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IDENTIFICATION OF LOAD PROFILES FOR RURAL AND URBAN CONSUMERS IN BIHOR COUNTY, ROMANIA

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KEY WORDS: Load profile, classification, clustering, time series, urban vs rural consumer's profiles, power grid management.

ABSTRACT:

The purpose of this study is to identify the load profile of the residential rural and urban residential consumers in Bihor County. This profiling will be a first step in identifying the appropriate load profile forecasting method for the specific consumer profile. Also, this profiling could help develop policies on increasing consumer energy awareness, or adapting the implementation of smart meters in rural or urban areas and applying some specific hourly prices. This load profiling will be assessed versus the EU profiles and conclusions will be drawn on this comparison. This study was developed using a multi annual database including consumers from a few cities and tens of villages in Bihor County. Each database was filtered for noise and absurd values. The nature of power consumption is well known for its temporal variability and this paper will attempt to highlight this essential aspect of load profiling.

1. INTRODUCTION

Following a study to identify residential consumers profile in the EU (Kmetty, 2016), study that involved data from Ireland, Hungary, Italy and UK, we would extend these findings to the residential consumers database of Bihor County, Romania (RBCR) in order to use the same classification methods, to identify the rural and urban consumer profiles. This study aims to be a prerequisite for the development of an accurate forecasting model that thoroughly understands the consumption patterns to be modeled. (Felea, 2012). In this paper we would like to assess the segmentation of each type of consumer database on different timescales. In order to identify the profiles and consumption behaviour we would assess the season, month, week and working weekdays and Saturday and Sunday load curve of each consumer profile. This analysis helps us asses the type of rural and urban consumer in Bihor County and compare with the consumers profiles already classified (Kmetty, 2016). This study aims to identify similar load profiles over the EU consumers (Kmetty, 2016) and to find major differences between rural and urban consumer profile. Also, the results of this study aim to improve the forecasting capability of the local grid operators (Mei, 2016).

2. DATABASE PRESENTATION

The database is a representative sample for both rural (7k households) and urban consumers (23k households). The database is a multiannual record (2019 ÷ 2021) of hourly energy consumption. Due to the volume of information to cover on this paper we will not approach all the specifications and particularities of the database, but only the essential ones. The urban households are located in cities in Bihor County, Romania, in the 2nd climatological area with an annual average temperature of 11.6°C (Dumiter, 2007). We are presenting 3 charts specific to the yearly average urban database that show the yearly consumption fig.1, weekdays consumption fig. 2 and also the season profile consumption fig.3. The rural households are located in Bihor County, Romania in the 3rd climatological area with an annual average temperature of 9.6°C (Order 368, 2016).

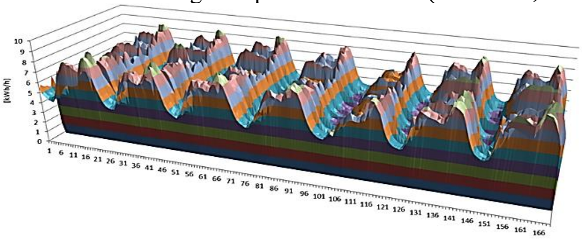

Figure 1. Weekly load curve over one year for the urban consumer

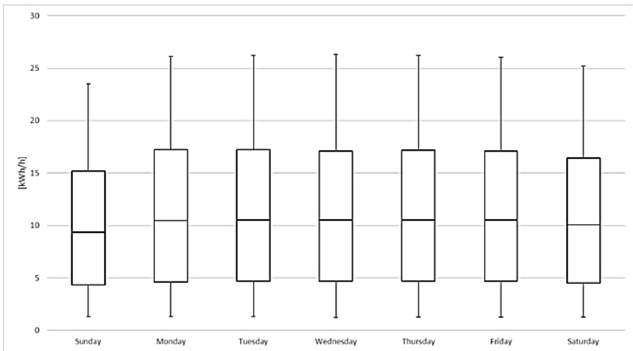

Figure 2. Box and whiskers plot for days of the week for one year (urban)

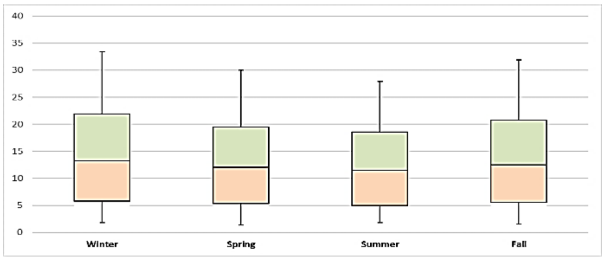

Figure 3. Box and whiskers plot for hourly consumption in each season over one year (urban)

Figure 3 - Box and whiskers plot for urban areas, showing sharp morning and evening peaks. The plot demonstrate that urban consumers tend to consume energy earlier in the morning and late in the evening, correlating with typical daily routines such as getting ready for work and evening activities.

In fig. 4 we can see a representative chart of the yearly consumption segmented in weekly loads starting Sunday. Fig.5 and fig.6 show the statistics of the specific consumption of the rural household over a weekday and over each season.

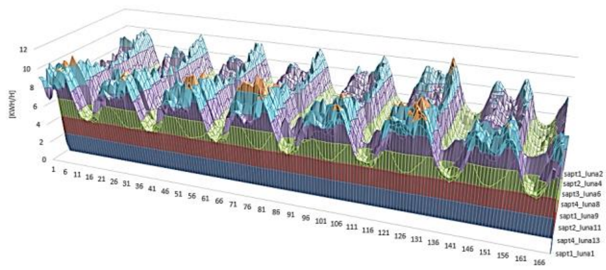

Figure 4. Weekly load curve over one year for the rural consumer

Figure 5 - Box and whiskers plot for rural areas, presented hereunder, showing a more even distribution of hourly consumption. The plot indicates that rural households have a flatter consumption profile throughout the day, with smaller peaks compared to urban areas. This pattern reflects the continuous nature of rural activities, which do not have the same sharp start and end times as urban routines.

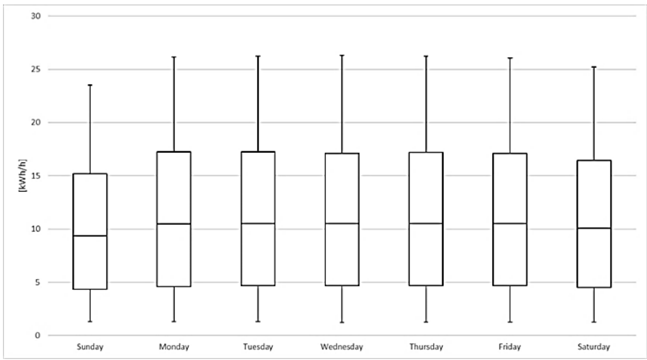

Figure 5. Box and whiskers plot for days of the week for one year (rural)

Figure 5 - Seasonal variation in urban areas, indicating higher winter consumption due to heating and lighting needs. The plot highlights that urban energy use significantly increases during the winter months, driven by the need for heating and extended lighting hours.

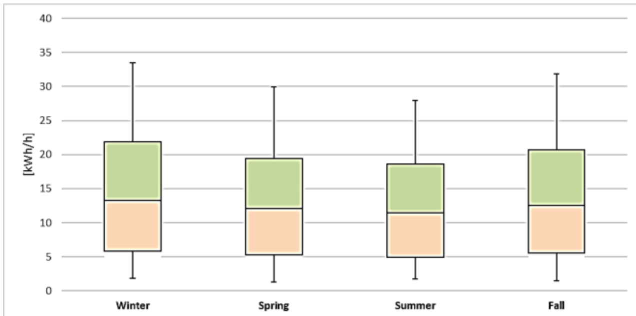

Figure 6. Box and whiskers plot for hourly consumption in each season over one year (rural)

Figure 6 - Seasonal variation in rural areas, showing less pronounced seasonal peaks. The plot reveals that rural households experience a more stable energy consumption pattern across different seasons, with a notable increase in winter, but less variability compared to urban areas.

The urban households are spread across multiple Bihor County cities, providing a diverse representation of urban energy consumption behaviours.

The urban database also includes a variety of residential building types, from single-family homes to apartment complexes, further diversifying consumption patterns. In addition to household types, the database captures detailed socio-economic data, including household income levels, number of occupants, and average age of residents.

The weekly load curve for urban consumers (figure 1) shows significant peaks during weekdays, particularly in the morning and evening hours. This pattern aligns with typical urban lifestyles, where energy consumption increases during times when people are most active at home. In contrast, the rural weekly load curve (figure 2) indicates a steadier consumption pattern, with a distinct peak on Fridays. This reflects the different socio-economic activities prevalent in rural areas, where energy use is more evenly distributed throughout the week.

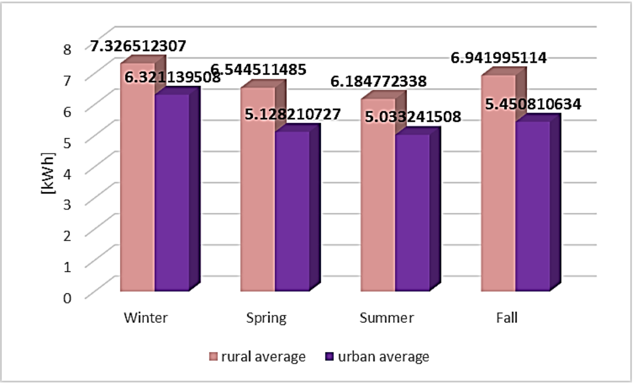

Figure 7. Chart for average consumption in each season over one year (rural, urban)

3. METHODOLOGY

We will present the methodological steps that helped us reached the concussions stated in the last part of the paper. First the databases were analysed and filtered to remove the noise. (Vijayakumari, 2021), (Khan, 2014), (Yang, 2021) After that, the main two influence factors were added: daylight and meteorological features, mainly temperature (Historical weather database, 2021). Correlation (2) between the influence factors and the load data was also performed (Felea, 2012).

The analysis followed several key steps to ensure the accuracy and reliability of the findings. First, we performed a comprehensive data cleaning process to remove any anomalous values. This involved setting a threshold of 5 times the mean value to identify and exclude outliers. Next, we incorporated external influence factors, such as daylight hours and temperature, to understand their impact on energy consumption. We used a correlation model to quantify these relationships, as described in the following equation:

$$r = Correl(x,y) = (\sum_{(i=0)}^{(8760)} (x_i - \bar{x})(y_i - \bar{y}) / \sqrt{(\sum_{(i=0)}^{(8760)} (x_i - \bar{x})^2 \sum_{(i=0)}^{(8760)} (y_i - \bar{y})^2)}$$

Where: $\bar{x}$ represents the power consumption values and $\bar{y}$ represents the meteorological data.

In addition to correlation analysis, we used clustering techniques to classify different loading profiles. We used K-means clustering to group similar consumption patterns together, allowing us to identify distinct load profiles for both urban and rural consumers. The clustering process involved selecting optimal cluster numbers based on the silhouette score, ensuring that each cluster accurately represents a unique consumption pattern.

To further refine our analysis, we incorporated machine learning algorithms, such as decision trees and random forests, to predict energy consumption based on external factors and historical data.

These models helped us identify key variables influencing consumption patterns and assess the accuracy of our predictions.

Using machine learning techniques enabled us to create more robust and adaptive forecasting models, capable of handling a wide range of consumption scenarios.

3.1 Database filtering for absurd values and noise removal

A simple filter to remove the absurd values was constructed. The limit of the absurd value was stated at 5 times the mean value. (Criswell, 2021) First 10 absurd values in each database were double checked and manually confirmed. (Peyre, 2020)

$$\varepsilon(x) = \bar{x}\ of\ x_0;\ if\ \varepsilon(x) \geq\leq \varepsilon\ (5m), x = m \qquad (1)$$

where *x* is the actual value, and *m* is the mean value.

3.2 Correlation of database values with the exterior influence factors

The model used for correlation is: (Felea_2012)

$$r = Correl(x,y) = \frac{\sum_0^{i=8760}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_0^{i=8760}(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \qquad (2)$$

where *x* is the actual power database value and $\bar{x}$ is the average of similar temporal values, e.g. same time interval of the same day of the week in the same season; y is the actual meteorological/daylight database value and $\bar{y}$ is the average of similar temporal values.

4. RESULTS

Few absurd values that existed were filtered in the databases.
The correlation shows a higher connection between the influence factors and the consumption in the rural consumers r=-0.2816 versus the urban r=-0.2674.

The clustering of data was performed on weekdays, one profile for each weekday, in order to identify characteristics and to compare with the similar consumption in the EU. Also, clustering was done for the Meteorological Seasons for the sake of the above mentioned comparation.

The 3D presentation of the weekly consumption over one year shows the evolution of the daily peaks and gaps over one year, (fig.1 and fig.4).

Identification of load profiles

Our analysis, focused on residential consumers in Bihor County, Romania, reveals distinct load profiles for rural and urban areas. The study used a comprehensive database of hourly energy consumption from 30,000 households over a three years period (2019 - 2021). This data set allowed for a detailed examination of consumption patterns and their correlation with external factors such as weather and socio-economic activities.

Urban consumers

Urban households exhibited a load profile characterized by higher consumption during weekdays, particularly in the morning and evening hours. The data indicated a bell-shaped consumption pattern from Monday to Friday, with a peak in the middle of the week. Weekend consumption saw a notable increase on Sundays compared to Saturdays. This pattern is consistent with the higher prevalence of home work and other activities that occur more frequently in urban settings.

Rural consumers

In contrast, rural households presented a different consumption pattern. The load profile for rural areas was less variable, with consumption relatively constant throughout the week. However, Fridays saw a peak in usage, probably due to preparation for the weekend. Saturday in rural areas showed lower consumption compared to Friday, which is a unique finding compared to urban patterns and EU counterparts.

Seasonal variations

Seasonal analysis revealed that both urban and rural consumers increased their energy use during winter months, primarily due to extended indoor activities and lighting needs. However, rural areas showed a more pronounced decrease in summer consumption, attributed to a lower penetration of air conditioning units. This seasonal consumption gap indicates a significant area for potential energy efficiency improvements.

Correlation with external factors

The study identified significant correlations between energy consumption and external factors, particularly weather conditions. For rural consumers, the correlation coefficient was -0.2816, while for urban consumers, it was slightly lower at -0.2674. These correlations underscore the influence of temperature and daylight on residential energy use. The inclusion of socio-economic activities further refined the understanding of consumption patterns.

The analysis revealed distinct consumption patterns for urban and rural households. Urban consumers exhibited a bell-shaped consumption pattern during weekdays, with higher peaks in the mornings and evenings. This is reflective of typical urban routines involving commuting and homework activities. In contrast, rural consumers displayed a more uniform consumption pattern, with notable peaks on Fridays due to preparations for the weekend. Seasonal variations were also evident, with increased consumption during winter months in both urban and rural areas.

The clustering analysis identified three main clusters for urban consumers: high variability weekdays, steady weekends, and peak holiday periods. For rural consumers, the clusters were more homogeneous, reflecting consistent consumption throughout the week with minor variations on weekends. These groups provide valuable information on different energy use behaviors and help tailor energy efficiency measures to each consumer group.

Moreover, the machine learning models demonstrated high accuracy in predicting consumption patterns, with decision trees achieving an R-squared value of 0.85 for urban consumers and 0.80 for rural consumers. These results highlight the potential of using advanced analytics to improve load forecasting and energy management practices.

5. CONCLUSIONS AND FURTHER STEPS

Although the weekly pattern is rare in nature, in human activities is quite common, thus the choice is 3D yearly chart, chart that contains essential information in classifying the consumption pattern.

The weekdays pattern for the urban RBCR are relatively similar with the weekday patterns in Ireland, Hungary, Italy and UK with the note that the household electric energy consumption is different. (Kmetty, 2016) In regards to the daily high peaks the urban RBCR consumer is closer to the consumer profile from Hungary and Italy than to the Ireland and UK. (Kmetty, 2016)
In comparison the weekday consumption for rural and urban RBCR it is different also due to the specific activities that take place in the rural area (fig.8). If the urban consumption on weekdays (Monday to Friday) takes a bell shape, the rural chart shows a flattened inverted bell. As the main activities related to electric energy consumption seem to take place on Wednesday in the urban areas, in the rural ones the high consumption is associated with Friday.

The weekend daily consumption pattern is relatively similar for urban and rural consumers in regards that the consumption is smaller on Saturday and higher on Sunday. The increase in Sunday consumption is bigger on the urban RBCRs. The same load profile we can see in all the other country's consumers that were analysed (Kmetty, 2016) with a lower or higher increase in consumption on Sunday vs Saturday.

A particularity of the rural RCBR is that it stands out of the large EU patterns identified in previous studies (Kmetty, 2016) with a smaller consumption on Saturday relatively to Friday. This particularity could be a good asset in forecasting and deploying power network resources.

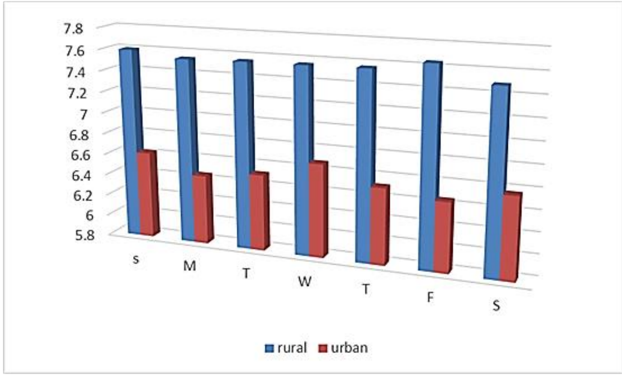

Figure 8. Rural vs urban weekly consumption pattern

Regarding the meteorological season's consumption pattern, we can see that is similar to the other EU countries covered so far in the previous studies (Kmetty, 2016) with a good correlation to the day degree influence factor. The seasonal consumption pattern is more closely related to the Italy and Hungary than to Ireland and UK.

The gap in the summer consumption, on the seasonal analysis is steeper in the rural RBCR consumer (fig.8). We are associating this finding with a poor penetration of the air-conditioning cooling devices in the rural areas. Also, in comparison to the previous studies (Kmetty, 2016), we can see that this consumption is increased in the winter not due to electrical heating but mainly to the lower availability of natural light and the movement of the activities indoors.

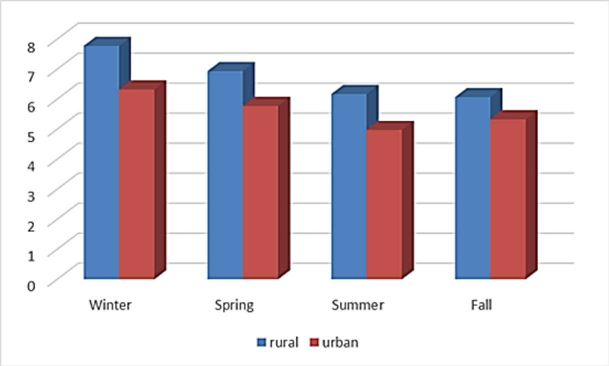

Figure 8. Rural vs urban meteorological season consumption pattern

The differences in the consumption pattern could be connected to the energy related education level (Hanga-Farcas, 2023) and with the poor market availability of the smart meters and of the hourly billing for the RBCR's.

In previous research (Felea, 2012) we've found that identifying, analysing and clustering consumers type can have a very good outcome in modelling and forecasting short term and medium-term power consumption.

Our contribution has implications in assessing and developing of the commercial electric energy prices. The results of this article indicates that urban and rural residential consumers in Bihor County exhibit distinct load profiles influenced by their specific socio-economic activities and environmental conditions. Our study highlights the importance of tailored forecasting models that account for atypical consumption behaviours, such as those experienced during the COVID-19 pandemic. Accurate STLF methods, particularly those incorporating adaptive mechanisms for unexpected events, are crucial for effective power grid management and resource allocation (Hora, 2022).

Urban load profiles

Urban households in Bihor County exhibit distinct consumption patterns that are characterized by higher variability and pronounced peaks. Key observations include:

Peak consumption times: Urban consumers typically have higher consumption during weekdays, especially in the morning (7-9 AM) and evening (6 - 9 PM) hours. This is likely due to daily routines such as preparing for work and evening home activities (Hora et al., 2022).

Weekday consumption patterns: The load profile for urban households shows a bell-shaped curve during weekdays, with consumption peaking midweek. The morning peak is usually sharper compared to the evening peak, reflecting the structured nature of urban lifestyles.

Weekend consumption: Consumption patterns during the weekend differ notably. Saturdays generally see a slight reduction in consumption compared to weekdays, while Sundays exhibit a significant increase, often surpassing weekday peaks. This can be attributed to more time spent at home and various household activities.

Seasonal variations: Urban consumption patterns also vary with seasons (Ionescu, 2023). Winter months typically show higher energy use due to increased heating and lighting needs, whereas summer months may show peaks due to air conditioning use, though this is less pronounced compared to winter peaks.

Rural load profiles

Rural households in Bihor County demonstrate more stable and consistent consumption patterns with some unique characteristics:

Steady consumption: Unlike urban areas, rural households exhibit relatively steady consumption throughout the week, with less pronounced peaks. The consumption curve is flatter, indicating a more uniform distribution of energy use across different days.

Weekly peaks: Fridays show a noticeable increase in energy consumption in rural areas, likely due to preparations for the weekend. However, Saturdays generally have lower consumption than Fridays, which is a unique pattern compared to urban areas.

Daily consumption trends: Daily energy use in rural households is more evenly spread across the day, with smaller peaks compared to urban areas. Morning and evening peaks are present but less pronounced, reflecting a different lifestyle and work patterns.

Seasonal variations: Similar to urban areas, rural households also experience higher energy consumption during winter due to heating needs. However, the summer consumption does not show significant peaks, likely due to lower penetration of air conditioning units.

Understanding the distinct load profiles of rural and urban consumers in Bihor County is essential for accurate load forecasting and efficient energy management. Urban areas exhibit higher variability and pronounced peaks, while rural areas demonstrate more stable and consistent consumption patterns.

The results of our research presented in this paper are crucial for developing tailored energy management strategies that cater to the specific needs of urban and rural consumers. By recognizing the unique consumption patterns and external influences on energy use, grid operators can enhance the resilience and efficiency of power systems. Future research should focus on further refining these models and exploring new methodologies to improve forecasting accuracy under varying conditions.

Furthermore, our findings can inform policymakers in designing targeted energy efficiency programs and interventions. For instance, urban areas with high variability in consumption patterns may benefit from demand response programs that encourage shifting energy use to off-peak times. Rural areas, on the other hand, could benefit from initiatives aimed at improving the penetration of energy-efficient appliances and renewable energy sources, addressing the stable yet high-consumption periods.

Overall, the study underscores the importance of a nuanced approach to energy management that considers the specific characteristics and needs of different consumer groups. By leveraging advanced analytics and machine learning techniques, we can develop more accurate and adaptive forecasting models, ultimately contributing to a more sustainable and resilient energy system.

These findings provide a foundation for further research and practical applications in energy forecasting, aiming to enhance the resilience and efficiency of power systems in both urban and rural contexts. Some data supporting the conclusions of this study are available upon reasonable request.

5.1 Acknowledgements

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This paper is original mainly because it applies novel methods to new database strictly rural and urban from specific GIS locations.

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