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Influence of Natural Parameters and Human Behaviour on Household Electricity Consumption: Analysis of Seasonal and Non- Seasonal Periods

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Abstract: This study investigates household electricity consumption patterns in Egypt, focusing on behavioural differences during the social/religious season of Ramadan compared to regular non-Ramadan days. Utilizing data from smart meters and temperature records, a probabilistic analysis was conducted to identify key consumption trends influenced by cultural and environmental factors. The independent variables considered in this study include Weather temperature, Time of day, Demographic factors such as season/events, and Location. The research aims to segment consumers into selected geographic areas based on their overall yearly consumption. The behaviour of each segment is analyzed throughout the day to assess their responsiveness to the independent variables.
Findings reveal significant differences in consumption patterns driven by daily routines during Ramadan. Synchronization of household activities, such as cooking, heating, and cooling, leads to distinct peaks in energy demand that align with typical daily schedules. This study underscores how routine activities significantly influence consumption patterns, corroborating observations made during both regular days and Ramadan.
The findings are expected to be valuable, as they represent the initial attempt to analyze power consumption behaviour using microdata obtained through the smart metering system from approximately 20,000 households. This data became available after the first phase of the Smart Metering System was implemented for the Egyptian Electricity Holding Company (EEHC).
Keywords: Consumption Patterns, Probabilistic Analysis, 3D-PDF, Daily Routine

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Introduction

Understanding the consumption behaviour of residential power consumers is crucial for developing effective energy management strategies and policies. As the global energy landscape evolves, characterized by increased integration of renewable energy sources and the transition towards decentralized energy systems, it becomes essential to gain deeper insights into how households use electricity. When predicting electricity consumption in the residential sector, customers' behaviour is an important influencing factor. This is because individual electricity consumption depends heavily on the process of people's decision-making, which has an inherent stochastic nature (Cheng et al., 2021).

Probabilistic techniques offer valuable tools for analyzing consumption data, as they allow for the modeling of uncertainty and variability inherent in energy use patterns. Electricity consumption in residential settings is influenced by multiple unpredictable factors, such as household routines, temperature fluctuations, economic conditions, and cultural events. Unlike deterministic models, which assume fixed relationships between variables, probabilistic methods incorporate randomness and variability, making them more effective in capturing the stochastic nature of electricity usage (Rafayal et al., 2022).

Traditional statistical methods often fall short of capturing the complex, non-linear relationships between consumption behaviour and influencing factors. For instance, cultural and religious events such as Ramadan significantly alter daily electricity demand due to changes in meal times, social activities, and sleeping patterns. These shifts introduce temporary but significant deviations from typical consumption trends, which deterministic approaches struggle to model accurately. Probabilistic techniques, such as Bayesian inference and Markov models, enable researchers to estimate the probability of different consumption scenarios under varying conditions, allowing for better anticipation of demand spikes and reductions (Park et al., 2021).

Environmental factors, particularly temperature, also play a critical role in electricity consumption patterns. The correlation between temperature extremes and increased electricity demand for heating and cooling is well-documented, yet this relationship is highly non-linear. Probabilistic models, such as Monte Carlo simulations and Hidden Markov Models, provide a more flexible framework for assessing how fluctuations in temperature, humidity, and other climatic variables influence household energy use over time (IEEE, 2024). By integrating these external influences into consumption forecasting, energy providers can design more resilient and adaptive grid management strategies.

Moreover, probabilistic models can help in segmenting consumers into different categories based on their consumption patterns, thereby allowing for more targeted and effective energy management practices (Kamakura & Russell, 1989). Such segmentation is particularly useful for tailoring demand response programs and pricing strategies to specific consumer groups, ultimately leading to more efficient energy usage and better alignment of supply and demand (Schlegelmilch, 2022). For example, high-consumption households may require dynamic pricing incentives to reduce peak load, whereas lower-income consumers might benefit more from subsidies or time-of-use tariffs. By incorporating probabilistic techniques into the analysis of residential consumption data, stakeholders can gain a deeper understanding of how various external factors influence electricity usage. This approach allows for the development of more adaptive forecasting methods, ensuring that energy policies and infrastructure investments align with actual consumption behaviour. Ultimately, probabilistic models not only improve forecasting accuracy but also contribute to the creation of fairer, more efficient, and sustainable energy systems.

In summary, understanding residential power consumption behaviour and applying probabilistic techniques for data analysis is essential for developing effective energy policies and management strategies. These approaches not only improve the accuracy of consumption forecasts but also enable more precise and equitable tariff designs, ultimately supporting the transition towards a more resilient and sustainable energy system.

This research focuses on the consumption side of the power system, by segmenting Egypt's residential consumers according to their maximum monthly consumption, using the consumption reads collected from smart technologies, IOT sensors in general and smart meters in specific, and analyzing the behaviour of consumers in each of the resulting segments, so we support Egyptian Electricity Holding Company (EEHC) to evaluate the consumption behaviour of households around the day. Then compare the consumption behaviour during major season and out-of-season days. Therefore, this study presents the first trial for probabilistic analysis of Egypt's household electricity consumption, leveraging hourly data collected from a smart metering system and considering the seasonal influence on consumption patterns, trying to clarify details about consumption behaviour, which can help EEHC to set up a more accurate pricing strategy for each consumer segment depending on deeper understanding of their demand and their responsiveness to major external factors, like temperature and live routine of households during season and out- of-season.

Literature Review:

The integration of electrified consumers, such as electric vehicles (EVs), into energy networks introduces significant challenges for local energy management systems. However, it also creates opportunities for optimizing energy system performance, including maximizing self-consumption, minimizing peak loads, and reducing CO2 emissions. In this context, accurate forecasting and uncertainty assessment are crucial for the efficient operation of energy system components. The uncertainties surrounding green energy generation and consumption demand have driven engineers to develop innovative solutions, sparking a revolution in power system analysis. A notable shift has occurred with the transition from deterministic approaches to probabilistic analyses, enabling a deeper understanding of the reliability, performance, and uncertainties of electrical grids.

The growing complexity of power systems, particularly with the integration of renewable energy sources, has exposed the limitations of traditional deterministic load flow analyses, which struggle to handle the inherent variability and unpredictability of renewable energy. As a result, accurate forecasting has become a pivotal factor in maximizing energy management efficiency and improving decision-making processes. Probabilistic methods have gained prominence due to their ability to quantify uncertainty, offering a more comprehensive approach compared to deterministic techniques (Petropoulos et al., 2022). These methods help address the uncertainties associated with energy generation and demand forecasts, enabling more resilient energy system planning and operation.

In recent years, artificial intelligence (AI) and machine learning (ML) models have been widely adopted for load demand prediction and renewable energy forecasting (Gaamouche et al., 2022); (Benti et al., 2023). Despite their impressive accuracy and ability to capture non-linearities in volatile data, deterministic ML models are often impractical for decentralized, small-scale energy management systems. These models require significant computational resources, data volumes, and expertise, leading to high implementation costs. Consequently, traditional approaches, such as standard load profiles (SLPs), are still widely used by distribution network operators for planning and balancing consumption with generation for smaller consumer loads, like outdoor advertising panels or small enterprises.

SLPs, employed across various temporal and spatial scales, estimate consumption in the absence of real-time measurements at the distribution grid level. (Yang et al., 2020) demonstrated that increasing the spatial resolution of SLPs can significantly enhance forecasting accuracy. The global rollout of smart meters has made decentralized-level data more accessible, providing valuable insights for grid operations and energy management (Wang et al., 2019). Smart meters enable detailed monitoring of electricity consumption at the household level, and numerous studies have explored consumption behaviour and customer segmentation based on this data. For instance, (Kaddour & Lehsaini, 2021) proposed a methodology for identifying abnormal energy consumption in residential buildings by analyzing hourly energy consumption patterns, while (Melzi et al., 2017) introduced an unsupervised classification technique to extract typical consumption patterns, incorporating contextual variables like temperature fluctuations.

Several studies have examined the influence of cultural and religious events on electricity consumption, revealing distinct patterns based on regional and sociocultural factors. During Ramadan, for example, electricity demand typically shifts due to altered daily routines, increased nighttime activity, and changes in meal preparation times. Studies from various countries highlight both similarities and unique patterns in consumption behaviour. In the Middle East and North Africa (MENA) region, studies by (Elgazzar & Hemayed, 2016) indicate that electricity demand increases significantly during Ramadan nights due to extended social and religious activities. Similar trends have been observed in Saudi Arabia and the United Arab Emirates, where peak consumption shifts to later hours. In Egypt, the load curves exhibited a bimodal structure, with a secondary peak occurring around Suhoor time.

Yakoub, Hanaa (2024) studied the effect of Ramadan on occupancy patterns and behaviours on energy use amongst Muslims residents in London compared to pre-Ramadan use, this study aimed to understand the reasons for changing behaviours and the impact on domestic energy use in Ramadan in UK homes, revealed significant shifts in routines, such as increased nighttime activity, altered sleep patterns, and more intense cooking and socialising. Occupancy sensors showed peaks in kitchen activity around mealtimes, and energy data indicated more peaks in electricity use. These findings highlight the need for culturally sensitive energy management strategies to reduce peak loads and promote energy-saving behaviours, especially given the current energy and climate crises and fuel poverty affecting many Muslims in the UK.

Beyond Ramadan, other religious and cultural events have also been analyzed. For instance, in China, a study by (Guo et al., 2018) showed Volatility of electricity consumption is higher in winter and summer than in spring and autumn, There are three typical load profiles during the Spring Festival, two typical load profiles during the Labor Day the National Day, High temperature in summer and low temperature in winter have obvious influence on electricity consumption.

Similarly, in Western countries, during holidays aggregate energy behaviours change, which in turn affects the timing and location of demand for energy services. For lighting, these changes in demand are now apparent from night- sky imagery. Román & Stokes, (2015) examine variations in urban lighting patterns across cultural and social boundaries for cities in the Southern United States (US), Northern Mexico, and the Middle East during two major holiday periods, Christmas and New Year's, and the Holy Month of Ramadan. The findings indicate that energy decision-making and demand is a sociocultural process as well as an economic process, often involving a combination of individual price-based incentives and societal-level factors.These comparative analyses suggest that while the specific impacts of cultural and religious events on electricity consumption vary by country, common factors such as altered routines, changes in lighting and appliance usage, and shifts in social behaviour play a significant role. Understanding these patterns within a global framework allows for better demand forecasting and more efficient energy management strategies.

In regions such as Qatar, where energy generation is a highly resource-intensive process, energy consumption patterns are shaped by both natural and socio-economic factors. Harsh weather conditions, particularly extreme heat during the summer months, significantly elevate electricity demand. Official smart meter data for Qatar, categorized into four sectors (commercial, government, hotel, and residential), has been utilized to perform load profiling and clustering analyses, revealing distinct consumption trends across these sectors. For instance, while all sectors exhibit daily and seasonal fluctuations, peak electricity demand times differ across sectors—such as the government sector's peak from 6 a.m. to 3 p.m. versus the hotel sector's higher demand beginning at
11 a.m. (National Sports Day and Eid Al-Fitr, for example, see spikes in consumption, while other holidays show demand drops due to travel). These insights support the formulation of demand-side management (DSM) and demand response (DR) policies tailored to local consumption behaviour, including strategies like reducing subsidies or introducing incentive-based DSM programs. Such sector-specific data can inform more efficient energy management policies and serve as a foundation for future energy-saving initiatives in Qatar. (Monawwar et al., 2024)

Deterministic forecasting models have gained popularity for predicting electricity demand (Petropoulos et al., 2022), heat load (Leiprecht et al., 2021), and photovoltaic (PV) generation power (Yang et al., 2020)(Das et al., 2018). However, recent advancements in Personalized Standard Load Profiles (PSLPs) offer an alternative by utilizing locally collected data and ML techniques, which are particularly beneficial in scenarios with limited data or computational resources (Bin et al., 2023). Probabilistic forecasting methods, though less studied compared to deterministic models, are gaining traction due to their ability to capture uncertainties in energy generation and demand. Evaluating these forecasts using appropriate metrics is essential for understanding uncertainty and improving prediction accuracy (Abdar et al., 2021).

Probabilistic load analysis has emerged as a groundbreaking tool for addressing the fluctuations and uncertainties present in electrical grids. Its primary goal is to compute nodal voltages and power flows in transmission lines under varying load conditions. As power grids become more complex, advanced strategies for probabilistic load flow analysis have been developed. These strategies fall into two main categories: parametric and nonparametric. Parametric methods rely on predefined statistical distributions, while nonparametric techniques make minimal assumptions about the distribution of variables, allowing for greater flexibility in modeling real-world uncertainties (Wang et al., 2018). The integration of advanced metering technologies and the shift towards renewable energy sources have transformed the landscape of electricity consumption and demand management. This transformation is evident across various regions, reflecting diverse approaches and challenges in handling residential and commercial energy use. (Alotaibi et al., 2020)

In recent years, the role of advanced metering technologies in understanding residential demand has become increasingly significant. The fine-grained electricity consumption data created by these technologies allows for a deeper understanding of residential demand patterns, particularly in regions like China where traditional research has been limited. For instance, a study on residential consumption in Chengdu utilized unsupervised machine learning tools to explore demand patterns and responses to different contexts such as seasonal changes, holidays, and extreme weather events. The analysis revealed two main clusters of households with distinct consumption profiles and highlighted that extreme heat events led to substantial increases in electricity use, primarily driven by air conditioner use. This study underscores the value of detailed, high-resolution data in identifying and understanding residential consumption behaviours and provides a framework for future research and policy development (Kang & Reiner, 2022).

In Qatar, the deployment of smart meters has facilitated sector-specific load profiling, revealing distinct consumption patterns across commercial, government, hotel, and residential sectors. The analysis identified variations in peak demand times and consumption trends, with temperature playing a significant role in driving electricity demand, especially during summer months. This granularity in data has supported the development of targeted Demand Side Management (DSM) and Demand Response (DR) strategies, advocating for policy adjustments such as reduced subsidies and incentive-based programs to enhance energy efficiency and sustainability (Monawwar et al., 2024)

Similarly, in Algeria, the electricity sector has undergone significant changes due to rising demand driven by demographic and socio-economic factors, coupled with climate change and the depletion of natural gas reserves. A multiple regression model developed to forecast electricity demand highlighted the crucial role of temperature, with Cooling Degree Days (CDD) and Heating Degree Days (HDD) being the primary factors affecting daily load. The study also noted that holiday periods generally reduce electricity demand, except for Ramadan, where increased consumption during summer was observed. These insights emphasize the need for incorporating climatic and socio-cultural variables into forecasting models to improve their accuracy and effectiveness (Chabouni et al., 2020).

In Dubai, detailed research on residential electricity consumption was conducted using 15-minute resolution smart meter data. The study explored the influence of dwelling characteristics, cooling systems, and the number of occupants on consumption patterns. K-Means clustering revealed that 43% of households with cooling systems had peak demand at midnight during weekdays and weekends in summer, while households without cooling systems peaked between 7:00 and 10:00 pm. The classification algorithms effectively identified key factors driving consumption patterns, demonstrating the importance of incorporating dwelling and occupancy characteristics into predictive models. (Rafiq et al., 2023).

These studies illustrate the diverse approaches and methodologies employed to understand and manage electricity consumption. The use of high-resolution smart meter data, machine learning techniques, and detailed contextual analysis provides valuable insights into residential and commercial energy use patterns. Such insights are crucial for developing effective DSM and DR strategies, optimizing grid operations, and enhancing energy efficiency across different regions. The transition from deterministic to probabilistic forecasting methods and the incorporation of advanced analytical tools reflect the growing complexity of energy management in response to changing consumption patterns. The findings from Qatar, Algeria, Dubai, and Chengdu highlight the importance of adapting forecasting models and policies to account for local climatic, socio-economic, and behavioural factors. By leveraging detailed data and innovative analytical methods, these studies contribute to a more nuanced understanding of energy demand and offer practical frameworks for improving energy management and sustainability.

Methodology

(Figure-1) Egypt's country map, locations of smart meters

Advances in smart meter technology have enabled the collection of high-granularity measurements, offering a more detailed view of energy consumption. However, literature reviews indicate that for modelling and forecasting energy demand, a coarser time scale—such as aggregated hourly data—yields more accurate and reproducible results. In this study, we focus on the hourly energy demand modelling for the Residential sector.

To analyze the overall demand on the electricity network, we employ a Quantitative Method, which leverages historical data to understand the behaviour of residential consumers. Quantitative analysis relies heavily on the availability of extensive historical datasets. The longer such data has been tracked, the more accurate the predictions become. In Egypt, the widespread implementation of smart metering systems began in 2019, providing a robust dataset that allows for the identification of consumption seasonality. The dataset is structured as "Nested Panel Data," comprising meter readings along with detailed weather data and notable calendar events (e.g., national holidays and Ramadan days), which are known to influence consumer behaviour.

Step 1: Data Collection and Integration:

Data Sources: The meter readings are automatically collected through IoT technology and sent to a central data center at EEHC, where specialized applications use this data for billing, monitoring, and maintenance of the power distribution network. For this study, we requested hourly consumption readings at the household level in kilowatt-hours (kWh), along with timestamps for each reading.

Sample Size and Structure:

In this study, a map (see Figure 1) was used to visualize the distribution of smart meters across the six distribution companies involved (Source: Author's own data). The map helped in identifying the geographical zones with distinct temperature profiles and consumption patterns. The spatial data were overlaid with temperature data, enabling the identification of regional consumption trends and their correlation with temperature fluctuations.

The available data is categorized as Convenience Sampling, as it comes from specific locations and a predefined group of consumers. The data spans from **October 2020 to September 2023**, covering over 20,000 smart meters segmented into seven consumer groups, as defined by EEHC's classification of monthly consumption. EEHC provided three years of historical data from six distribution companies across Egypt, covering the most populate regions, as mentioned on the map, resulting in 26,280 hourly readings per meter. This data is augmented with temperature observations from meteorological authorities, and important events like Ramadan are also factored in to account for major socio-religious impacts on energy consumption patterns.

The raw consumption data collected from the smart meters includes hourly energy usage (in kWh) for individual households, with corresponding timestamps. **Table 1** provides an example of the raw data, showing the original consumption readings before any cleaning or preprocessing (Source: EEHC data). The table illustrates the typical format of the data, which includes the meter ID, timestamp, and hourly energy consumption values. This raw data serves as the foundational dataset for subsequent analysis, like identifying consumption patterns, segmenting households, and performing probabilistic analysis. Key features of this data, such as daily fluctuations and nighttime consumption lows, were pivotal in understanding the impact of external factors such as temperature.

Table 1: Example of Raw Hourly Consumption Data

Meter ID	Date/Time	Reading KWH	Reading Condition	Consumption KWH	Consumption Condition
4220664	01/10/2020 00:00	4252.42	Regular	0.59	Regular
4220664	01/10/2020 01:00	4252.94	Regular	0.52	Regular
4220664	01/10/2020 02:00	4253.52	Regular	0.58	Regular
4220664	01/10/2020 03:00	4254.00	Regular	0.48	Regular
4220664	01/10/2020 04:00	4254.47	Regular	0.47	Regular
4220664	01/10/2020 05:00	4254.99	Regular	0.52	Regular

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The total number of households is 21,940, for 3-years, 365 days, 24 hours, The total number of analyzed reads in the collected data set is 21,940 x 3 x 365 x 24 = 576,583,200 reads.

Step 2: Data Cleaning and Integration

During the data-cleaning process, few meters were found to be frequently disconnecting from the network between the meter and the backend, giving huge gabs in the collected readings, the main reasons behind these communication interruption in the poor coverage of the mobile network, and the hot spots on the power cable connections, the first step was to eliminate those meters with high rate of disconnections, which were found to be about 4.58% of the total number of meters in the collected data set. For the remaining meters, approximately 20% of the total readings were identified as outliers due to communication interruptions, resulting in zero consumption values, followed by one high cumulative value once communication is restored. Another reason for these outliers is the poor or faulty grounding in homes, leading to occasional negative readings, moreover, wiring errors in homes, where the line and neutral terminals are reversed at the meter input, also causing negative readings that need to be considered during analysis.

For this research, all such erroneous readings were removed from the dataset to ensure accuracy.Following the cleaning of raw consumption data, it was merged with temperature data obtained from meteorological stations for each corresponding geographic area. This integration allowed for the analysis of energy consumption in relation to external weather conditions. **Table 2** presents an example of the merged dataset, which includes energy consumption alongside temperature readings and geographic location (Source: EEHC data and Weather Dataset). This merged dataset was essential for analyzing the influence of temperature on hourly consumption patterns.

Table 2: Example of Merged Consumption and Temperature Data

Meter ID	**Date/Time**	Reading KWH	Reading Condition	Consumption KWH	Consumption **Condition**	Temperature
4220664	01/10/2020 00:00	4252.42	Regular	0.59	Regular	**26**
4220664	01/10/2020 01:00	4252.94	Regular	0.52	Regular	**26**
4220664	01/10/2020 02:00	4253.52	Regular	0.58	Regular	**25**
4220664	01/10/2020 03:00	4254.00	Regular	0.48	Regular	**24**
4220664	01/10/2020 04:00	4254.47	Regular	0.47	Regular	**24**
4220664	**01/10/2020 05:00**	4254.99	Regular	0.52	**Regular**	**25**

Step 3 : Segmenting Energy Consumers

Energy consumption is mainly triggered by the consumer activities. Every consumer is different and the energy usage profiles differ from each other based on their energy demand characteristics and geo area. The variation depends on the types and number of appliances/machines used, the frequency of use, number of members staying at home, etc. In this study, EEHC classification is used to segment consumers based on monthly consumption for individual month, this way takes into consideration the consumption capability of the house, then we study the behaviour of the consumer through analysis of the hourly consumption within the segment analysis.

Egyptian Electricity Holding Company (EEHC) identified 7 classes of residential consumption segments, based on total monthly consumptions, as follows:

- 0 to 50 kilowatt-hours,
- 51 to 100 kilowatt-hours,
- 0 to 200 kilowatt-hours,
- 201 to 350 kilowatt-hours,
- 350 to 650 kilowatts-hours,
- 650 to 1,000 kilowatts-hours,
- More than 1,000 kilowatt-hours.

Source: EEHC annual report 2021-2022. Retrieved February 28, 2024, from https://www.eehc.gov.eg/CMSEehc/Files/AnnualReport2022.pdf

Hence, the data model used for 7 clusters of consumers based on their monthly consumption. For each meter, the 36 monthly consumption is calculated for all months from October 2020 to September 2023, and the consumer segment identified according to the month with maximum consumption in comparison to EEHC billing segment classification.This way, the consumers are grouped according to their consumption capability, and then we use the analysis model to capture the properties of each segment of users and differences across the demand profiles of individual type/segment of consumers.

The segmentation step produced data in **Table 2,** presenting merged meter reads and temperatures in each segment (Source: Author's data extracted from EEHC data and Weather Dataset):

Table 2: Segmented Consumption and Temperature Data

DISCO	**South Delta**	**Alexandria**	**Canal**	**Middle Egypt**	**North Cairo**	**South Cairo**
Segment 1	245	341	126	159	262	647
Segment 2	123	190	61	121	215	512
Segment 3	307	404	131	304	561	1,180
Segment 4	670	522	215	540	890	1,789
Segment 5	863	733	264	766	999	1,973
Segment 6	461	431	104	506	476	932
Segment 7	244	394	74	291	399	511
20,936	2,913	3,015	975	2,687	3,802	7,544

Step 4: Isolating Seasonal Intervals:

In this final step, the calendar days of Ramadan are identified in the previous three years, and the relevant data is in a separate data set. This allowed us to assess how major religious and cultural events, such as Ramadan, influence energy consumption patterns.

Step 5: Grouping Hourly reads: The Consumption reads are grouped by each specific hour of the day across the three years. For instance, all consumption data of 12:00 PM over the entire dataset were grouped together. This process was repeated for each hour of the day (i.e., 24 hourly groups). Each hourly group was analyzed individually to detect specific consumption patterns for that hour. Statistical Analysis in performed on each hourly group, including the calculation of means, variances, and Correlation with Temperature, to examine how temperature influences consumption at different times of day. A

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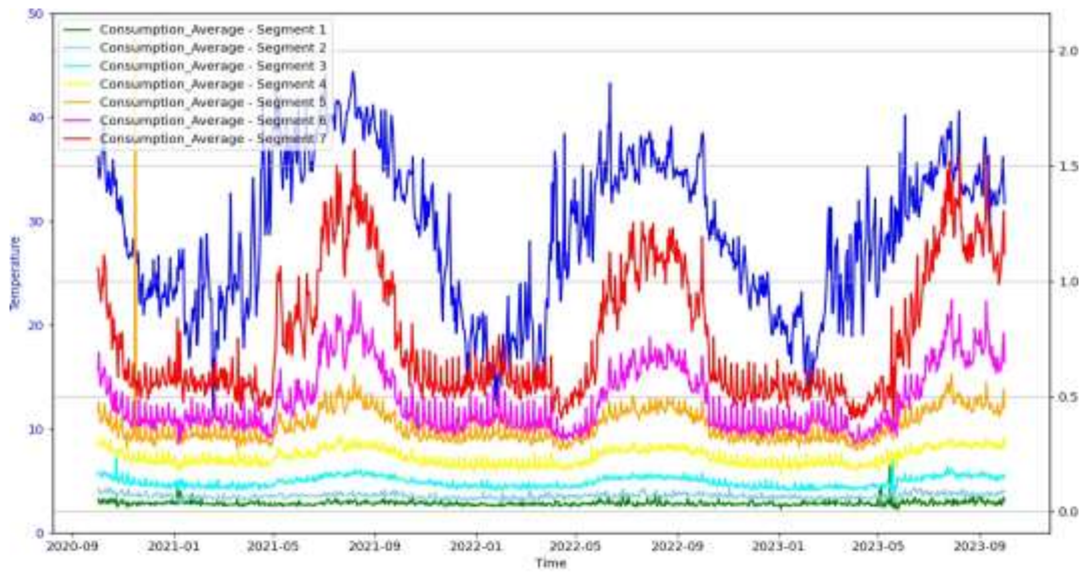
correlation analysis was performed to understand the sensitivity of consumption to temperature changes, focusing on how this relationship differs between daytime and night-time hours

.**Figure-2** illustrates the temperature and consumption reads of (12:00 H) for all the seven consumer segments in the South Delta region (city of Tanta) from October 1st, 2020, to September 30th, 2023 (Source: EEHC data and Weather Dataset). These graphs demonstrate that the wealthier consumers in the seventh segment are more responsive to temperature fluctuations than consumers in the lower segments. The intermediate segments show varying degrees of responsiveness

Step 6 : Analysis of Temperature and Consumption Data

Kernel Density Estimation (KDE) is a statistical technique used to estimate the probability density function (PDF) for each hour-of-the-day consumption pattern. The Gaussian kernel was employed to smooth the consumption data



(Figure-2) Temperature and Consumption Curves for Hour: 12:00

and reveal the distribution characteristics for each hour. The KDE analysis identified the probability distribution of energy consumption at each hour and how this varied across consumer segments and seasons. For example, we observed that during peak hours (e.g., early evenings), the consumption distribution was wider, indicating greater variability in demand across households.

The analysis was conducted using Python, employing the Gaussian kernel for kernel density estimation. The specific libraries used included SciPy for statistical computations and Matplotlib for visualizations.

Basic KDE Theory:

Suppose we have an input variable (X = {x1, x2,. . ., xs}) with (s) dimensions, where each Xs (s = 1, 2,. . ., S) is a sample of random variables following the PDF f(x). Kernel estimate ˆ f(x) of original f(x) allocates an individual ith sample data point xi a function K(xi), termed as the kernel function. According to KDE theory (Parzen, 1962) , the PDF f(x) can be expressed as:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x_i - x}{h}\right)$$

Where h is bandwidth, N is the number of samples, and K is the kernel function.

In this study, we use the Gaussian kernel to estimate the PDF. KDE is particularly advantageous for arbitrary distributions, as it relies solely on samples and is not constrained by predefined assumptions about the data distribution. According to (Pagan & Ullah, 1999), as n → +∞ , h → 0, and nh → +∞, KDE converges to the true distribution.

The equation of PDF for 2D normal distribution:

The probability density function for a bivariate normal distribution is given by:

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}}\exp\left(-\frac{1}{2(1-\rho^2)}\left[\frac{(x-\mu_x)^2}{\sigma_x^2} - 2\rho\frac{(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y} + \frac{(y-\mu_y)^2}{\sigma_y^2}\right]\right)$$

Where (x, y) are the two variables of the bivariate normal distribution, μ_x and μ_y are the means of variables X and Y , respectively, σ_x and σ_y are the standard deviations of variables X and Y , respectively, ρ is the correlation coefficient between X and Y. This formula describes how the probability density is distributed across the bivariate space. The term inside the exponential represents a quadratic form, and the denominator term involving $\sqrt{1-\rho^2}$ is a normalization factor to ensure that the integral of the PDF over the entire space equals 1.It's worth noting that when ρ= 0 (no correlation), the formula simplifies to the product of the PDFs for two independent univariate normal distributions.

KDE was applied **separately for each hour of the day** across the dataset to analyze variations, the resulting PDFs were compared across different temperature bands and consumer segments.

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Volume: 4, Issue:2, Year: 2025 pp.78-104

Step 8: Covariance Analysis and 2D Normal Distribution:

For each hourly dataset, a 2D covariance matrix was calculated to understand the relationships between consumption and temperature. The covariance matrix captured how temperature and consumption co-varied at each hour. A 2D probability density function (PDF) was derived for the joint distribution of temperature and consumption, providing a comprehensive picture of how these two variables interact throughout the day.

For a bivariet normal distribution (2D normal distribution), the covariance matrix Σ can be represented as:

$$\Sigma = \begin{bmatrix} \sigma_x^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_y^2 \end{bmatrix}$$

Where σ_x^2 is the variance of variable X, σ_y^2 is the variance of variable Y, σ_x and σ_y are the standard deviations of variables X and Y , respectively, ρ is the correlation coefficient between X and Y.

The correlation coefficient ρ is a measure of the strength and direction of the linear relationship between X and Y, it ranges between -1 and +1,

where: ρ = +1 indicates a perfect positive linear relationship, ρ = -1 indicates a perfect negative relationship, ρ = 0 indicates no linear relationship.

The covariance equation for a bivariate normal distribution involves the product of the standard deviations of the variables (σ_x and σ_y) and the correlation coefficient it quantifies how much the variables change together. In the context of a 2-variable probability density function (PDF), the standard deviation provides a measure of the spread or dispersion of the distribution along each axis. For a bivariate distribution, you may have two variables, let's say X and Y. The standard deviation for each variable provides information about how the values of that variable are scattered around their respective mean.

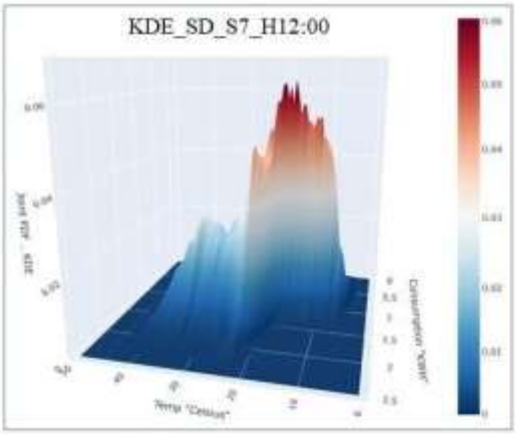
In summary, the standard deviations of the variables in a 2-variable PDF help characterize the shape and spread of the distribution along each axis. They, along with covariance and correlation, provide insights into the relationships between the variables.Covariance was calculated separately for **each of the 7x6 consumer segments**, across all collected data (October 2020 – September 2023)**, separately for Ramadan vs. normal months,** allowing differentiation between normal consumption bahaviour and the exceptional consumption during the season of Ramadan.

Step 9: Preliminary Visualization of equation results:

The hourly consumption patterns were visualized using time-series plots and KDE graphs for each hour. These visualizations highlighted key findings, such as Consumption Peaks in the early evening (6:00 PM - 8:00 PM), aligning with post-work and pre-dinner routines. While Night-time Lows shows the consumption is significantly dropped between midnight and early morning hours (12:00 AM - 5:00 AM), except during Ramadan, where consumption patterns shifted. Also, a strong positive correlation was observed between consumption and temperature during daytime hours (especially around 12:00 PM - 3:00 PM), but this relationship weakened during cooler night hours.

More insights from the Data:

Based on the collected data, the probability density function (PDF) is plotted in **Figure-3** (Source: Author's analysis according to KDE theory (Parzen, 1962)), which reveals several key characteristics, for instance, there is a positive correlation between temperature and energy consumption, i.e., as temperature increases, consumption also rises. While most days of the year, at 12:00 PM in the area of South Delta, the temperature is less than 30°C, for consumers in the SD_S7 segment, consumption is generally less than 2 kWh during these conditions.



(Figure-3) Calculated PDF for 7th segment in the area of SD, at 12:00 PM

This stepwise methodology allowed us to capture detailed hourly consumption patterns and their relationship to external factors such as temperature and calendar events. By focusing on specific hours of the day, the analysis provides actionable insights into demand-side energy management and supports the development of targeted energy-saving strategies for different consumer segments.

Findings:

Consumption Behaviour Outside of Peak Seasons (Normal Year-Days):

As illustrated in the **Figure-4,** the analysis shows a strong correlation between temperature and electricity consumption during normal year-days, with a correlation coefficient of 0.8 throughout the day (Source: Author’s own analysis). This suggests that temperature plays a key role in driving energy use patterns. Additionally, the covariance is consistently high, ranging from 1.5 to 2.0, which further underscores the significant influence of temperature on consumption. These findings affirm that electricity demand rises in response to temperature changes, especially during the hottest and coldest parts of the day, as households rely more on cooling and heating systems.

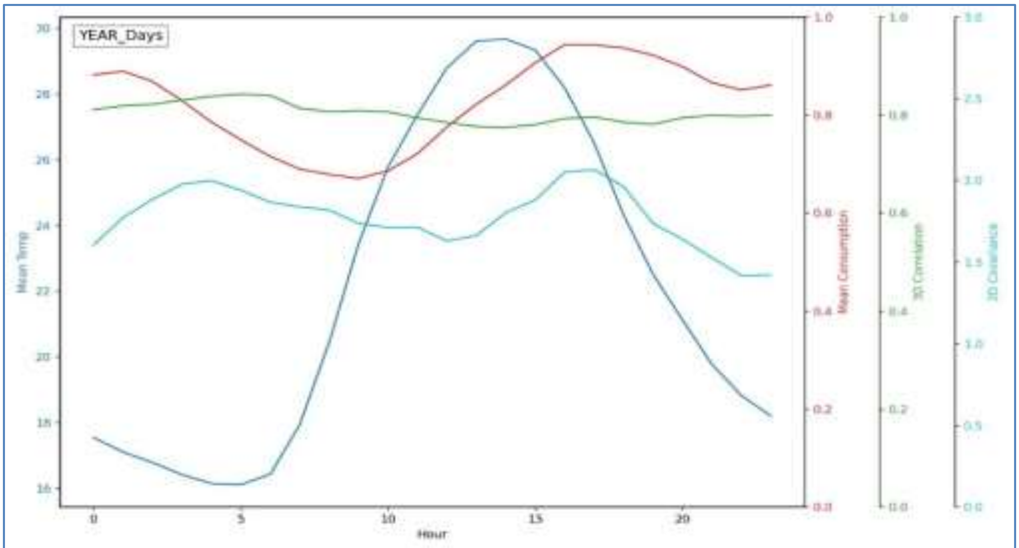
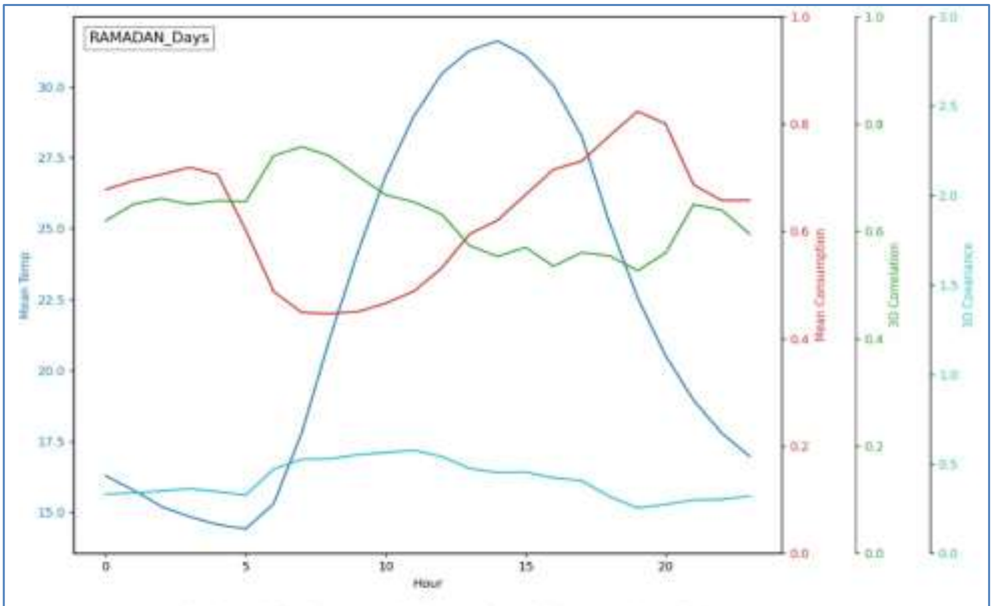


Figure-4. Analysis results for 7th Segment in the area of SD during normal year-days

Consumption Behaviour during Ramadan (Seasonal Days):

Figure-5 shows the correlation between temperature & electricity consumption fluctuates, with an average correlation value of 0.6 (Source: Author’s own analysis). The covariance drops to below 0.5, indicating a reduced impact of temperature on consumption patterns. Instead, daily activities, particularly the timing of meals, heavily influence energy use. Notably, consumption decreases sharply just before sunrise as households prepare for sleep, and peaks occur at sunset, coinciding with the Iftar meal when families gather to break their fast. This distinct consumption pattern reflects the central role of Ramadan’s religious & social practices in shaping electricity usage.

Comparing In-Season and Out-of-Season Results:



(Figure-5) Analysis results for 7th Segment in the area of SD during season (Ramadan)

- Normal Year-Days: The highest consumption is typically observed between noon and late evening, peaking from 14:00 to 2:00, while the lowest consumption occurs in the morning between 8:00 and 9:00. The 3D-correlation coefficient reaches 0.8, and the covariance values remain high (1.5 to 2.0), confirming the influence of weather conditions on energy usage. These trends suggest potential for differentiated tariffs based on seasonal temperature variations, particularly for summer and winter months.

- Ramadan (Seasonal Days): Electricity consumption follows a different pattern, with two notable peaks—just after sunset (17:00) and just before sunrise (4:00)—and a noticeable drop

the morning (6:00 to 11:00). The 3D-correlation coefficient is lower (around 0.6), as is the covariance (0.3 to 0.6), indicating that consumption is more influenced by Ramadan's daily routines than by temperature. These findings highlight the need for tariff adjustments during Ramadan, with separate rates for daytime and nighttime to account for this shift in consumption behaviour.

Discussion:

Our findings align with those of (Tureczek & Nielsen, 2017) who, in their structured literature review on electricity customer classification using smart meter data, emphasized the pivotal role of external factors such as temperature in shaping electricity consumption. This is particularly evident in normal year-days, where temperature strongly correlates with consumption patterns. (Ozarisoy, 2022) further support this by demonstrating that fluctuations in

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temperature—especially during heatwaves—lead to a surge in cooling demand. Their study identified a clear link between rising temperatures and increased residential energy use, mirroring our observations of strong temperature-consumption correlation (0.8) on typical days. Similarly, (Chen et al., 2022), using smart meter data across multiple regions, found temperature to be a key driver of energy consumption, with regional variations largely explained by weather conditions. (Hache et al., 2017) have also identified the transparent and straightforward set of socioeconomic, dwelling and regional characteristics as critical drivers of the different levels of French households' energy consumption using the CHAID (Chi-Square Automatic Interaction Detection) clustering methodology. These studies collectively reinforce the significance of environmental factors in shaping electricity consumption during non-seasonal periods.

However, our analysis highlights that during Ramadan, routine activities become a more dominant driver of electricity consumption than temperature. (Sahin & Rau, 2023) explored the effects of daily routines on energy use, showing that synchronized household activities—such as cooking, heating, and cooling—create distinct peaks in demand. This resonates with our findings, where consumption patterns during Ramadan are driven less by temperature and more by the altered daily routines tied to religious practices. Specifically, the Suhoor meal before dawn and the Iftar meal at sunset create two distinct consumption peaks. Energy use drops sharply before sunrise as households finish Suhoor and go to sleep, and surges again in the evening when families gather for Iftar. These cultural and religious observances shift consumption behaviour significantly, reducing the midday and early afternoon peaks typical of normal year-days.

Our findings diverge from the methodology proposed by, (Kaddour & Lehsaini, 2021) which focuses on detecting abnormal energy consumption without accounting for the impact of daily routines. Their model may be effective in identifying anomalies, but it overlooks the predictable, routine-based consumption spikes observed during Ramadan. Specifically, the Suhoor and Iftar meals drive clear and repeated patterns of energy use, which, while predictable, deviate from the temperature-driven trends seen during other times of the year. This discrepancy suggests that models focusing solely on anomalies may miss important behavioural insights, particularly in culturally or religiously significant periods. Abnormal consumption detection tools must integrate routine-based patterns to effectively capture the dynamics of energy demand during Ramadan and similar cultural events.

Moreover, (Adams et al., 2021) underscore the importance of including social and cultural factors in energy consumption analysis. Their study of public holidays and cultural events shows that routine shifts during these periods lead to significant deviations from normal consumption patterns. This is consistent with our findings, where daily routines during Ramadan override the influence of temperature on electricity consumption, leading to unique behaviours that standard consumption models might fail to capture. By focusing on both cultural routines and environmental variables, a more holistic and accurate model of energy consumption can be developed.

The importance of incorporating temporal and behavioural dimensions into energy consumption models cannot be overstated. While temperature is undoubtedly a significant factor in driving electricity demand during normal days, the impact of daily life routines, especially during cultural or religious periods like Ramadan, is equally profound. Routine-based consumption patterns provide a critical lens for understanding energy use, particularly during periods when traditional environmental drivers like temperature are less influential. By integrating both environmental variables and routine-driven behavioural patterns, energy consumption models can more accurately reflect actual consumption dynamics.

Conclusion

In conclusion, our study demonstrates the dual impact of temperature and routine-based activities on electricity consumption. While temperature plays a major role during non-seasonal periods, cultural practices during Ramadan significantly reshape energy demand. For energy forecasting and policy development to be effective, they must consider both natural environmental conditions and the socio-cultural context. Tailored energy policies that reflect these combined factors will provide more precise consumption predictions and support efficient energy management during culturally significant periods.

The novelty of this research lies in its detailed examination of routine-based electricity consumption for a large number of households distributed over many cities across the same country, during season (Ramadan) and out of season, a focus that has received limited attention in the existing literature. By comparing normal and season-specific consumption behaviours, this study provides new insights into how cultural practices shape energy demand. This approach not only enhances the understanding of consumption dynamics during significant cultural periods but also offers practical implications for energy management.

Tailored energy policies and demand forecasting models that integrate both environmental and behavioural patterns will result in more effective management strategies, especially during culturally significant times such as Ramadan. These findings hold particular relevance for regions where similar cultural practices influence electricity consumption, providing a framework for more responsive and efficient energy policies.

Policy Implications:

This study offers a pioneering analysis of electricity consumption behaviour in Egyptian households, based on high resolution consumption data, providing a nuanced comparison between typical year-round consumption and the unique patterns observed during Ramadan. By applying advanced probabilistic analysis to data from smart meters and temperature records, this research illuminates the intricate relationship between environmental factors and socio-cultural practices.

Our findings highlight that while temperature significantly drives consumption during normal days, cultural routines take precedence during Ramadan. This dual insight underscores the importance of adopting a holistic approach to electricity consumption analysis, one that acknowledges both environmental conditions and cultural practices.

The implications of this research are profound, offering a framework for energy policy that not only enhances operational efficiency but also promotes environmental sustainability and social equity. By integrating these insights into policymaking, energy management can become more responsive to the diverse factors shaping consumption behaviour, making this study a noble contribution to both academic literature and public policy.

For example, in the dimension of Energy Management, our research emphasizes the dual influence of temperature and cultural routines, offering a pathway for more accurate demand forecasting. Policymakers and utility companies can leverage these insights to refine load predictions, ensuring a stable power supply while preventing outages. This more sophisticated forecasting will better prepare the energy sector for seasonal peaks and behavioural shifts, particularly during cultural events like Ramadan. Recognizing distinct consumption peaks during periods like Ramadan also allows energy providers to implement advanced load management strategies. By adjusting power plant operations and incorporating flexible energy resources such as demand response programs and energy storage systems, providers can efficiently manage peak demand, reducing strain on the grid and improving overall reliability.

In another dimension, Tariff Design at utility companies can make benefit from the study’s findings which support the introduction of dynamic tariff structures that reflect the varying electricity consumption behaviours during normal days and special periods like Ramadan. Implementing tariffs that vary by peak and off-peak hours can encourage consumers to shift their usage to periods of lower demand, flattening demand curves and reducing the need for additional power generation capacity. Policymakers can also design tariffs that account for seasonal variations in consumption, such as higher tariffs during summer months to address increased cooling demands or tailored rates during Ramadan to accommodate unique consumption patterns. Such tariffs could incentivize energy-saving behaviours while ensuring equitable access to electricity.

Taking about Economic Impacts, dynamic and seasonal tariffs, informed by this study, can lead to significant cost savings for consumers. By shifting energy usage to off-peak periods or capitalizing on lower rates during specific times, households can lower their electricity bills. This is particularly advantageous for low-income households, where energy cost sensitivity is higher. Our study suggests that the weight of each segment’s consumption relative to the overall grid load should be a key consideration in tariff structuring. High-consumption segments with low price elasticity may require different pricing strategies than low-consumption, price-sensitive segments. By integrating these insights, dynamic pricing models can become more effective in balancing demand, optimizing grid performance, and ensuring affordability across different socio-economic groups.

Optimized Infrastructure Investments can benefit from more accurate demand forecasting and load management, by directing the investment away from costly new power plants towards smart grid technologies, energy storage, and demand response initiatives. These infrastructure investments will not only enhance grid resilience but also reduce long-term costs, fostering sustainable economic development. Efficient energy management leads to a reliable and stable power supply, which is essential for economic growth. Reduced operational costs for businesses, improved productivity, and new job opportunities in the renewable energy and smart grid sectors contribute to broad economic development, positioning the energy sector as a driver of sustainable progress.

The study’s recognition of the impact of cultural practices on energy consumption offers a unique perspective on developing culturally responsive energy policies. These policies can ensure that energy supply and pricing mechanisms are aligned with the specific needs and behaviours of diverse communities, promoting social equity and inclusivity. Policymakers can implement targeted education and awareness programs to inform consumers about the benefits of shifting their energy usage patterns. By raising awareness of dynamic and seasonal tariffs, consumers can be empowered to make informed decisions that promote energy efficiency and cost savings.

By addressing the complex interplay between environmental factors, socio-cultural practices, and energy consumption, this study provides a valuable contribution to energy policy. The findings are not only essential for enhancing the resilience and sustainability of energy systems but also for ensuring that policies are responsive to the diverse needs of society. In this way, the study serves a noble purpose, advocating for energy strategies that are both environmentally sustainable and socially equitable.

Disclosure statement

The authors declare that they have no competing financial, professional, or personal interests that might have influenced the research or the results presented in this article.

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