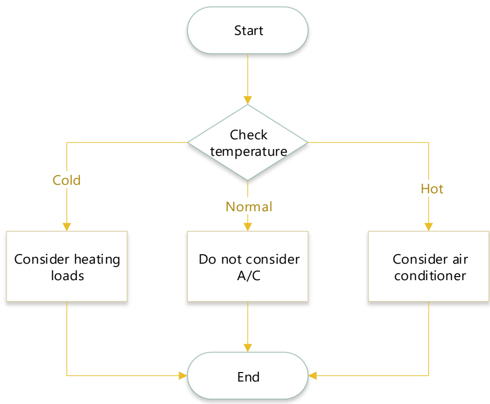

Fig. 3: Impact of climatic conditions on the model

However, in variable loads, it models different usage durations and their varying power ratings. This model also considers other inductive loads such as fans, refrigerators, dishwashing machines, vacuum cleaners, water pumps, and many other appliances that have motors. Typically, these loads have a spike in their consumption, when starting which is also considered. Spike of the refrigerator is shown in figure 4 [30]. Figure 5 shows the modelling process of inductive and non-inductive loads.

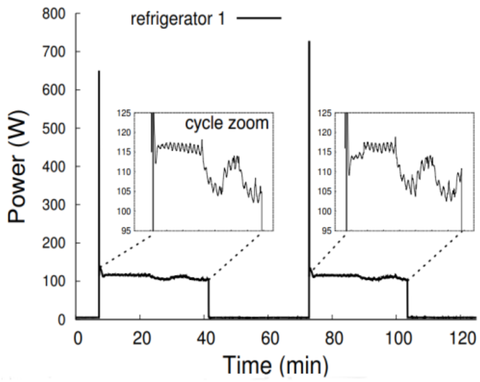

Fig. 4: The power consumption of a refrigerator [30]

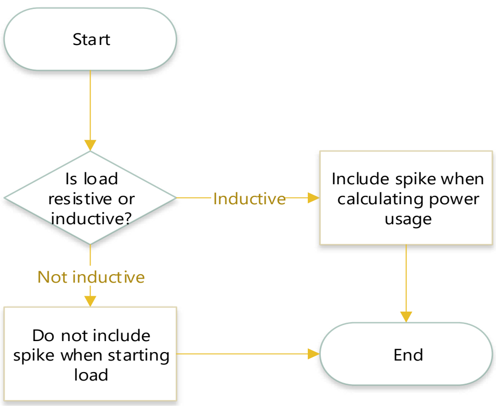

Fig. 5: Process flowchart showing modeling of inductive and non-inductive loads

5. Results

This research work examines the load profiles of 300 households to understand their energy consumption patterns. Monthly and seasonal assessment is done using separate simulation with varying time duration. Table II lists the parameters for household appliances and load scheduling according to three different categories of loads.

Table II: Parameters for Appliance Agents

Load category	Appliances	Service time	Power rating
Occupancy dependent load	Computer	State dependent	100W
	Television	State dependent	60W
	Lighting load	State dependent	40W
Adjustable / Variable load	Air conditioner	Run time Temperature dependent	350-2400W
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

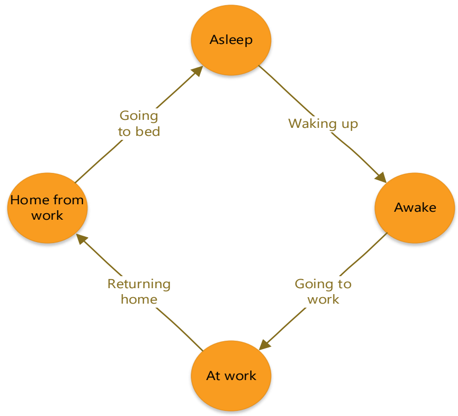

Fig. 6: The four states/transitions of proposed occupancy model

The input of the proposed model is states and transitions, which is shown in figure 6. The model uses numerical values for variables and graphs to represent variable values during runtime. Table III outlines conditions and constraints related to occupancy states. The model incorporates triangular distribution for time periods and power consumption calculations. It defines average durations for occupants at work, at home, and awake, with four independent phases: morning, working, evening, and sleeping. The simulation includes variations in power consumption based on activities and time periods. The model spans 24 hours and estimates total electricity consumption, providing insights for enhancing energy efficiency and demand-side management.

Table III: Timing and behaviour of each state

State	Behaviours	Time
1	Awaking up	0300-0530 hrs
2	Going to work / Leave home	0600-0800 hrs
3	Returning home	1700-2100 hrs
4	Going to bed	2000-2359 hrs

The estimated weekly load profile is shown in figure 7, which shows that major share of power consumed by EV load is 430 kWh in one day of the week which turns out to be weekend and Heater recording second most consumption given reading taken in month of winter season. Other loads such as baseloads are shown to consume less amount of power because of low power rating.

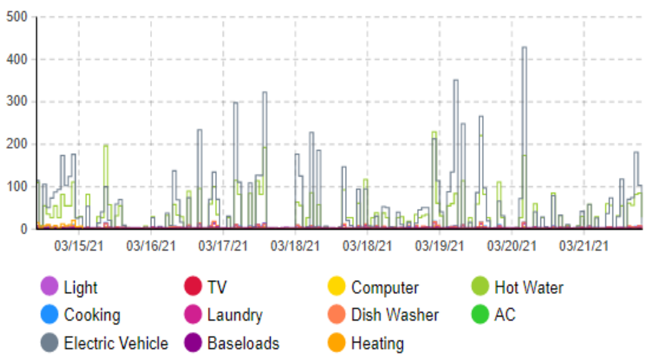

Fig. 7: Power of different loads within a week

The proposed model has been designed to have an automatically updating temperature that corresponds with actual values depending on climatic conditions. Specifically, it simulates temperatures for winter from December to March and summer between June and September. Therefore, when the simulation runs, the values for A/C and heating loads will change depending on corresponding climatic conditions. Moreover, the model allows one to change the temperature, making it possible to simulate different temperature conditions and override the climatic temperature. Figure 8 shows the corresponding result of air-conditioner and heating loads depending on the two main seasons. Air conditioner load gives maximum spike of 50 kWh on one instance in August while average consumption of heating load is 12 kWh. This is due to the fact that heating loads are resistive in nature and energy drop out occurs by converting flow of electrical energy to thermal energy.

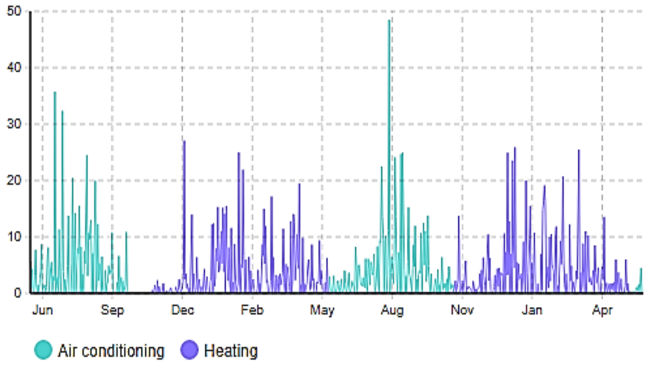

Fig. 8: Influence of climate on A/C and heating loads

The climatic condition not only affects the heating and air conditioning loads, but it also influences the total power consumed in a household for a given time duration. For instance, considering the case above of two years, the graph in figure 9 shows the corresponding total power consumed depending on the climatic conditions.

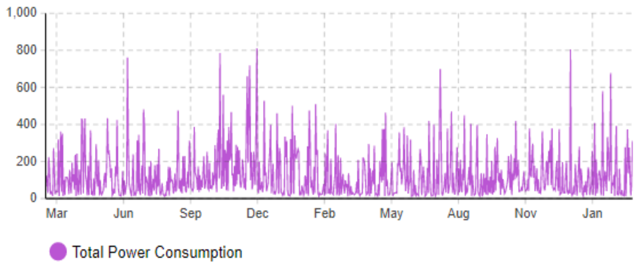

Fig. 9: Impact of climate on A/C, heating, and total power consumption

Furthermore, figure 10 shows the consumption during winter, in the first week of January. At that time, the temperatures are low, and therefore, A/C loads are missing, while heating load is high. Maximum value of consumption on one day of corresponding period is 8,750 kWh. It also shows that electricity consumption is higher in weekends since people are in their homes. This relates to the modelling of occupancy profiles of the occupants. The model simulates weekends by letting all people to stay at home and not go to work. Therefore, their consumption is much higher than during weekdays when they are not at home.

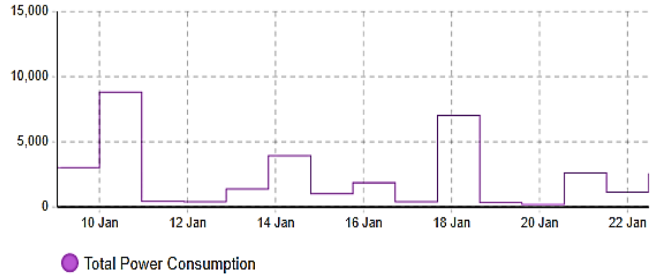

Fig. 10: Winter loads two weeks in January

It is essential to find the validity of this data by comparing with actual results collected. This process helps show if the developed model simulates a practical case of power consumption or not. This paper compares the results with those of a similar case titled *"Agent-based modelling of high-resolution household electricity demand profiles: A novel tool for policy evaluation"* [31]. The results of that study showed a similar response over a day.

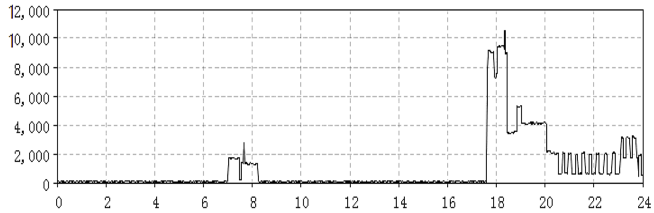

Fig. 11: Reference results for evaluation purposes [31]

Figure 11 displays the total load for one day in a study on domestic power consumption which shows that power usage varies based on occupancy patterns, with lower consumption when users are not at home or sleeping. Models indicate that even when houses are occupied, power loads fluctuate due to different activities. This study validates its results using actual data from 300 urban households, collected from 14,000 houses in 2020. The data includes total power and average consumption values for validation.

6. Conclusion

This study analyzed the energy consumption habits of 300 families by examining their load profiles using monthly and seasonal assessments of different time durations. The research established guidelines for household appliances and load scheduling based on three load categories, emphasizing the complex nature of residential power usage. The model uses numerical information and graphs to display real-time changes in values, utilizing triangular distributions for periods and power consumption calculations. This approach calculates the total electricity usage within a 24-hour timeframe and provides essential information to improve energy efficiency and demand-side management. The model updates temperature values dynamically depending on real climatic circumstances, resulting in significant effects on A/C and heating loads as per simulations. The research validates its findings by comparing them with previous studies and real data from urban families, demonstrating the usefulness and importance of the suggested model in analyzing and predicting patterns of domestic electricity usage.

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