

Smart meters & smart grids

The emergence of smart grid technologies and applications has meant there is increasing interest in utilising smart meters. Recent residential applications such as home and battery energy management systems leverage smart meter data in various ways:

- 🌿 Household appliance monitoring and scheduling
- 🌿 Optimization of battery charging/discharging patterns

Furthermore, utilities and networks are becoming more aware of the potential benefits of using household smart meter data in:

- 🌿 Demand side management strategies such as demand response and energy efficiency to reduce the peak and overall demand
- 🌿 Optimization of distributed generation & electricity consumption

In order to improve the effectiveness of these strategies, we need to have a clear understanding of household consumption habits and underlying factors causing day to day variations. Moreover, the household energy management applications require accurate load forecasts in order improve economic and environmental benefits.

Residential electricity load analysis and forecasting

Household load curve analysis

Household's daily habitual consumption patterns can be investigated by clustering which is an unsupervised data-mining method. In the below **Figure 1.a**, an example household's 365 daily profile can be seen. These profiles are separated into four distinctive clusters and each cluster centre represents the typical load profiles of the household (**Figure 1.b**).

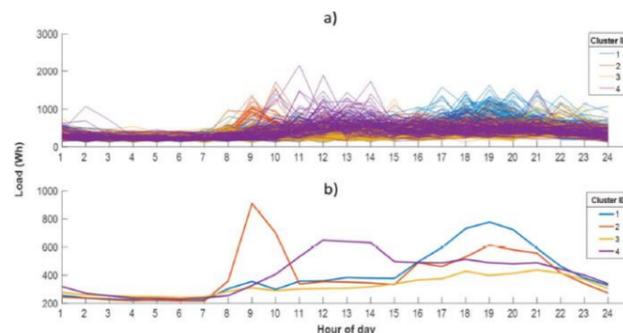


Figure 1 365 daily load profile separated into 4 clusters

Relationship between daily load profiles and climatic and calendar variables

Once the most typical and habitual load profiles of a household are found, a further investigation can be made for the underlying factors causing a household to behave differently in different days. In particular, by using classification which is a supervised data-mining method, the relationship between the typical daily load profiles and climatic (temperature, humidity, irradiation etc.) and calendar variables (weekday/weekend, holidays, seasons etc.) can be discovered.

In the below Figure 2, climatic and calendar variables are given in terms of the importance in determining the shape of daily load profiles. Especially, daily mean dry bulb temperature (DBT_mean) was identified as the most important climatic variable in determining the shape of daily load profiles of an example household.

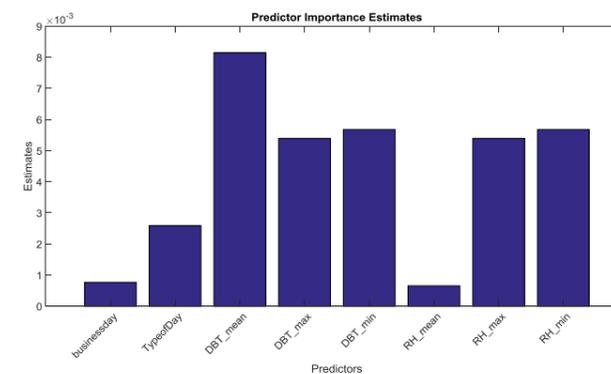


Figure 2 Importance of calendar and climatic variables in determining the shape of daily load profiles

Household electricity load forecasts with using habitual load profile information

Understanding the impact of climatic and calendar variables on load profile shapes can be helpful in predicting household electricity load. For this combined method, initially, the general shape of next day's load profile can be predicted by using next day's predicted climate variables and calendar information.

Once the load profile shape is identified, a specific forecast model curtailed for that particular profile shape can be used. More generic forecast models on the other hand predict loads without this initial step of identifying the general profile shape.

Results

- 🌿 This novel integrated forecast approach improves the next day forecast accuracy.
- 🌿 Results have shown that the initial prediction of load profile shape can be used for monitoring purposes such as left on appliances.

Anticipated impacts

- 🌿 Predicting load profile shapes can be useful for energy companies, retailers and utilities in determining their demand response strategies.
- 🌿 The improved forecast accuracy will increase the savings achieved by home and battery energy management systems. The savings will be more significant with increased penetration of these systems.

KEY POINTS

- 🌿 *Smart meter data can reveal important information about households consumption habits through use of data mining methods*
- 🌿 *Understanding behavioural consumption profiles can be useful for predicting household electricity loads.*

Further information

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