Demand Side Flexibility Envelope Quantification Under Data Scarcity

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Abstract

Efficient management of distributed energy resources often requires a tremendous amount of data to model component constraints and consumer behaviors. However, in many practical scenarios, collecting high-resolution demand data is significant costly, which jeopardizes the efficient utilization of demand-side resources. This paper proposes a novel learning framework to quantify demand-side flexibility envelope under data scarcity. We construct a long-short-term memory network to capture the relationship between consumers' load consumption behavior and demand flexibility envelope. The network only uses low-resolution load data to predict consumers' personalized flexibility envelope and able to extrapolate across various stakeholders and conditions. We provide a flexibility envelope generation algorithm to generate the training label and expedites the training process with limited high-resolution historical load data and environmental data. Simulations using Pecan Street consumer data demonstrate that our method generate effective demand flexibility envelopes for network training, and the cross-validation results shows our learning framework accurately predict the demand flexibility envelope despite data scarcity.

Challenges

- Non-intrusive load modeling relies on high-resolution load data, and its algorithms require substantial data processing, leading to high energy consumption;
- Most DR programs operate on an hourly basis and utilities can only provide smart meter data up-to quarter-hour resolution, and most of then cannot be disclosed due to privacy issue.

Proposed Method

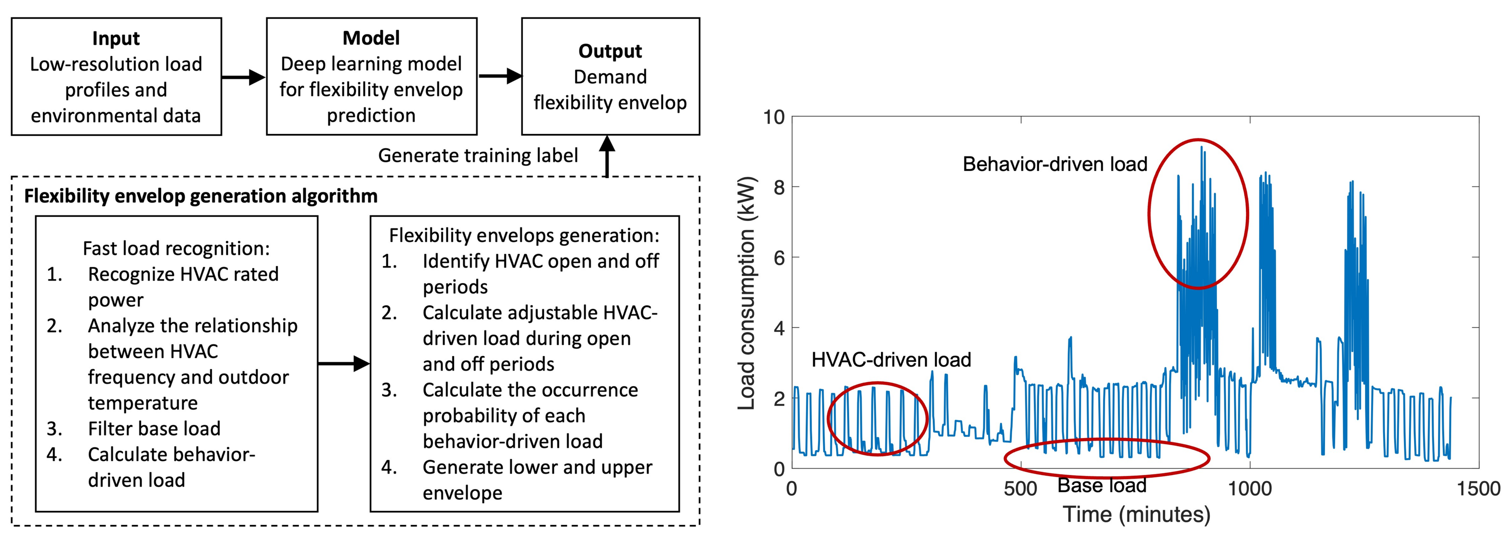
We formulate a flexibility envelope learning framework (Fig. 1(a)) that quantifies consumers' personalized demand flexibility envelopes by training a neural network with low-resolution load data:

$$Y = f(X), X = [l, T], Y = [E_h^+, E_h^-] \tag{1a}$$

where Y, X are the output labels and input features; l is a matrix with hourly load consumption of historical days and target days; T is the target days' outdoor temperature; E_h^+, E_h^- are the upper and lower flexibility range.

We develop a flexibility envelope generation algorithm includes a fast load recognition algorithm to identify specific load patterns from high-resolution load profiles.

Base load: $l_{\text{base},t'} = \min(l_t, ..., l_{t+t_w}),\ \forall t' \in [t, t+t_w]$ (2)



(a) Flexibility envelope learning framework (b) Load patterns from high-resolution load profiles

Figure 1. Flexibility envelope quantification method.

HVAC rated power: l_{HVAC} 3 threshold parameters & frequency (3)

HVAC frequency: $f_{\text{HVAC},T}$ linear with outside temperature (4)

Behavior load: $l_{\text{B}} = l - l_{\text{base},t'} - l_{\text{HVAC}}$ (5)

Upper and lower envelop E_h^+, E_h^-

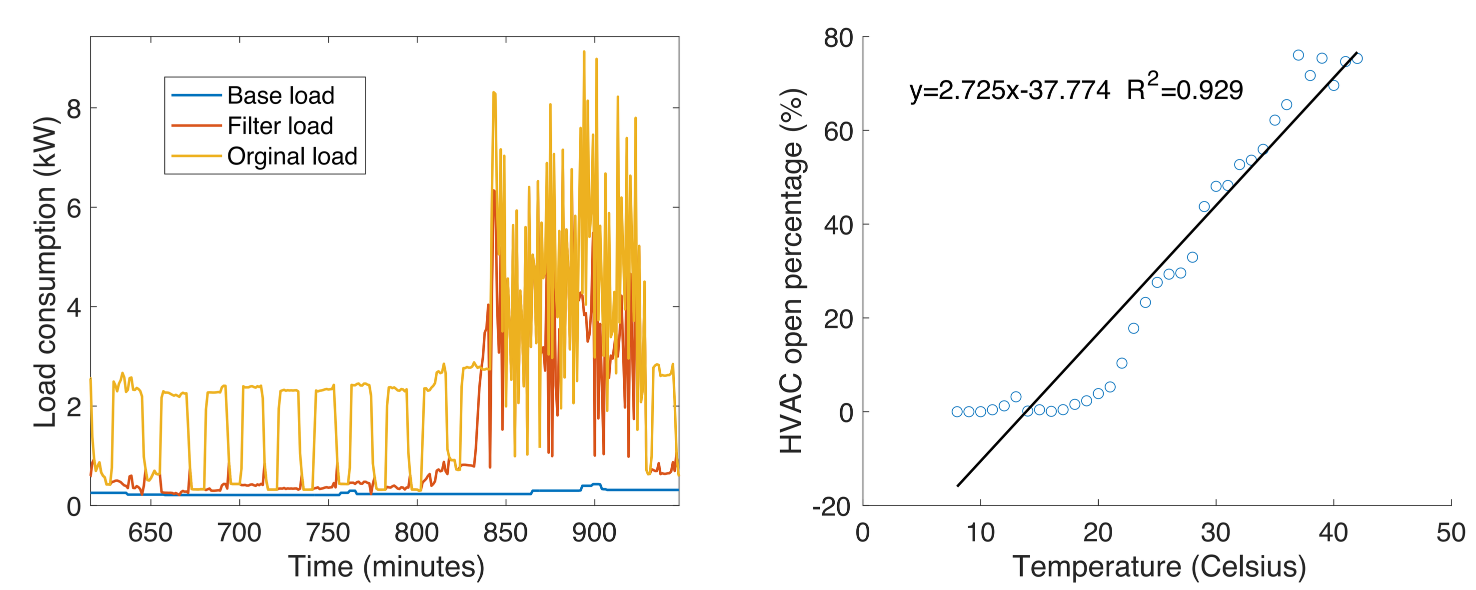
$$E_h^+ = s_h * (l_{\text{HVAC}} - l_{\text{V},h}) + \mathbb{E}[l_{\text{B},h} - l_{\text{Bt},h}] \tag{6}$$

$$E_h^- = (1 - s_h) * l_{\text{V},h} + \min([l'_{\text{B},h}, l_{\text{Bt},h}]) \tag{7}$$

Data & Flexibility Envelope Generation and Prediction

We use the raw data from Pecan Street, which includes one year of minute-level load consumption data for 148 consumers in Texas, USA. The hourly temperature data is collected from the National Solar Radiation Database of the NREL.

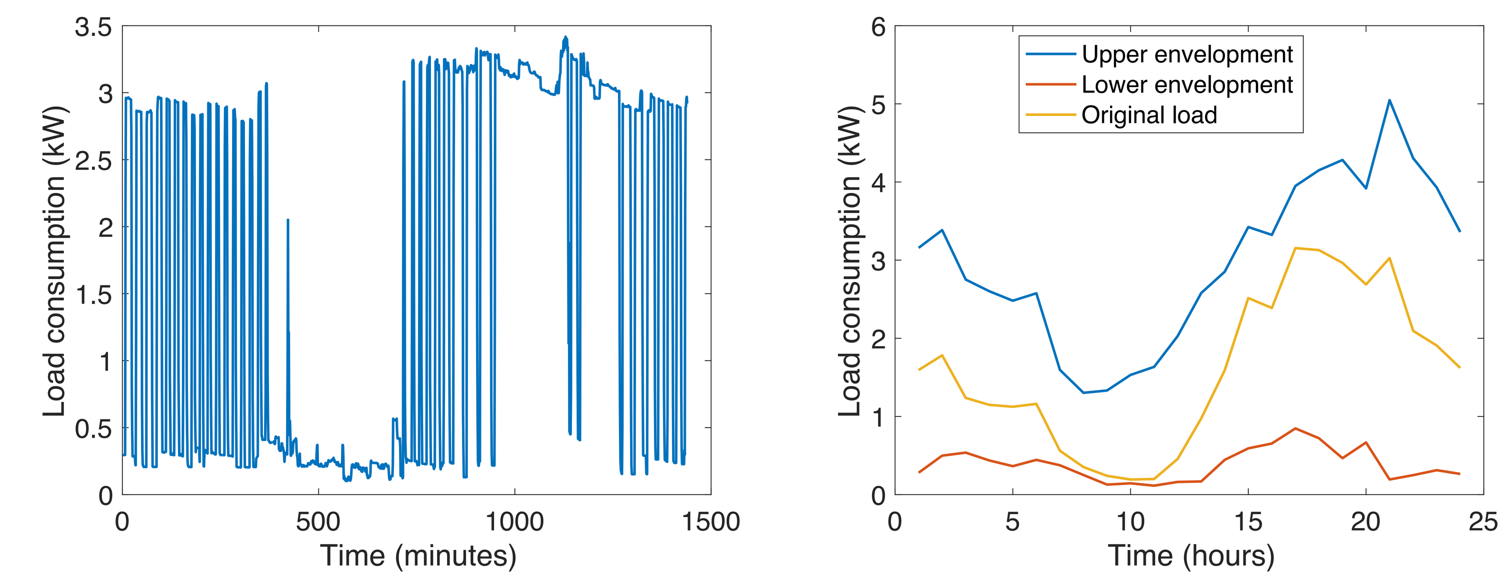
We then show load recognition results.



(a) Three load patterns recognition (b) HVAC frequency with temperature

Figure 2. Load recognition results.

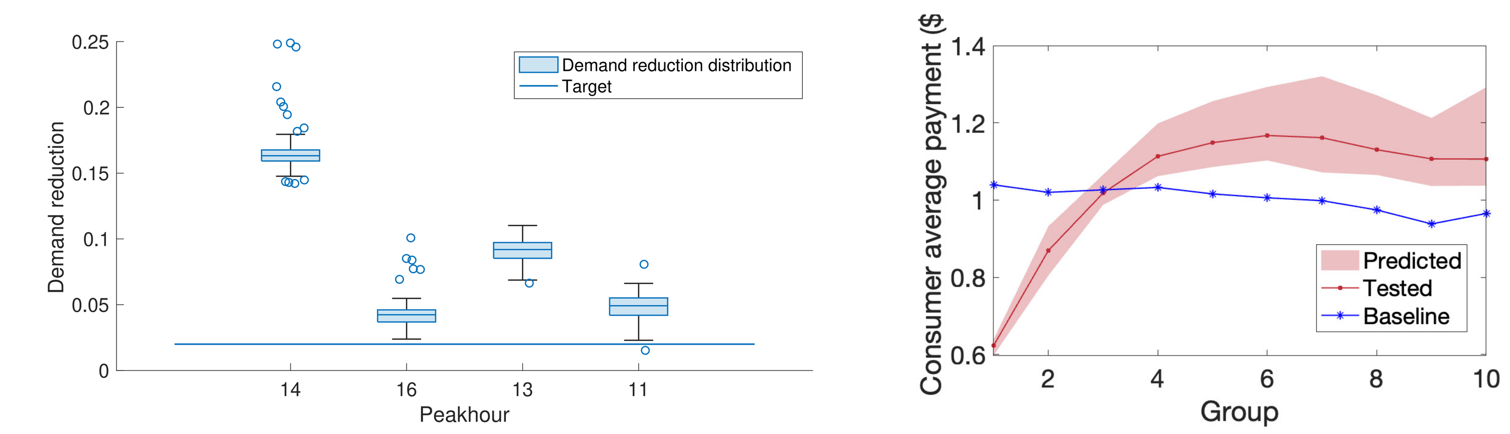
- Given the original high-resolution load profiles, first recognize the HVAC load, then get the base load and behavior load;
- A strong linear relationship between HVAC frequency and outdoor temperature with an R^2 value of 0.93.



(a) High-resolution original load profiles (b) Low-resolution upper and lower envelope

Figure 3. Upper and lower envelope development results.

- During the peak time slots, the difference between the upper envelope and the original load is small, while the difference between the lower envelope and the original load is large.
- Maximum value of the upper envelope lies within the consumers' whole rated power, and lower envelope always keeps a small load range, providing for the basic energy requirement of consumers



(a) Learning process (b) Envelope prediction

Figure 4. Upper and lower envelope prediction results.

- Use cross-validates LSTM for prediction. Inputs are 29 days of low-resolution load profiles and hourly temperature of the 29th day. Outputs are 29th day's flexible upper and lower envelope.
- Use 5-fold cross-validation, and the validation RMSE reaches 0.22, the MAE is 0.17, and the loss is 0.07. The model accurately capture the correlation between demand flexibility and historical load consumption.

Demand side flexibility envelop quantification is essential to DR, resilience enhancement, system planning, and market design. For new applications, the training samples can be replaced or scaled.

The data and code used in this study are available from the authors upon reasonable request.

References

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