Energy Disaggregation and Short-Term Load Forecasting

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Introduction

The main idea of the implemented system is to make sure that the supply of energy mirrors the demand for the proper/regulated usage of appliances. First, the overall electricity consumption of a particular household is disaggregated and appliance wise consumption is found using a combination of a Hidden Markov Model (HMM) and the Viterbi Algorithm. Next, short term load forecasting (STLF) is done, appliance wise, in order to predict the load power consumption in the future. This is done using an ANN, which feeds this information into the microgrid. The microgrid can then increase or decrease the total power supplied to the household, forming a sort of feedback loop.

Performance Analysis

The data to test out the validity of this system comes from the GREEND dataset, which is implemented in Python3 using the NILMTK toolkit. This very data is used to train a HIdden Markov Model (HMM), a powerful statistical tool. Once trained this HMM selects the most probable state an appliance can be in (ON, OFF, etc.) using the VIterbi Algorithm.

The ANN was chosen here over DL Models as it gives higher accuracy historically than Deep-Learning Models, which succumb to overfitting. The ANN uses the GREEND data with the disaggregated data of the appliance to find out the future states of a given appliance, and therefore, the household as well.

Results

- Figure B represents the loss curve, were in the trend of test data follows the training data, and attains less than 60% at the end of the dataset.
- In the ideal case, the accuracy needs to be increasing linearly, but due to the usage of a smaller number of data sets and proof of concept level, the accuracy is flat for short period of epoch/time. increasing gradually attaining 100% accuracy in the last set of training data.
- The application of Viterbi to the HMM system yields which state an appliance is going to be in, for a given observation.

B

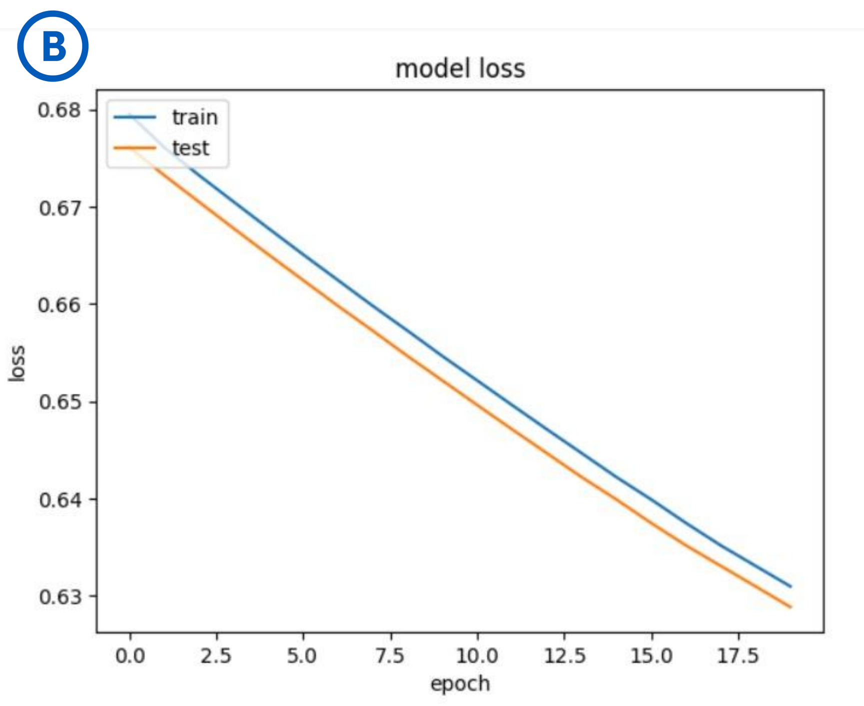

Figure B: The following figure represents the loss curve, were in the trend of test data follows the training data, and attains less than 60% at the end of the dataset.

C

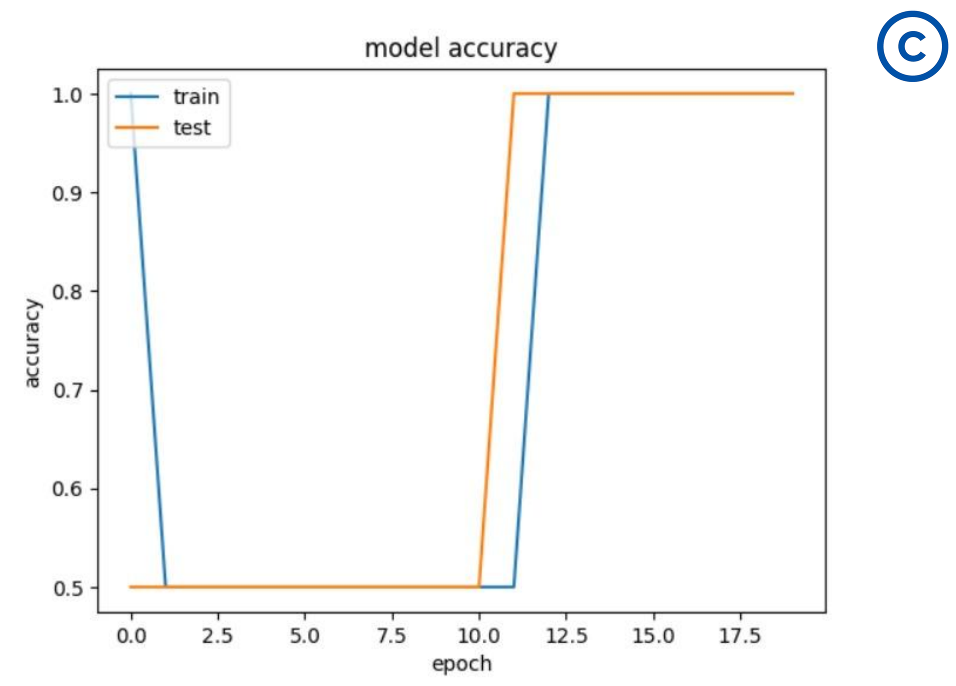

Figure C: ANN Estimation Accuracy

Figure D: Probability of a given observation being in either OFF state or ON state, post disaggregation

D

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[0.43335798 0.566642  ]
[0.5017501 0.4982499]
[0.43335798 0.566642  ]
[0.5017501 0.4982499]
[0.43335798 0.566642  ]
[0.5017501 0.4982499]
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[0.5017501 0.4982499]
[0.433358 0.566642]
[0.5017501 0.4982499]
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System Design

A

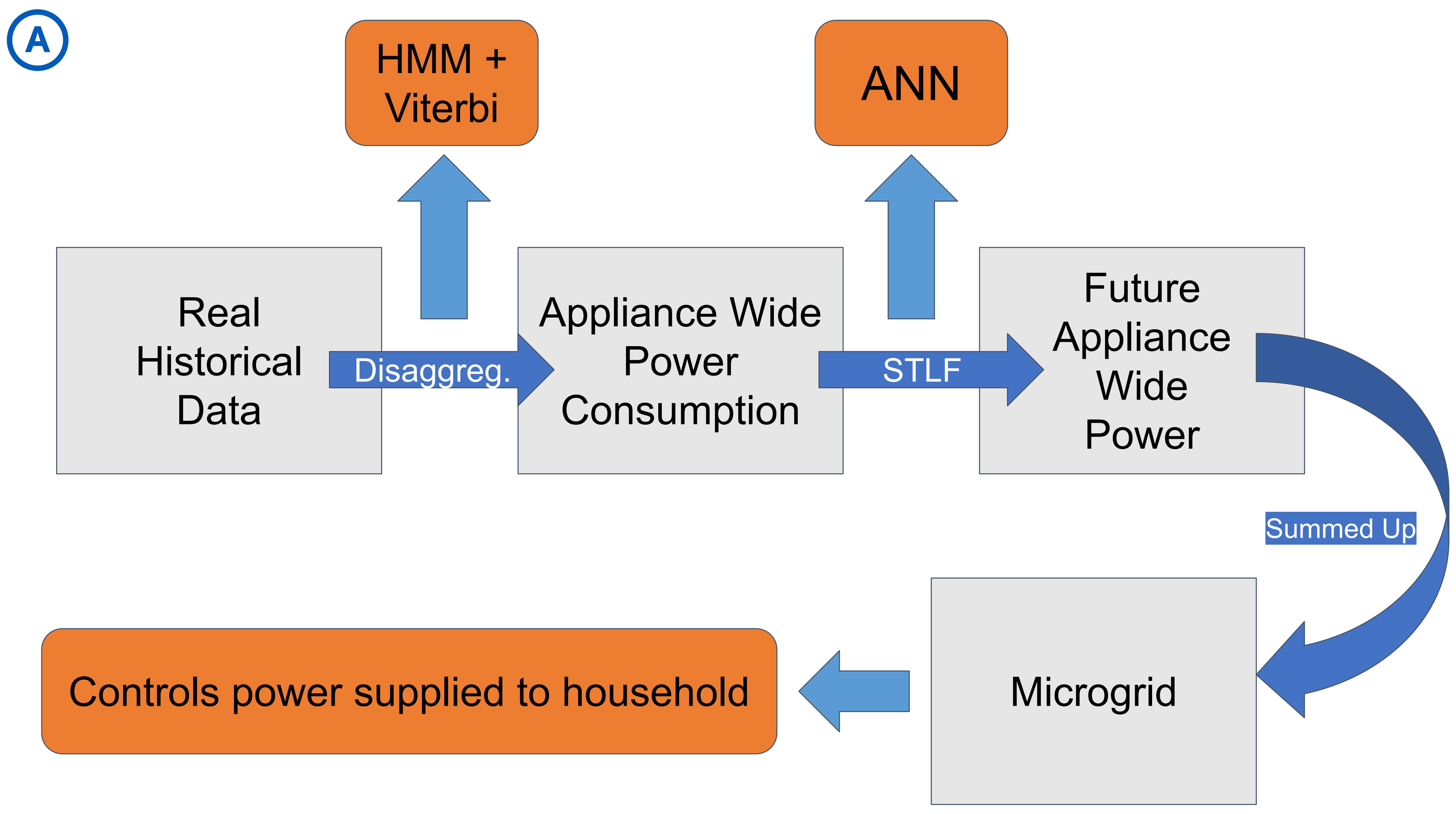

Figure A: Overall System Design

Conclusions

The system formed here is intended to give feedback to the household from which it is collecting data. The combination of power disaggregation via the HMM, implemented with the Viterbi Algorithm, and the subsequent short-term forecast of the disaggregated appliances yields a fairly accurate reading of future power demands of the household.

The advantage of feeding the ANN disaggregated data is that it reduces the amount of data a given ANN has to deal with, while simultaneously increasing the confidence with which a given appliance's future requirements can be understood.

References

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