Optimal Operation of Smart Home Appliances using Deep Learning

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***Abstract*—This paper discusses an optimal operation of smart home appliances using deep learning. A yearly dataset was used to predict the day-ahead energy consumption pattern of household appliances. The preliminary findings indicate promising improvement in forecasting accuracies for smart home appliances. The forecasted result is integrated with Linear Programming based optimization model to make an appliance management system suitable for demand response. In addition, constraints for price, demand and equipment rating were used in the optimization model to generate the appliance schedule.**

Keywords*—*Deep Neural Network (DNN), Day-Ahead load forecast, Demand-Response, Appliance management, Linear Programming, AMPL

I. INTRODUCTION

The smart home system is envisioned to have more distributed renewable sources and smart appliances able to participate in demand response. An important difficulty faced by the current power generation and distribution system is the surge in energy demand during peak hours [1], [2]. Power system companies are forced to install additional generating units, just to support the peak energy demand. The power transmission infrastructure also presents an additional bottleneck to support the ever-increasing growth in power demand. One way to overcome this surge in demand during peak hours is to encourage consumers to operate their equipment during off peak hours [3]. With advent of smart appliances, the consumers can take the advantage of time-of-use pricing scheme to reduce their electricity cost.

The paper presents a DNN based predictive model to forecast the next day energy consumption at an appliance level from a one-year historical residential dataset. The forecasted consumption data along with the day-ahead energy price from MISO is used to model the smart home appliance management system. The concept of linear programming is used to do the optimization with the help of the AMPL (A Mathematical Programming Language) software.

II. DNN BASED DAY-AHEAD ENERGY FORECAST

It is significant to forecast a particularly household daily consumption in order to design and size suitable renewable energy systems and battery storage. In this work, we did a Short-Term Load Forecasting (STLF) of household equipment. It is a challenge to forecast the household energy consumption in an appliance level because of its uncertainty [4]. Despite the uncertainty associated with household electric power consumption, we were able to forecast the energy consumption with a significant accuracy using DNN.

A. Designing Deep Neural Networks

Selecting an appropriate design of deep neural network is the first step of DNN-based forecasting system. In the current studies, the network architecture was built based on multilayer perceptron (MLP), full-connected, which is a feed-forward type of neural network, and the training task was performed through a backpropagation learning algorithm [6].

B. Backpropagation learning algorithms

The backpropagation learning algorithms, most commonly used in feed-forward DNN, are based on steepest-descent methods that perform stochastic gradient descent on the error surface. Backpropagation is typically applied to multiple layers of neurons and works by calculating the overall error rate of an artificial neural network. The output layer is then analyzed to see the contribution of each of the neurons to that error. The neurons weights and threshold values are then adjusted, according to how much each neuron contributed to the error, to minimize the error in the next iteration.

C. DNN energy Forecasting Models

The neural network model of this work is developed using the TensorFlow deep learning platform. TensorFlow is an open source software library for numerical computation using data flow graphs. The nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) communicating between the nodes. The flexible architecture of TensorFlow allows one to deploy computations to one or more Central or Graphical Processing Units (CPUs or GPUs) on a desktop, server, or mobile device with a single Application Process Interface (API). TensorFlow was originally developed by researchers and engineers working on the Google Brain Team within Google's Machine Intelligence research organization for the purposes of conducting machine learning and deep neural networks research. However, the TensorFlow system is general enough to be applicable to other domains as well [5]. The structure of load forecasting model of DNN is given below.

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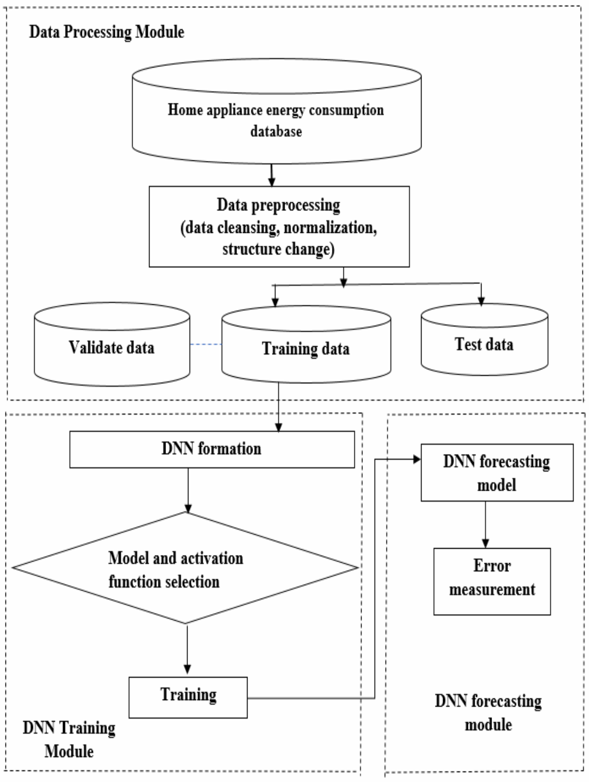

Figure 1: DNN energy Forecasting Models [6]

One-year smart home appliance data with one minute resolution is used to predict the next day. The previous load consumption of different appliance along with weather data was used to train our neural network model. In this work, an ADAM optimizer inside TensorFlow framework is used to train our model. It uses gradient descent algorithm. This method is faster in convergence than Stochastic Gradient Descent (SGD) approach [7]. The simulation settings and parameters used are listed in Table 1.

Table 1. Simulated TensorFlow Parameters

Parameters	***Values***
Total number of samples	236970
Training samples	235530
Validation samples	1440
Shape of training input data set	(235530, 11)
Shape of training target data set	(235530, 1)
Shape of validation input data set	(1440, 11)
Shape of validation target data set	(1440, 1)
epochs	100
Learning rate	0.001
mini_batch_size	100
Activation function	Linear
Number of hidden layer	3
Learning rate	0.001
Training epochs	500000

D. Dataset

The size of dataset impacts the accuracy, training, and transfer of learning within the deep neural network [6]. In this work, we used 1 year 1 minute resolution data of UMass Smart Home Data Set. In this dataset contains data for 114 single-family apartments for the period 2014-2016. This data set includes a variety of traces from three separate smart homes [8]. In our work, we used single smart home data of 2016 to predict next day different home appliance energy consumption.

E. Error Metrics for Evaluation:

Mean absolute percentage error (MAPE) is used to assess the accuracy of the forecasting models. It is commonly used metric for the accuracy evaluation [6].

$$MAPE = \frac{1}{T}\sum_{t=1}^{t=T}\frac{A_T - F_T}{A_T}\times 100\% \qquad (1)$$

where,

F_T = Forecasted load

A_T = Actual load and

T = Test set size

F. Forecasting Evaluation of different home appliance

The one day ahead predicted energy usage of different home appliance is given below (figs 2 to 10).

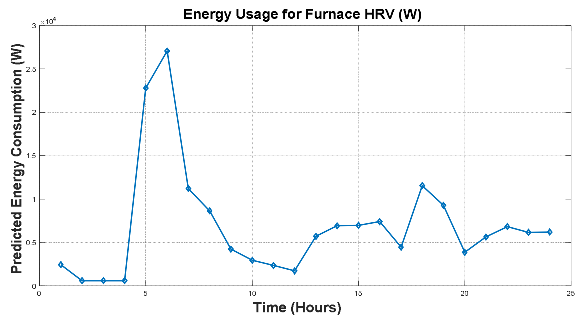

Figure 2: Predicted day ahead energy usage for Furnace HRV

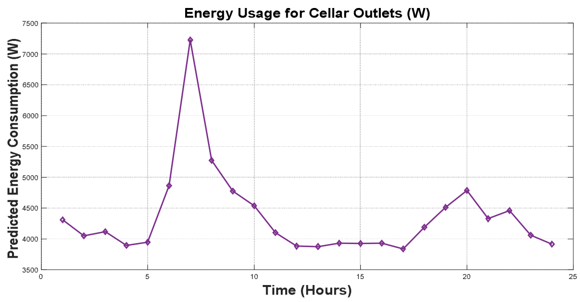

Figure 4: Predicted day ahead energy usage for Cellar Outlets

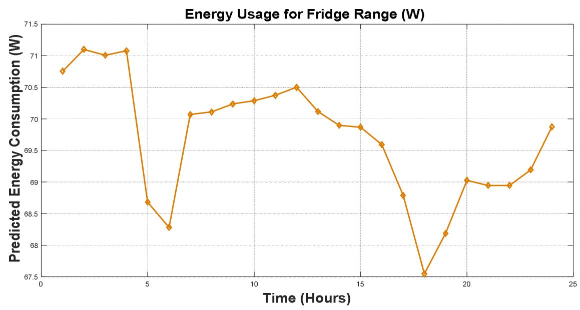

Figure 5: Predicted day ahead energy usage for Fridge Range

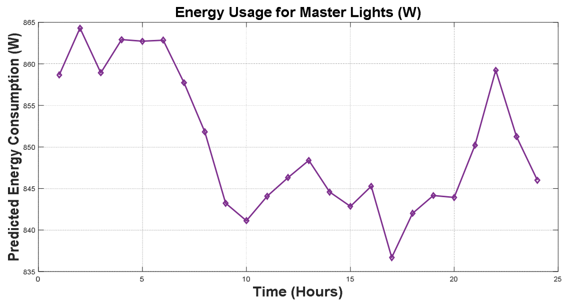

Figure 6: Predicted day ahead energy usage for Master Lights

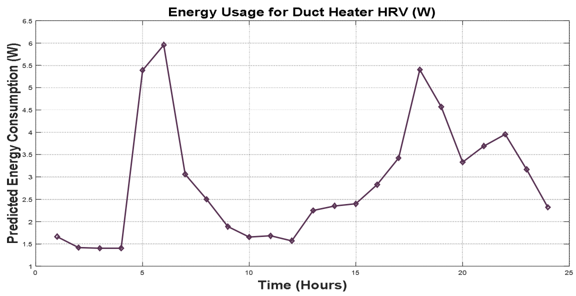

Figure 7: Predicted day ahead energy usage for Duct Heater HRV

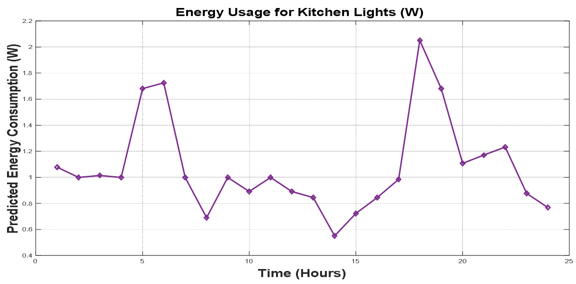

Figure 8: Predicted day ahead energy usage for Kitchen Lights

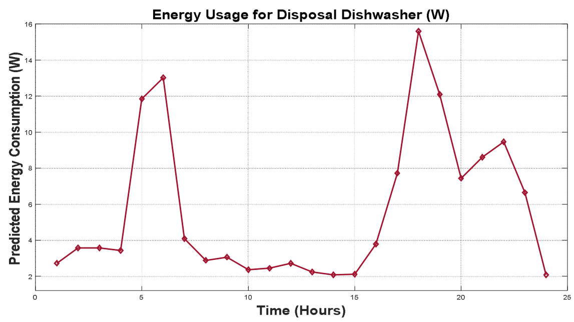

Figure 9: Predicted day ahead energy usage for Disposal Dishwasher

Table 2: MAPE evaluations for smart appliances

Sr. no	***Appliance***	***MAPE value (%)***
AP1	Furnace HRV	1.575
AP2	Cellar Outlets	3.23
AP3	Fridge Range	5.24
AP4	Master Lights	0.509
AP5	Bedroom Outlets	1.7359
AP6	Duct Heater HRV	10.8561
AP7	Bedroom Lights	1.7359
AP8	Kitchen Lights	2.23
AP9	Disposal Dishwasher	3.2

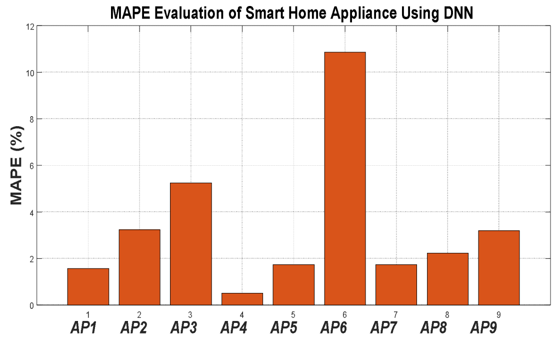

Figure 10: MAPE comparison of different smart home appliance

Table 2 and figure 10 shows the MAPE evaluation of different appliance. We got higher accuracy (MAPE of 0.509%) for master-lights (AP4) and lower accuracy (MAPE of 10.8561%) for Duct Heater (AP6). It can be explained by the actual energy consumption behavior of this appliance. Figure 6 and Figure 7 showing the daily energy usages for master light and duct heater. The pattern of energy consumption of master lights is easily understandable, in the morning and night energy consumption is high compared to other times on the day. Figure 11 and 12 shows the actual load consumption of master lights and Duct heater. It shows the Master lights have more continuous energy consumption pattern compared to Duct Heater.

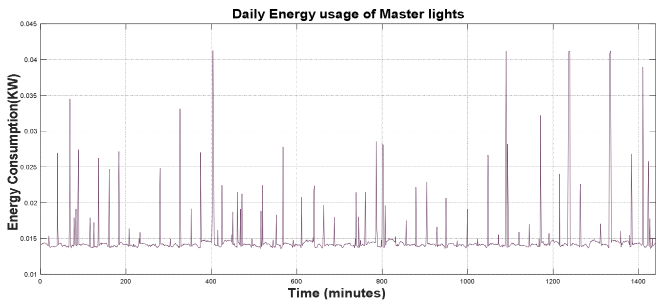

Figure 11: Predicted day ahead energy usage for Master lights.

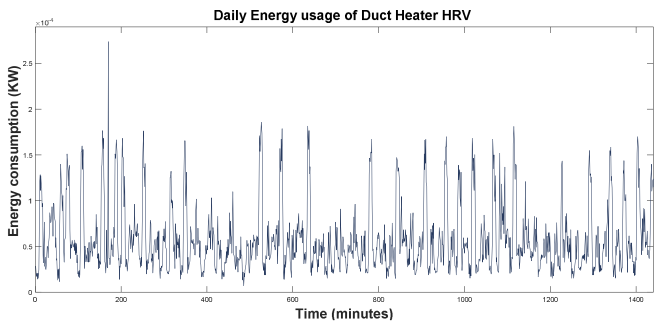

Figure 12: Predicted day ahead energy usage for Duct Heater HRV

III. RESIDENTIAL APPLIANCE SHEDULING

A. Smart Home Management System

The introduction of distributed energy sources has necessitated the need for improved metering and home management systems. The new generation residential appliances are becoming more smarter and energy efficient to reduce the energy cost and improve the convenience for the customer. There is a need for an appliance management system which considers consumer energy usage and preferences to schedule the household devices.

B. System Modeling

The objective of the proposed optimization model is to reduce the total electricity cost for a residential customer, as shown in equation 2. In this paper, cost is calculated on 24-hour period (e.g. USD per Wh). Here, C_j denote the day-ahead energy price in each time period, P_{ij} represents the energy used by appliance i in time period j, M represents the number of appliances and N represents the number of time-periods.

$$Min \sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij}C_j \qquad (2)$$

The optimization is performed subjected to several constraints [9]–[14]. They are listed below.

(1) Energy Constraint

This constraint makes sure that the scheduling process allocates the required energy requirements for all the appliances in a residential home.

$$\sum_{i=1}^{N} P_{ij} = E_i \qquad (3)$$

For each appliance i, the total allocated energy in all the time-period should meet the predicted electricity usage for each appliance.

(2) Power safety constraint

The allotted energy in each time-period for each appliance should not cross a power limit. Residential appliance would not be able to use more than the rated power of the appliance. If more power is allocated to the appliance, it won't be able to use more than its rated power and will result in not meeting the energy requirements for a day.

$$P_{ij} \le Rating[i] \qquad (4)$$

Rating[i], stands for the rated power of each appliance in the scheduling problem. The scheduled power allocated to an appliance in each time period should be less than the maximum power for the appliance.

(3) Production capacity constraint

The energy usage during peak hours creates a challenge for power companies to generate and transmit the required power. An important requirement of bringing forth the demand-response and time-of-use pricing scheme is to reduce the peak energy usage. This constraint prevents the allocation of all the appliance to the lowest price time slot. If all the house hold appliances are scheduled to the same time, it can create transmission constraints for the power companies.

$$\sum_{i=1}^{M} P_{ij} = K * \sum_{i=1}^{M} E_i \qquad (5)$$

Here, K percentage of total demand that can be scheduled in each hour. In this paper, the percentage was assumed to be 10%.

(4) Consumer Preference

The user preference for the scheduling of the appliances is also considered in this optimization model. The consumer can specify the preferred time of use each individual appliance. The optimization model will schedule appliances in the user preferred time-slots.

(5) Equipment Flexibility

All the consumer residential appliances won't be committed to do scheduling based on energy price. Consumers prefer some appliances to be keep running without interruption for their comfort. The residential appliance committed to the scheduling and those which are supposed to be run at customers preferred time can be achieved in this model.

C. Optimization Tool

AMPL is an algebraic modeling language to solve large scale optimization and scheduling problems. It was developed at Bell Laboratories by Robert Fourer, David Gay, and Brian Kernighan. The software supports several open-source and commercial solvers. The AMPL coding syntax is similar to mathematical notation of optimization problems, which helps developers to develop their model [15], [16].

Table 3. Residential day-ahead energy price ($/KWhr)

Hours	***Energy Price***	***Hours***	***Energy Price***
0	0.01976	12	0.03376
1	0.01828	13	0.02172
2	0.01595	14	0.02297
3	0.01545	15	0.02397
4	0.0151	16	0.02611
5	0.00778	17	0.03861
6	0.01488	18	0.03391
7	0.00725	19	0.02094
8	0.01823	20	0.01891
9	0.01655	21	0.01643
10	0.0234	22	0.01885
11	0.02247	23	0.0165

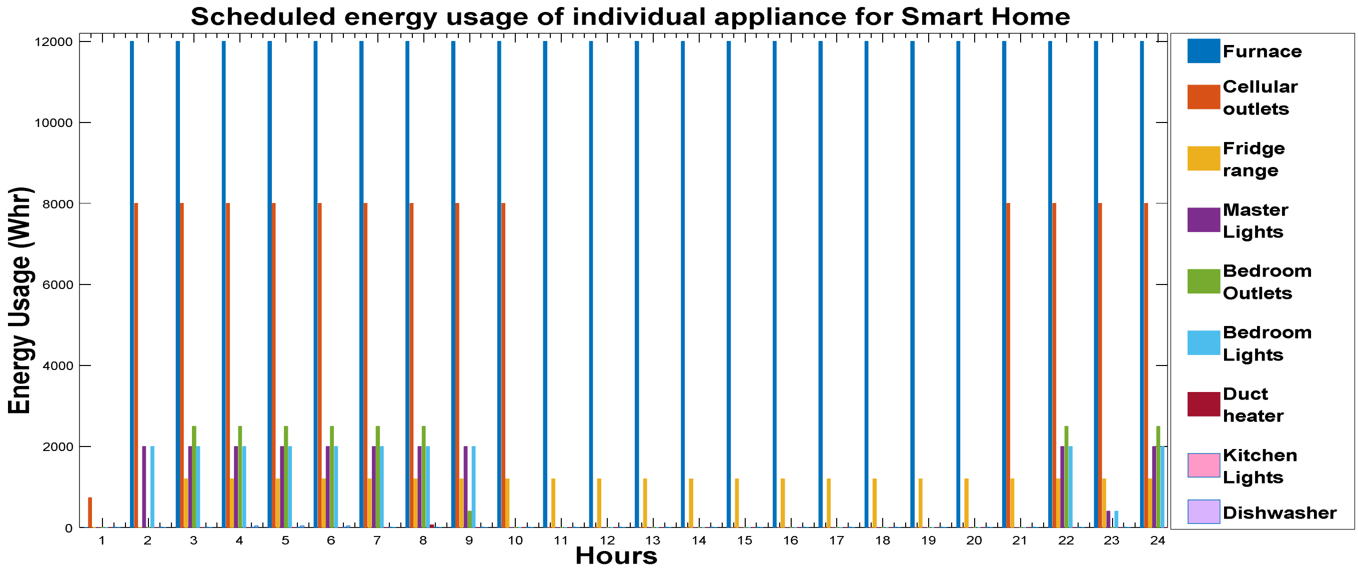

Figure 6: Scheduled energy usage of individual appliance for the residential customer

Table 4. Residential appliance rating and user preference

Equipment	*Rating*	*Flexibility*	*Preference*
Furnace	12000	0	1AM:11AM
Cellar Outlets	8000	1	12AM-12PM
Fridge Range	1200	0	2AM-11PM
Master Lights	2000	1	12AM-8AM 4PM-11PM
Bedroom Outlets	2500	1	12AM-8AM 4PM-11PM
Bedroom Lights	2000	1	12AM-8AM 4PM-11PM
Duct Heater	3000	1	3AM-8AM 10AM-4PM 6PM-8PM 10PM-11PM
Kitchen Lights	10	0	12AM-12PM
Dishwasher	45	1	12AM-5AM

The day-ahead energy price for the residential customer is shown in Table 3. The day-ahead energy price data for Minnesota hub region (MISO-Midwest Independent Transmission System Operator), was used as the residential energy price [17]. Table 4 lists the equipment rating, flexibility and preferred time of appliance usage. The scheduling model developed in this paper allows the consumer the flexibility to decide which appliances to commit for scheduling. If the flexibility parameter in the table is set to 0, the appliance will not be committed for scheduling and will be run at the costumer preferred timing without any interruption. The optimized appliance scheduling for the household appliances based on the consumer preferred timing and flexibility is shown in figure 6.

IV. Conclusion

A smart home management system to schedule the appliance for a residential customer is presented in this work. A deep learning based approach was investigated to predict the daily energy usage pattern of smart home appliances. A linear programming based optimization model was used to develop a scheduling scheme based on day-ahead energy price. Residential customers will be able to achieve savings in energy bills by the deployment this scheduling scheme. A large scale application of LP based scheduling model will help the utilities to reduce the peak load and transmission constraints in the grid.

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