Benchmarking of Aggregate Residential Load Models Used for Demand Response

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Motivation

- ***Introduction:*** Aggregate models of residential loads aim to capture the dynamics of residential demand-responsive loads in an accurate and computationally-tractable way. This allows the models to be incorporated into controllers and observers used by demand response providers. A variety of aggregate models have been developed; however, their accuracy has not been benchmarked against one another in comparable scenarios.
- ***Contribution 1:*** We extend two existing models to cope with a time-varying outdoor air temperature.
- ***Contribution 2:*** We compare the accuracy of two Markov-based and one transfer function-based aggregate air conditioner (AC) models against a common, detailed simulation model.

Method

- ***Overview:*** We use several aggregate models, detailed below, to predict the power consumption of 10,000 ACs over a 24 hour period with a time-varying outdoor temperature. Simulations evaluate the aggregate models' prediction accuracy using a hybrid model, detailed below, to represent individual ACs. We assume that the ACs are not coordinated by a load aggregator.
- ***Individual TCL Model:***
  - The hybrid model representing individual ACs contains two continuous states representing the internal air and mass temperatures of the house and one discrete state representing the on/off mode of the AC
  - The cooling capacity, coefficient of performance, and power draw for each AC is time-varying and depends on the outdoor temperature

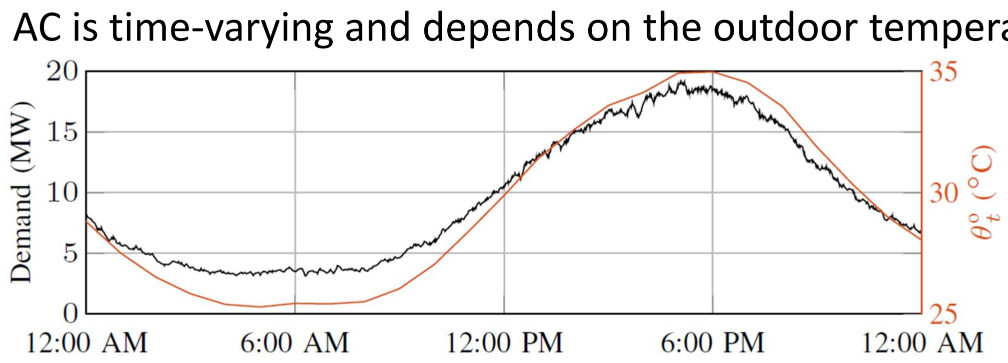

Figure 1): The aggregate demand of the simulated ACs and the outdoor temperature for the case study setup

- ***Aggregate Models:***
  1. Two-State Markov Model [1]: Defines discrete state bins based on the air temperature and on/off mode of each AC, constructs an aggregate state as the portion of ACs in each bin, and uses a Markov transition matrix to update the aggregate state
  2. Three-State Markov Model [2]: Similar to the two-state Markov model, but bins are based on the air temperature, mass temperature, and on/off mode
  3. Transfer Function Model [3]: Maps a change in the ambient temperature to a change in the steady state aggregate demand

Table 1): Variations of the base aggregate models used within this work.

Abbreviation	Base Model	Model Details
MM2-C	Two-State Markov Model	Linearly interpolates between a set of models identified at different outdoor temperatures; data for model ID generated using a constant outdoor temperature
MM2-V	Two-State Markov Model	Linearly interpolates between a set of models identified at different outdoor temperatures; data for model ID generated using a varying outdoor temperature
MM2-S	Two-State Markov Model	Linearly interpolates between a set of models identified at different outdoor temperatures and for different trends in outdoor temperature; data for model ID generated using a varying outdoor temperature
MM3-C	Three-State Markov Model	Linearly interpolates between a set of models identified at different outdoor temperatures; data for model ID generated using a constant outdoor temperature
MM3-V	Three-State Markov Model	Linearly interpolates between a set of models identified at different outdoor temperatures; data for model ID generated using a varying outdoor temperature
MM3-S	Three-State Markov Model	Linearly interpolates between a set of models identified at different outdoor temperatures and for different trends in outdoor temperature; data for model ID generated using a varying outdoor temperature
TF-O	Transfer Function Model	Single model; assumed transfer function structure of two poles and one zero; parameters computed using [3]
TF-ID	Transfer Function Model	Single model; transfer function structure of two poles and two zeros identified from historical model accuracy; parameters identified with historical input-output data

References

[1] J. L. Mathieu, S. Koch, and D. S. Callaway, "State estimation and control of electric loads to manage real-time energy imbalance," IEEE Transactions on Power Systems, vol. 28, no. 1, pp. 430–440, 2013.
[2] W. Zhang, J. Lian, C.-Y. Chang, and K. Kalsi, "Aggregated modeling and control of air conditioning loads for demand response," IEEE Transactions on Power Systems, vol. 28, no. 4, pp. 4655–4664, 2013.
[3] N. Mahdavi, J. H. Braslavsky, and C. Perfumo, "Mapping the effect of ambient temperature on the power demand of populations of air conditioners," IEEE Transactions on Smart Grid, 2016.

Results

Table 2): Root mean square error (RMSE) in predicting the aggregate AC demand

Abbreviation	MM2-C	MM2-V	MM2-S	MM3-C	MM3-V	MM3-S	TF-O	TF-ID
RMSE (kW)	436.7	437.1	226.2	320.9	322.9	213.4	504.4	447.0

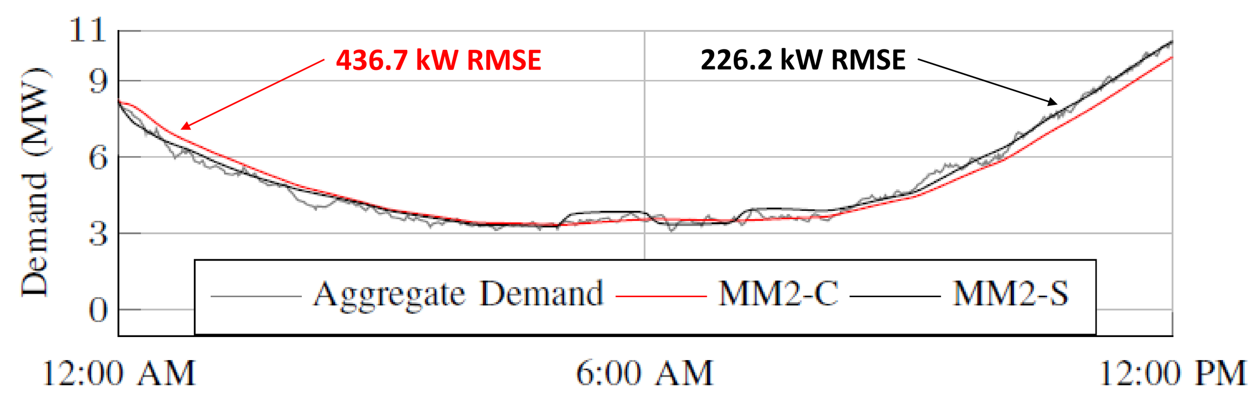

Figure 2a): Time series of the aggregate AC demand, the MM2-C predictions, and the MM2-S predictions over 12 hours

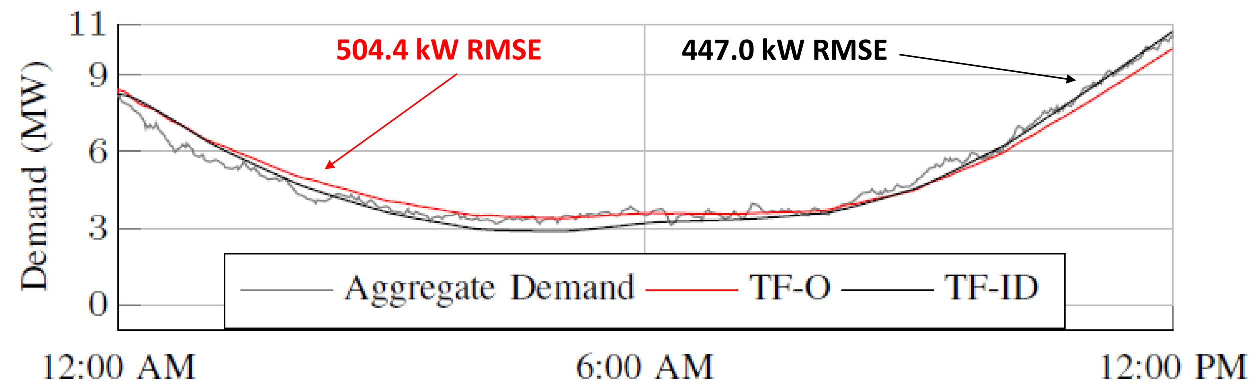

Figure 2b): Time series of the aggregate AC demand, the TF-O predictions, and the TF-ID predictions over 12 hours

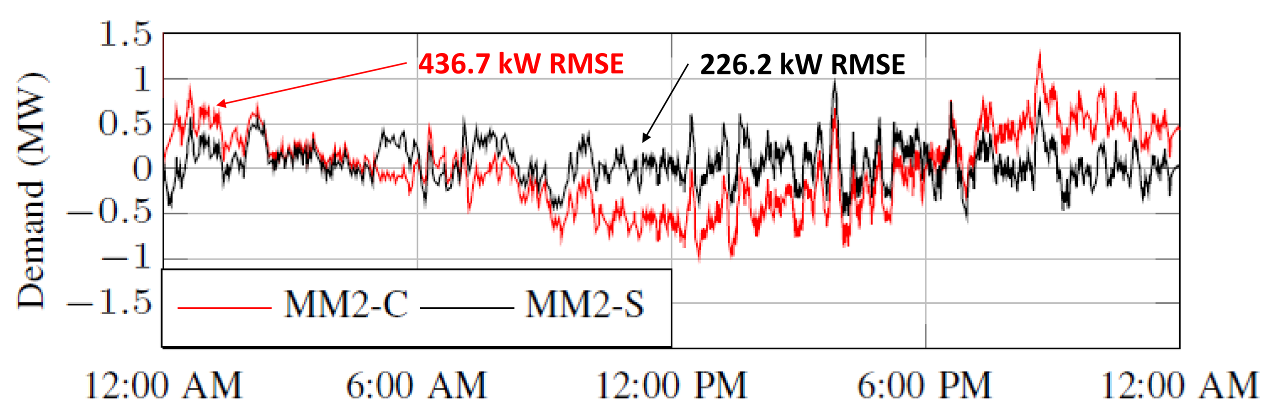

Figure 3a): Prediction error of the MM2-C and MM2-S models over the course of 12 hours

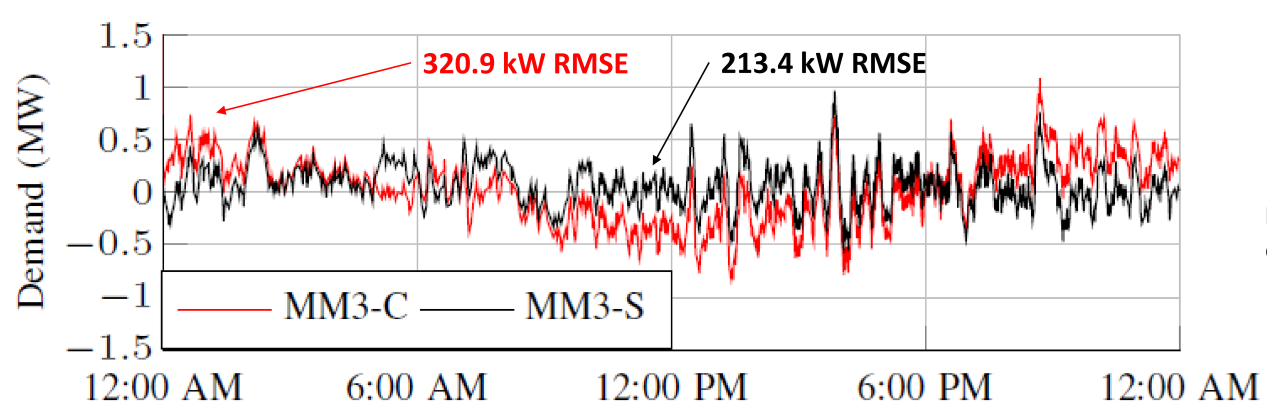

Figure 3b): Prediction error of the MM3-C and MM3-S models over the course of 12 hours

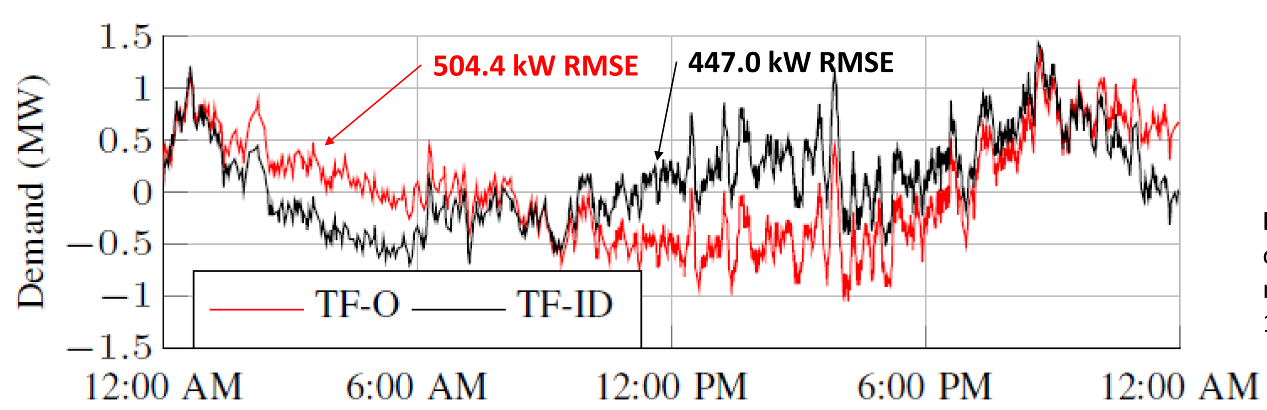

Figure 3c): Prediction error of the TF-O and TF-ID models over the course of 12 hours

Conclusions

- ***Results:***
  1. The three-state Markov model is the most accurate of the three aggregate models
  2. Updating the Markov transitions using the outdoor temperature trend decreases prediction error in both Markov models
  3. The transfer function model performs worst, likely because the simulation scenario differs significantly from the assumptions used to develop the model
- ***Future Work:***
  1. Develop a variation of the Markov-based models that accounts for times where the temperature is relatively constant
  2. Derive transfer function parameters for an AC aggregation undergoing a sinusoidal input rather than a step input, which better approximates realistic temperature changes
  3. Evaluate prediction performance under aggregator control

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