Poster Abstract: Disaggregated Forecasting for Large Office Buildings

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ABSTRACT

In the direction of minimal and cost effective sensing, working with few meters/sub-meters together with other information in the context of energy models for office buildings is an important problem to address. In this paper we propose a technique dubbed as disaggregated forecasting using sophisticated function approximation. The results obtained using the real data of an office building justifies the usefulness and the efficacy of the proposal.

1. INTRODUCTION

Buildings consume almost 40% of the total energy, thus driving researchers to focus on energy-management solutions [2]. Utilities try to minimize the costs of generation and meeting the energy demand at the same time. Peak demand is very difficult to handle as it results in additional generation costs; so utilities opt for demand response programs. Building managers need to take appropriate measures towards handling the peak-load shaving and demand response to minimize the electricity bills. This may require controlling of different loads appropriately, necessitating more granular information about the various loads in the building. One way to accomplish this is by metering individual loads which results increased installation costs. To overcome this, we propose a novel technique, referred to as disaggregated forecasting, where together with the single smart-meter measurements, all the available contextual information like occupancy, weather and historical consumption information are utilized.

The existing solutions mostly focused on forecasting power consumption for the whole building and disaggregation is mostly addressed for residential to small commercial buildings, where individual load signatures are available. In this paper, we address disaggregation for large buildings and forecasting the disaggregated results for providing fine granular energy models.

In most of the office buildings energy consumption is due to the loads like HVAC (Heating, Ventilation and Air Conditioning), lighting and computing (computers, laptops and servers etc.); constituting around 80% of the total energy consumption. The sampling frequency of the smart meter data can range from once in 15 minutes to an hour. This time series data is coupled with other time series from different sensors like occupancy, weather etc., to develop the energy models for aforementioned loads. Towards this end, Non-linear Auto Regressive eXogenous neural network (NARX neural network) is used for forecasting the smart meter data (in terms of total energy consumption of the building). NARX architecture is rather very well known for time-series prediction [1], where past output values are also used in the input layer apart from the exogenous inputs. This makes the network more dynamic with respect to time and helps in capturing temporal dependencies in the data. The forecasting is carried out for the period of next one day. Further, this forecasted output is combined with the other contextual information (time-series) like occupancy and temperature towards developing the different energy models for individual loads, resulting in useful power consumption profile. In this stage linear regression is used to arrive at the requisite models.

2. APPROACH

Towards validating the proposed models in our approach, the energy models for different loads are developed by considering the building which is fully instrumented. That is, we have sub-meters to measure the power consumption of all the individual loads. The sampling frequency of the power measurements is once in 15 minutes. The external temperature and occupancy are of different frequencies and are interpolated appropriately to synchronize in time with the power-consumption values. Missing data, which is rather prevalent in the large building set-ups, is taken care of by using the nearest neighborhood approach i.e. missing values are replaced by taking the mean of all the values of the same day and time in the historical data. The energy forecasting model for total power consumption is developed using NARX neural network as a function of historical power consumption, occupancy and external temperature and is elaborated little more in Section 3. This total energy consumption forecast is used again in developing the energy models for the individual loads. The energy models for individual loads are developed using linear regression as a function of total power consumption forecast for 24 hours (with 15 minutes granularity), occupancy, and external temperature. Historical power consumption of individual loads was not used while developing the energy models to mimic the

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situation where sub-metered data is not available. The sub-metered data is used only for checking the accuracies of the developed energy models.

3. ADDITIONAL DETAILS ON THE PROPOSED METHODOLOGY

The total power consumption based on NARX network can be written as

$$TP_{fcst}(t) = f(TP(t-T), TP(t-2T), Occ(t), Temp(t)), \quad (1)$$

where f indicates the function approximation carried out by neural network. TP_{fcst} is the total power consumption forecast at time t, $TP(t-T)$ is the previous week same day same time power consumption, $TP(t-2T)$ is the two weeks previous same day same time power consumption, $Occ(t)$ is the occupancy estimated at time t and $Temp(t)$ is the external temperature forecast at time t. When it comes to individual loads, each is characterized by linear regression model in our proposal. Through this, we capture how different time series values affect the individual power consumption. Starting with fully metered buildings, the coefficients of the linear regression models are estimated and are validated on other similar buildings for the efficacy of the models. In this way, we are utilizing the notion of inductive learning, albeit in a primitive way. For HVAC, the model is

$$\begin{aligned} &AC_{Power}(t) = g_1(log(TP_{fcst}(t)), Occ(t), Temp(t)) \\ &= \phi_0 + \phi_1 \times TP_{fcst}(t) + \phi_2 \times Occ(t) + \phi_3 \times Temp(t) \end{aligned} \quad (2)$$

where $TP_{fcst}(t)$ is the total power consumption forecast from Equation 1, g_1 indicates the function approximation carried out by linear regression with parameters $\phi_0, \phi_1, \phi_2, \phi_3$. In a similar fashion, g_2 and g_3 are developed for computing and lighting loads. These models (parameters) are applicable to other *similar* buildings as well, due to the well known facts that power consumption by aforementioned loads are related to the occupancy and external weather in situations like office buildings. For instance, if the number of occupants increases the power consumed by AC will also increase and this in turn can result in more overall power consumption and so on. But, it is to be noted that one of the inputs for the linear regressor itself is obtained from the output of non-linear NARX network. This two-staged function approximation approach, to the best of our knowledge does not exist elsewhere.

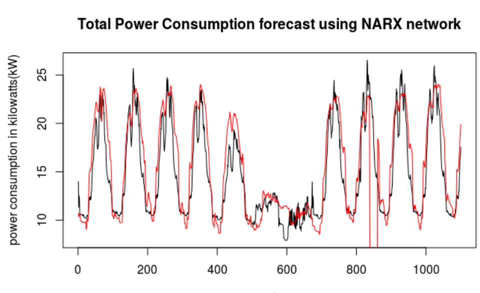

Figure 1: Total Power Consumption Forecast

4. RESULTS AND DISCUSSION

The forecasting accuracy is around 90% and the results for forecasting the total power consumption are depicted in Figure 1.
The disaggregated forecasting accuracies are around 70% for HVAC and computing, more than 80% for lighting and are depicted in Figures 2 and 3. In all the figures red line represents the actual load and black line represents the disaggregated forecast load.

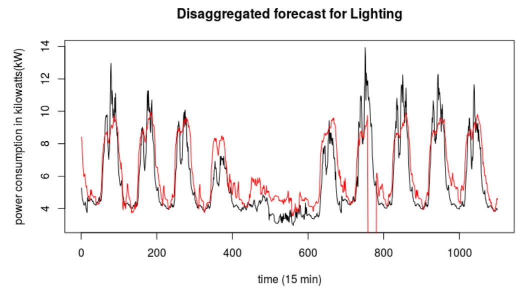

Figure 2: Disaggregated forecast for Lighting

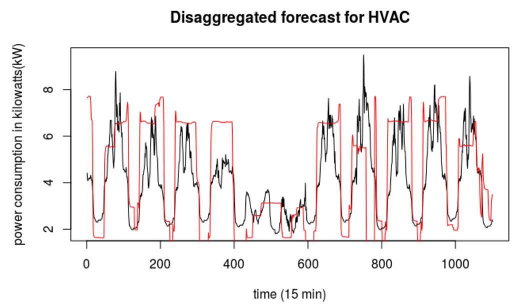

Figure 3: Disaggregated forecast for HVAC

5. CONCLUSION

The proposed two-staged disaggregated forecasting supported by reasonably accurate results, suggests that one can arrive at useful energy models for loads of interest in buildings with minimal number of sub meters, when coupled with other readily available information like occupancy and temperature. Additional information like size of the building, loads specific to the particular building might help in more accurate disaggregated forecasting.

6. REFERENCES

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