A Smart Home Demand Response System based on Artificial Neural Networks Augmented with Constraint Satisfaction Heuristic

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***Abstract*—Distributing the peak load and alleviating grid stress by considering hourly electricity prices are some of the main research problems for current smart grid systems. This paper deals with the scheduling problem of home appliances' operating hours in smart grids, which aims to achieve minimum cost in user-defined operation intervals. To this end, scheduling via Artificial Neural Networks Augmented with Constraint Satisfaction Heuristic (ANN-AH) method that emulates the operation of the optimization for smart home demand response is developed. Our results show that a home demand response via ANN-AH achieves close to optimal performance with 10 times lower execution time than the optimal scheduling. These results suggest that the ANN-AH based demand response is highly successful and practical, and it is promising for future applications in micro-grid and decentralized renewable energy systems.**

***Index Terms*—demand response, optimization, artificial neural network, scheduling**

I. Introduction

Smart Grids are networks that provide sustainable, economical and secure electricity distribution. These networks provide bidirectional information transfer and immediately intervene in the system [1]. Due to the rapid increase in electricity consumption, it is expected that the current electricity networks will be inadequate over time [2]. Thus, in order to meet this increasing energy demand, smart grids will be used. In the current literature, there are several ways to develop smart grids one of which, the most used, is demand response system [3].

A demand response system aims to distribute the energy consumption over time so that the consumption curve in the peak hours will be flattened [4]. In this way, energy is consumed at the most affordable cost within the capacity of the system resources.

In general, demand response is categorized as time-based and incentive-based. Consumers are offered time-variant pricing policy under the time-based demand response, while the policy of incentive-based demand response is to regulate the load at times of intense demand by offering customers different incentives for payments [5]. The consumers for both of these categories can be commercial, industrial, and residential users, where the demand response system is mostly used by residential customers which are more sensitive to the price of electricity [6].

In this paper, we propose a smart home demand response based on a novel methodology, called Artificial Neural Networks Augmented with Constraint Satisfaction Heuristic (ANN-AH). The ANN-AH is the combination of Artificial Neural Network (ANN) and an heuristic algorithm. While it emulates the optimal scheduling via ANN, the computations of ANN revised to satisfy scheduling constraint via the heuristic algorithm. The usage ANN-AH for demand response has the following advantages: 1) It achieves close-to-optimal schedule with significantly smaller computation time than the optimal scheduling. 2) It is highly robust against the rapid changes in the electricity prices, which may be occurred due to some abnormal activities. 3) It may be easily used with minor addition when a new appliance is added to the network; so, its scalability is significantly high.

For demand response systems, a group of past works [7]–[14] provided optimal scheduling approaches. Another group of works [15]–[17] used machine learning techniques in demand response to predict electricity prices, weather conditions, energy consumption or its significance. Furthermore, a recent trend of research develops machine learning based scheduling methods for demand response, e.g. by using reinforcement learning [18], [19], ANN [8], and ANN with genetic algorithms [20]. Although the recent research trend considers the integration of scheduling and machine learning techniques, according to the best of authors' knowledge there is no work that directly emulates the optimal scheduling of appliances for demand response.

The remainder of this paper is organized as follows: Section II describes the optimization problem for scheduling the use of appliances in a residential demand response system. Section III proposes our novel ANN-AH scheduling algorithm that mimics the optimization process, taking into account constraints. Section IV presents performance evaluation of a smart home demand response system based on ANN-AH. Finally, Section V summarizes the paper.

II. Optimization Problem

We now briefly define the optimization problem of non-preemptive scheduling[1] the working hours of appliances in order to distribute the energy consumption over time prioritizing "inexpensive" hours. To this end, first, let P_t denote the predicted value of price in cents per watt for time $t \in \{1, \ldots, T\}$ and E_n denote the energy consumption in watts of appliance $n \in \{1, \ldots, N\}$ per an active hour. Moreover, we assume that an appliance n should stay active without an interruption for a_n hours.

Furthermore, to create optimization program, we let $x^*_{(n,t)}$ denote a binary decision variable on the activity of appliance n at time t, and Θ be the upper limit for the total energy consumption in one hour. Accordingly, the optimization program is defined as

$$min \sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{t'=t}^{t+a_n-1} P_{t'}E_n x^*_{(n,t)} \tag{1}$$

subject to

$$\sum_{t=1}^{T} x^*_{(n,t)} = 1, \qquad \forall n \in \{1, \ldots, N\} \tag{2}$$

$$\sum_{n=1}^{N}\sum_{t'=t}^{t+a_n-1} E_n x^*_{(n,t')} \leq \Theta, \qquad \forall t \in \{1, \ldots, T\} \tag{3}$$

$$\sum_{t=r_n}^{d_n} x^*_{(n,t)} = 1, \qquad \forall n \in \{1, \ldots, N\} \tag{4}$$

In this optimization program, (1) minimizes the total cost of the consumed power over all appliances over all time considering the constraints (2), (3) and (4). Note that the objective function (1) is equivalent to the cost that has been proposed in Reference [21]; however, we have originally defined constraints (2), (3) and (4). Constraint (2) ensures that the start of each appliance n is scheduled at only a single time. Constraint (3) limits the total energy consumption of the active appliances to Θ for each time t. Constraint (4) says that each appliance n can only be active between its earliest start time r_n and its latest start time d_n.

III. Artificial Neural Networks Augmented with Constraint Satisfaction Heuristic (ANN-AH)

Since the optimization program has high computational complexity and low generalization ability, we now present a methodology, called Artificial Neural Networks Augmented with Constraint Satisfaction Heuristic (ANN-AH), that emulates the optimization program to generate a schedule with close-to-optimal performance.

The ANN-AH system, which is shown in Fig. 1, is comprised of two main subsystems as Block of ANNs and Constraint Satisfaction Heuristic. Mainly, while Block of ANNs emulates the optimal scheduling based on the forecast electricity price, Constraint Satisfaction Heuristic satisfies the constraints on the emulated scheduling.

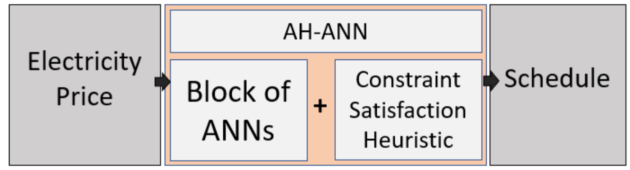

Fig. 1. Block diagram of ANN-AH for execution

The Block of ANNs is comprised of N parallel ANNs each of which is associated with each appliance n and computes a schedule $\{x_{(n,t)}\}_{t\in\{1,\ldots,T\}}$ for appliance n over a window with length T based on the forecast electricity prices for that window. Note that we assign a single ANN to each appliance because the methodology is intended to be scalable for adding new devices. That is, when a new device is installed in the smart home environment, a new ANN can be trained separately and added to the ANN Block without changing the existing ANNs in this block.

We let $\mathbf{X}$ denote the schedule matrix which is the output of Block of ANNs that combines the schedules for individual appliances, where (n, t) entry of matrix $\mathbf{X}$ equals $x_{(n,t)}$. One should note that $\mathbf{X}$ does not necessarily satisfy the constraints (2), (3) and (4). Thus, the Constraint Satisfaction Heuristic in Fig. 1 revise $\mathbf{X}$ in post-process to satisfy these constraints.

In the remainder of this section, we first present how the optimization program for scheduling is emulated via ANN. Then, we present Constraint Satisfaction Heuristic which is executed on the output of ANN to satisfy the constraints of scheduling.

A. Artificial Neural Network based Emulation of Optimal Scheduling

In order to emulate the optimization we propose the training procedure which is shown in Fig. 2. As shown in this figure, the optimal schedule matrix, denoted by $\mathbf{X}^*$, is considered as a ground truth for the output $\mathbf{X}$ of Block of ANNs during the training of Block of ANNs, where (n, t) entry of $\mathbf{X}^*$ equals $x^*_{(n,t)}$.

Based on $\mathbf{X}^*$ and $\mathbf{X}$, the scheduling error is calculated as categorical cross entropy which is denoted by vector $\mathbf{e}$ whose n-th entry is the error for appliance n.

ANN for each appliance n, namely ANN$_n$, is separately trained to minimize the corresponding scheduling error which is the n-th entry of $\mathbf{e}$, via Adam optimization algorithm [22]. To this end, before training starts 1) The electricity prices are forecast[2] hourly; and 2) The optimization program in (1)-(4) is solved to collect $\mathbf{X}^*$.

B. Constraint Satisfaction Heuristic

Although the emulation of optimization is practical with respect to real-time operational costs and robust against the

[1]Since we assume that the operation of each appliance is uninterruptible, we use non-preemptive scheduling.

[2]Note that within the scope of this paper, we assume that the hourly forecast of electricity prices are available, so we do not perform forecasting.

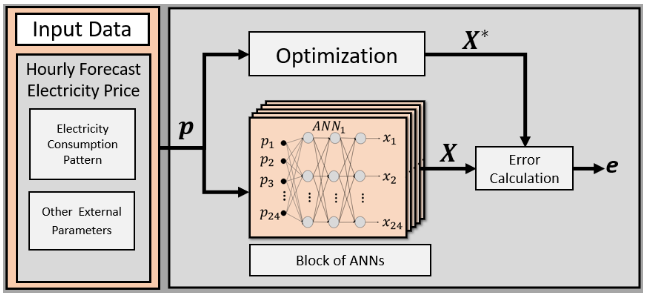

Fig. 2. Design architecture block diagram

changes in the forecast prices as well as the forecasting errors, the Block of ANNs itself is not able to satisfy the scheduling constraints. Thus, we propose a heuristic post-processing algorithm that minimally revise the emulated schedule to be sure the final schedule satisfies the constraints (2), (3) and (4). We present the pseudo-code of this algorithm, called *ConstraintSatisfactionHeuristic*, in Fig. 3.

schedule **ConstraintSatisfactionHeuristic**($\mathbf{X}$, Θ) {
1 $\mathbf{E}$ = ComputeTotalConsumption($\mathbf{X}$);
2 for($t = 1;\ t \leq T;\ t++$){
3 while($\mathbf{E}(t) > \Theta$){
4 $\Phi = \mathbf{E}(t) - \Theta$;
5 $n^* = argmin(\langle E_n \rangle_{\{n | E_n \geq \Phi \text{ and } \sum_{t'=t-a_n+1}^{t} \mathbf{X}(n,t')==1\}} - \Phi)$;
6 $\mathbf{X}(n^*, t') = 0 \quad \forall t'$;
7 $\mathbf{E}$ = ComputeTotalConsumption($\mathbf{X}$);
8 $\mathcal{T}^{n^*}_{\text{available}} = \{t \ | \ r_{n^*} \leq t \leq d_{n^*}$ and $(\mathbf{E}(t') + E_{n^*} \leq \Theta)_{\forall t' \in \{t, \ldots, t+a_{n^*}\}}\}$;
9 $t^* = argmin(\langle P_t \rangle_{t \in \mathcal{T}^{n^*}_{\text{available}}})$;
10 $\mathbf{X}(n^*, t^*) = 1$;
11 $\mathbf{E}$ = ComputeTotalConsumption($\mathbf{X}$);
12 }
13 }
14 return $\mathbf{X}$;

Fig. 3. The Heuristic Algorithm

As shown in Fig. 3, the inputs of the *ConstraintSatisfactionHeuristic* algorithm are $\mathbf{X}$ and Θ. In addition to these inputs, we assume that $\{r_n\}_{n \in \{1,\ldots,N\}}$, $\{d_n\}_{n \in \{1,\ldots,N\}}$, $\{E_n\}_{n \in \{1,\ldots,N\}}$, and $\{P_t\}_{t \in \{1,\ldots,T\}}$ are globally available parameters.

The algorithm first computes the total consumption at each time t via *ComputeTotalConsumption* function which returns the consumption as a vector of time on Line 1. This function computes the consumption as

$$\mathbf{E} = \langle \sum_{n=1}^{N} E_n \delta_{\sum_{t'=t-a_n+1}^{t} \mathbf{X}(n,t')==1} \rangle_{t \in \{1,\ldots,T\}} \tag{5}$$

The main loop of the algorithm works over time between Line 2 and Line 13. For each time t, until the hourly energy consumption constraint in (3) is satisfied (i.e. as long as the total energy consumption of the appliances that are scheduled at t by the ANN module is greater than a threshold Θ), Lines 4-11 of the algorithm are executed. On Line 4, the difference Φ between the total consumed energy at t and Θ is calculated. On Line 5, the algorithm finds the appliance n^* which is operating between $t - a_n + 1$ and t and whose hourly energy consumption is the closest as well as greater than or equal to the value of Φ. On Line 6, the schedule for appliance n^* is cleaned, and on Line 7, $\mathbf{E}$ is computed for resulting schedule.

On line 8, a set of available time slots $\mathcal{T}^{n^*}_{\text{available}}$ that may be scheduled for the start of operation of appliance n^* is computed. Each of these slots must satisfy two conditions: 1) It should fall between the ready time r_{n^*} and deadline d_{n^*} of appliance n^*, so constraint (4) will be satisfied. 2) If the time slot is used, the total energy consumption at this slot and each of the following a_{n^*} slots must not exceed Θ, so constraint (3) will be satisfied.

On Line 9, to schedule the start of n^*, the algorithm selects the time slot t^* which has the minimum energy consumption cost among the slots in $\mathcal{T}^{n^*}_{\text{available}}$. On Line 10, the start of appliance n^* is scheduled at t^*. Finally, on Line 11, $\mathbf{E}$ is computed for resulting schedule.

IV. Results

A. Dataset

During the performance evaluation of ANN-AH, we use electricity prices dataset for Portland, Concord and Hub from the data shared by ISO New England [23]. We use the hub data collected in 2020 for testing and the rest for training. In detail, 365 of 7665 samples is used for testing while 730 of the reaming samples are used for validation during the training of ANN. We also converted data from $/MWh to cents/Wh and normalized it between 0-1 by dividing the original values to their maximum.

Furthermore, we consider a smart home with 5 appliances, dishwasher, Washing Machine, computer, Vacuum Cleaner and LCD TV. For each of these appliances, we select an set of feature by considering a real-life use case where the resulting set of features are presented in Table I. We also set $\Theta = 2000W$.

TABLE I
Features of Appliances

Name	**Power** (E_n)	**Start Time** (r_n)	**Deadline** (d_n)	**Active Duration** (a_n)
Dishwasher	400	06:00	20:00	2
Washing Machine	510	09:00	21:00	2
Computer	90	01:00	21:00	4
Vacuum Cleaner	2000	10:00	19:00	1
LCD TV	98	18:00	21:00	3

B. Design and Parameters of ANN

We use Multi-Layer Perceptron (MLP) for each ANN in Block of ANNs in the design of ANN-AH. The MLP model is comprised of two hidden layers and an output layer with 128, 48 and 24 neurons respectively. In addition, the activation function of each neuron is set to ReLU for each hidden layer and to Softmax for the output layer. This model is implemented by using Keras API in Python.

C. Experimental Results

We now evaluate the performance of ANN-AH for the presented use case of smart home energy management. To this end, the optimization program given in (1)-(4) solved by CPLEX solver through using the docplex library on Python. In this way, we computed the optimal schedule which is used for the comparison during this subsection. Furthermore, we created a benchmark random schedule in which the operation of appliance n is started at random time from uniform distribution between r_n and d_n and continued for a_n successive hours.

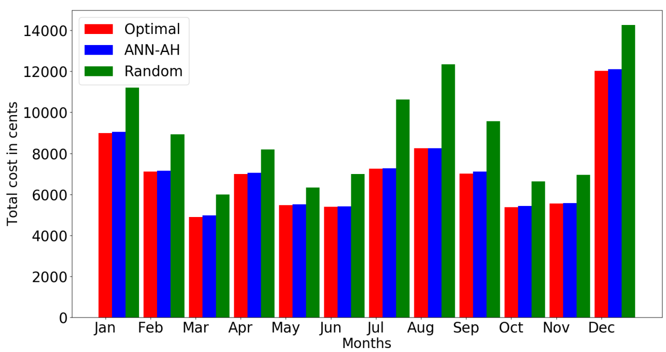

Fig. 4. Monthly Electricity Cost

First, Fig. 4 presents comparison of total monthly cost of the considered smart home under ANN-AH with that under optimal schedule and a schedule that is generated randomly. In this figure, we see that the cost under ANN-AH is very close to the cost under the optimal schedule for all months,where the percentage cost difference is between 0.16% and 1.4%. In addition, ANN-AH achieves considerable lower cost than a random schedule which might emulate the usage of an human-user. The cost reduction provided by ANN-AH over random scheduling is between 13% and 33%.

Next, in Fig. 5, we present the histogram of the absolute time differences between the schedule of ANN-AH and optimal schedule over all appliances and all test cases. Our results in this figure show that the absolute time difference equals zero for the majority of cases while the occurrence of at least 1 hour difference is less than 200 which is 9.97% of the total cases. In addition, the occurrence decreases with increasing absolute time difference. One may indicate from the results in this figure that the schedule of ANN-AH is significantly matches with optimal schedule.

Moreover, Table II presents the difference between the optimal scheduling and ANN-AH in absolute time for each appliance. The results in this table show that the schedule of LCD TV created by ANN-AH is almost the same with that created by optimization because the time interval that LCD TV can operate is only 1 hours greater than the required active

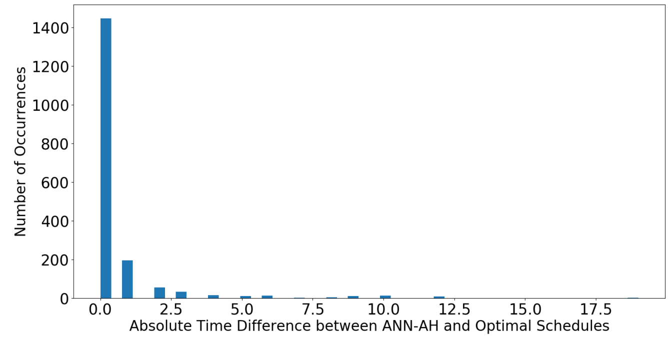

Fig. 5. Error distribution for all appliances

duration (see Table I) so the schedule of this appliance can be changed for only 1 hour. The average difference between schedule of ANN-AH and optimal schedule is about half hour for Dishwasher, Vacuum Cleaner and Computer while it is about 1.5 hours for Washing Machine. In addition, the standard deviations are between 0.16 and 2.76 hours.

TABLE II
MEAN AND STANDARD DEVIATIONS OF ERRORS FOR EACH APPLIANCE

Name of appliances	Mean (hours)	Standard Deviation (hours)
Dishwasher	0.463	1.501
Washing Machine	1.457	2.762
Computer	0.652	2.633
Vacuum Cleaner	0.553	1.292
LCD TV	0.008	0.156

Finally, we present the comparison of ANN-AH and optimal scheduling with respect to execution time in Table III. Note that simulation and numerical studies held on this study are carried out on a HP laptop with an Intel Core i7 2.80 GHz CPU and 16GB RAM. In addition, for each method, the mean and standard deviation are computed over 20 runs.

TABLE III
MEAN AND STANDARD DEVIATION OF EXECUTION TIME FOR EACH OF ANN-AH AND OPTIMIZATION (SECS)

	Optimization	Heuristic
Mean	1.465	0.146
Standard Deviation	0.900	0.037

In this table, for a smart home with 5 appliances for a single day, we see that ANN-AH computes a feasible and close-to-optimal schedule in only 0.146 secs on average while the optimization takes 1.465 secs to compute a schedule. That is, the execution time difference between ANN-AH and optimization is measured as 1 order of magnitude. We also see that the standard deviation of ANN-AH is significantly lower than that of optimization.

Our results that have been presented in this section indicate that ANN-AH achieves very low total monthly cost which is close to the cost of optimal scheduling while offering a fast, practical and robust schedule that also satisfies the considered constraints.

V. Conclusion

Demand response that aims to distribute the peak load and relieve the system operators is crucial enabler of the energy management in smart home. In a smart home demand response, scheduling the operation times of connected appliances is one of the main challenges. To this end, in this paper, we propose a novel methodology ANN-AH that computes the scheduling via ANN while satisfying the considered constraints.

The proposed methodology in this paper provides the following advantages over using optimal scheduling: 1) ANN-AH is able to achieve close-to-optimal schedule while it only requires 10 times lower computation time than the optimal scheduling. 2) ANN-AH is highly robust against the changes in the variables such as forecast of electricity prices which may be due to forecasting error or abnormal activities in the system. 3) ANN-AH can easily be used while new appliances are being added to the operating system, while training is only required for the recently added appliances.

Furthermore, we extensively evaluated the performance of ANN-AH for home demand response system with 5 appliances using the publicly-available electricity prices dataset. Our results have shown that ANN-AH achieves significantly low operating cost while achieving close-to-optimal schedule under sub-second computation time.

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