

Abstract

In modern era to maintain the uninterrupted electricity supply, keeping track for the consumer demand pattern is a dire necessity particularly in case of smart grid system. In this research, an approach is proposed to estimate the energy consumption patterns of residential and industrial consumers by classifying them according to their load usage pattern as well as timing of peak usage of electricity. Applying classification techniques to classify customer according to load curves is more efficient. The two-fold classification algorithm followed by supervised learning techniques to classify electric customers.

Research Challenges

The following challenges are associated with the analysis of load grouping:

- ❑ Vague interpretation: The load patterns of the customers belonging to the same type of activity or associated to the same commercial code may exhibit large differences.
- ❑ Efficiency: As such, categorization based on the type of activity and on commercial codes are generally not efficient for representing the specific aspects of the electricity consumption.
- ❑ Macro categorization: The distinction can then be limited to a few macro categories (e.g., residential, industrial, commercial, or other specific categories such as electric lighting and traction)

Research Objective

- ❑ A multidimensional deep learning algorithm was proposed for classification of collected load consumption — daily and weekly by AMI.
- ❑ Classification results are obtained, compared with other each other

Background

Smart Grid: Applications

- ❑ Two-way delivery of energy information
 - Consumers to receive accurate real-time prices and bills
 - Grid operator can receive consumers' real time information about the amount of the consumed energy
- ❑ Manage energy delivery and transmission
- ❑ Empower consumers to have more control over energy decisions
- ❑ Facilitate the almost instantaneous stability of supply and demand on the electrical grid.

Smart Grid System

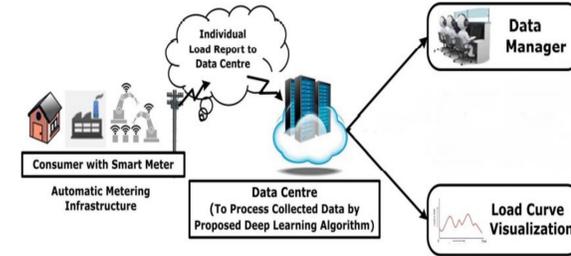


Fig 1: Smart Grid Technology

Flowchart: Load Usage Pattern Recognition

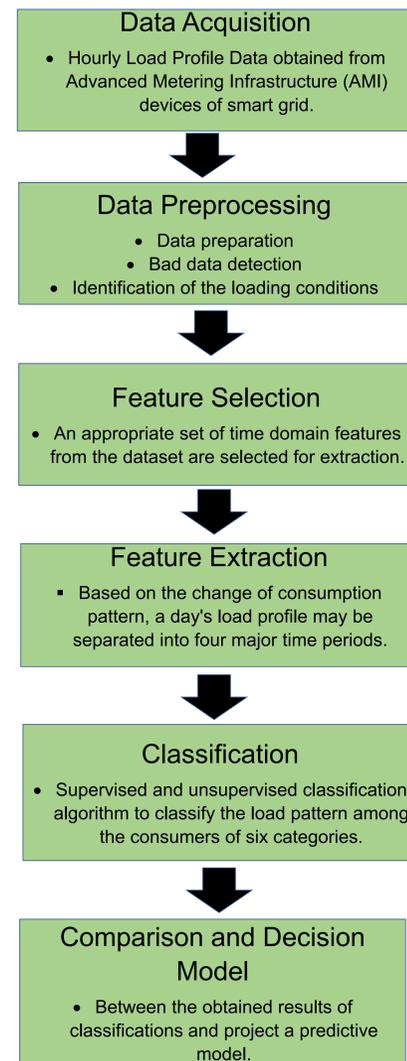


Fig 2: Workflow of consumer classification

Phase 1: Data acquisition and preparation

Data Acquisition

Dataset: This is Hourly Load Profile Data obtained from Advanced Metering Infrastructure (AMI) devices of smart grid.

Glimpse of dataset

Table 1: Load Pattern Data

98923621	98923641	98923648	98923655	98923661	98923662	98923663 Residential	
84.704	42.264	34.896	30.8	122.88	73.7	17.688	77775.233
84.868	34.896	31.452	33.408	100.74	67.55	16.212	77775.233
84.54	87.48	75.684	43.248	179.4	94.2	32.928	97189.032
84.54	80.604	72.744	41.28	172.02	100.35	29.484	97189.032
84.376	89.94	69.3	49.152	181.86	106.45	35.88	138917.767
84.54	79.62	65.856	49.152	152.34	129	40.296	138917.767
169.189	138.268	116.644	82.347	303.080	190.417	57.496 Baseline	
84.212	115.5	100.26	62.912	223.62	112.6	58.488	177255.747
84.376	116.484	101.244	55.696	226.08	141.3	53.568	177255.747

Data Pre-processing

- ❑ Data sampling preparation
- ❑ Bad data detection
- ❑ Identification of the loading conditions

Phase 2: Feature Extraction and Classification

- ❑ **Feature selection:** An appropriate set of features is selected for describing the representative load patterns for customer classification purposes.
- ❑ **Customer classification:** Involves suitable machine learning technique, resulting in K classes of customers.

Feature Extraction

- ❑ The feature extraction is performed on the load data after pre-processing (removing bad data, sampling and selecting loading condition).
- ❑ Over the course of a month, identical consumption behavior was observed on the same day of the week (e.g., all Mondays have a similar load profile, etc.).
- ❑ Based on the change in their consumption pattern, a day's load profile may be separated into four major time periods.
- ❑ Relevant clustering attributes were found in these time periods (each with 16 samples).

Time domain data:

There is a simple way to define the features of the m th representative load pattern, form $1 \times 1, 2, y, M$, is to consider all or a part of the normalized power values obtained from the measurements in the time domain. In such a way, a set of H direct shape features is readily available without performing load pattern post-processing.

$$C = \{c^{(m)}, m = 1, \dots, M\}$$

whose m th component is represented by the vector

$$c^{(m)} = [c_1^{(m)}, \dots, c_H^{(m)}]^T$$

Hence, the set of features characterizing the representative load patterns based on time domain is as follows:

- **Time period 1:** 6:00 pm to 10:00 pm.
- **Time period 2:** 6:00 am to 10:00 am.
- **Time period 3:** 1:00 am to 5:00 am.
- **Time period 4:** 10:00 am to 2:00 pm.

Energy Consumers Classification and Analysis

There are two-fold steps to carry on the analysis as follows:

- 1) Supervised and unsupervised classification algorithm to classify the load pattern among the consumers of six categories. For supervised The k-nearest neighbors (KNN) algorithm is a simple, supervised machine learning algorithm that is used to solve classification problem here. Moreover, the core of the categorization process is carried on by applying the appropriate clustering techniques to perform load pattern grouping as unsupervised algorithm.
- 2) Comparisons among these techniques have been carried out by resorting to various clustering validity indicators. Generally, these comparisons are based on individual executions of the various algorithms, for instance with the same number of clusters to be formed.

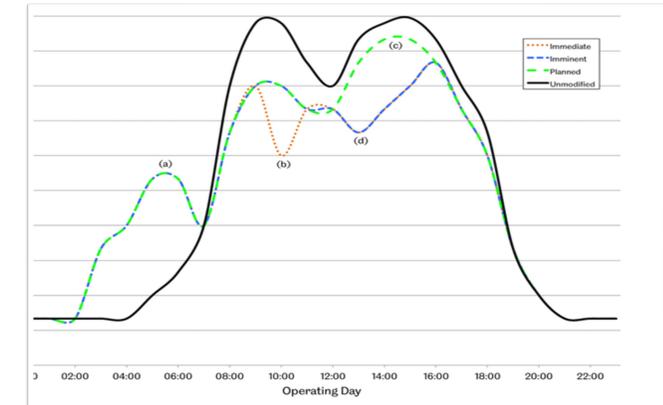


Fig 3: Load Pattern Classification among varied customers

Conclusion

Load profiling can extract a lot of information from electricity consumption data of individual customers thanks to the widespread use of AMI equipment. We presented a comprehensive assessment of data mining strategies for load profiling in terms of clustering techniques and clustering results evaluation criteria in this study.

References

- I. Y. Wang, Q. Chen, C. Kang, M. Zhang, K. Wang, and Y. Zhao, "Load profiling and its application to demand response: A review," *Tsinghua Science and Technology*, vol. 20, no. 2, pp. 117–129, 2015.
- II. X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—the new and improved power grid: A survey," vol. 14, no. 4. *IEEE*, 2011, pp. 944–980.