Computing Electricity Consumption Profiles from Household Smart Meter Data

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Your Smart Meter is Watching!

Smart Meters are Ubiquitous
Motivation for Smart Metering
Electricity Consumption Profiles
The Need for Electricity Consumption Profiles
Prior Work on Electricity Consumption Profile Generation

• Rely on data that is not easily available

• Use a black box method which is not interpretable

• Are not robust to noise

• Do not remove the effect of temperature and activity
  – cannot be extended to other regions and activity patterns
Takeaways

• Electricity consumption profile generation has several applications

• A profiling framework must be simple, interpretable, yet practical

• Time series analytics can be used to generate such consumption profiles
Key Observations
Residential Load Varies with Temperature
Residential Load Varies with Activity
Residential Load Varies with Activity

Activity level must be inferred from data
Our Methodology

- **Hourly consumption**
- **Hourly temperature**

Remove outliers and temperature-dependent consumption component

- Average consumption for each hour of day (weekdays)
- Average consumption for each hour of day (weekends)
PARX Model

\[ Y_t = \sum_{i=1}^{p} \phi_{is} Y_{t-i} + \psi_{1s} XT1_t + \psi_{2s} XT2_t + \psi_{3s} XT3_t \\
+ \psi_{4s} XO1_t + \psi_{5s} XO2_t + C_s + \epsilon_t, \quad \text{for } t \in s \]
PARX Model – cont’d

\[
XT1 = \begin{cases} 
T - 20 & \text{if } T > 20 \\
0 & \text{otherwise}
\end{cases}
\]

\[
XT2 = \begin{cases} 
16 - T & \text{if } T < 16 \\
0 & \text{otherwise}
\end{cases}
\]

\[
XT3 = \begin{cases} 
5 - T & \text{if } T < 5 \\
0 & \text{otherwise}
\end{cases}
\]
Handling Outliers

![Scatter plot showing energy consumption at noon vs. temperature (C)].

- 10% of Observations
- 10% of Observations
Computing Consumption Profiles

• Parameter Estimation
  – Number of seasons
  – Coefficients

• Subtracting the effect of exogenous variables

\[ Y_t^* = Y_t - \psi_{1s}XT1_t - \psi_{2s}XT2_t - \psi_{3s}XT3_t - \psi_{4s}XO1_t - \psi_{5s}XO2_t \quad \text{for } t \in s \]
Weekday and Weekend Profiles

![Graph showing weekday and weekend profiles of hourly energy consumption (kWh) over the day. The graph plots time of day on the x-axis and hourly energy consumption on the y-axis. The data points for weekdays are represented by blue circles, and the data points for weekends are represented by red triangles.]
Comparison – Predictive Power

• Data set
  – Residential hourly electricity consumption data of 1000 homes from March 2011 to October 2012
  – Hourly air temperature data of that region

• Prior work
  – 3-Line Method
    • Fits a tree-piece linear regression after removing outliers
  – Hourly Mean
  – Convergent Vector
    • The same as ours but does not remove the effect of exogenous variables
Results

Avg. RMSE

[Graph showing the average root mean square error (RMSE) for different datasets (3-Line, Hourly Mean, Convergent Vector, PARX) across various categories (1 to 20). The graph compares the performance of these datasets with each other, highlighting the variability and differences in performance across the categories.]
Conclusions

• Electrical consumption profile generation is **important** and has many **applications**
  – water and gas consumption

• Time series auto-regression framework enables us to remove the effects of temperature and activity

• We demonstrated a **simple**, **interpretable**, and **practical** profiling model with **high predictive power**