A Neural Network-based Appliance Scheduling Methodology for Smart Homes and Buildings with Multiple Power Sources

Raj Mani Shukla*, Prasanna Kansakar† and Arslan Munir‡
Parallel and Distributed Computing and Embedded Systems Laboratory
Department of Computer Science and Engineering
University of Nevada, Reno
Email: *rshukla@unr.edu, †pkansakar@nevada.unr.edu, ‡arslan@unr.edu

***Abstract*—The increased production of electrical energy from various power sources, such as solar, wind, and nuclear, allows smart buildings to be connected with multiple power sources. In an effort to conserve environment, electrical energy usage is gradually shifting towards renewable and green energy sources, such as wind, hydro, and solar. Regardless of power sources, a user demands for continuous energy supply and also desires to minimize the electricity bill. Further, in a dynamic pricing environment, the price of electricity varies throughout the day. In such a dynamic pricing environment, appliance scheduling with multiple power sources tied to a smart home/building is an important research problem. In this paper, we propose a methodology to abet green environment by prioritizing green energy sources and to minimize the electricity cost for the user. Our proposed methodology leverages a smart grid architecture which employs a greedy strategy to select the most feasible power source amongst the available power sources tied to a smart home/building. Our proposed methodology further leverages a neural network-based approach for appliance scheduling that optimizes the use of power sources in a dynamic pricing environment to minimize the total cost of electricity usage.**

***Keywords*-Smart grid, renewable and non-renewable energy sources, appliance scheduling, Boltzmann machine**

I. Introduction and Motivation

Electricity generation which has largely been dependent on non-renewable and non-green energy sources, such as coal and oil, is slowly transitioning to renewable and green energy sources, such as wind, solar, and nuclear. With the recent push towards adopting sustainable green energy policies in many parts of the world, the study of renewable and green energy sources for electricity generation, and, smart electricity utilization has gained much interest. Consequently, the reliance on non-renewable and non-green energy sources is slowly decreasing with the increasing proliferation of renewable and green energy sources.

There are, however, several challenges that need to be addressed when using green energy sources for electricity generation. Perennial green energy sources, such as solar and wind, are not stable energy sources as the electricity generation from these sources fluctuates based on weather conditions, such as rain, air pressure, and temperature, etc. Other forms of green energy sources, such as nuclear power, have high implementation, operation and maintenance costs. Hence, in order to maintain a smooth supply of electricity using renewable green energy sources, it is necessary to find a balance between cost and availability. Because of these challenges, traditional non-renewable and non-green sources like coal and diesel are still used as major energy sources for electricity generation in most parts of the world.

The transition to renewable and green energy sources for electricity generation also requires study of electricity consumption patterns. For example, if the electricity demand during peak hours exceeds the electricity generation by renewable and green energy sources, then, traditional non-renewable and non-green energy sources must be used to meet demand. The objective is to decrease the reliance on traditional energy sources by spreading out electricity demand in such a way that the demand is mostly satisfied by renewable and green electricity generation.

To consider the effects of electricity consumption pattern on electricity generation, it is imperative to study household sector as it is the major consumer of electric power. The push towards sustainable renewable and green energy for electricity generation is assisted if the electricity consumption pattern of households is regulated. As more and more homes are equipped with smart devices and appliances that are automated or centrally controlled, monitoring, collection, and maintenance of usage statistics become possible. These statistics can be leveraged to determine a schedule for device and appliance usage such that the maximum electricity demand remains below a threshold that can be satisfied by renewable and green electricity generation.

The use of smart home technology not only assists the transition towards renewable and green energy, but also decreases the average energy expenditure of households. The price of electricity generation fluctuates based on the prices of non-renewable as well as renewable energy sources. Given an estimate of non-renewable and renewable energy prices, a smart home/building can schedule device and appliance usage such that the electricity bill of a household is minimized.

In this paper, we propose a smart-grid architecture which leverages our proposed scheduling scheme for energy usage by devices and appliances in a smart home or building that strongly favors renewable green energy sources for electricity generation while minimizing the electricity generation costs. The smart grid communicates with a smart scheduler which is implemented on the consumer-side/demand-side and responds to the fluctuating price of energy sources by modifying the electricity consumption pattern of the smart home or building. Our proposed smart grid economizes electricity bills by implementing a *demand side management (DSM)* model. The implemented DSM model regulates electricity usage patterns by adapting the *demand response (DR)* to dynamic pricing change of energy sources.

Our main contributions in this paper are as follows:

- We propose a smart grid architecture for the scenario where multiple power sources are connected to a smart home/building.
- We propose a greedy algorithm to order different energy sources based on their estimated price forecasts with strong priority given to renewable energy sources.
- We propose a neural network-based optimization scheduler that generates an optimal schedule for devices and appliances using the order of energy sources determined by the greedy algorithm.

The remainder of this paper is organized as follows. Section II summarizes related work. Section III describes the algorithms used in our proposed appliance scheduling methodology. Section IV presents the results obtained from our methodology and Section V concludes this study.

II. Related Work

Electrical appliance scheduling for smart homes and buildings has been extensively studied and several innovative articles using analytical models, algorithms and optimization techniques are available in literature [1] [2].

Vardakas et al. [3] proposed analytical models for appliance scheduling in smart homes using online and offline implementation methods. The offline implementation method used historical data or prediction models to extract electricity consumption pattern of households whereas the online implementation method monitored ongoing/current electricity consumption to determine electricity consumption pattern. They found that offline implementation presented a better estimate of electricity consumption pattern than online implementation. They also noted that the use of a scheduling method whether offline or online significantly decreased the total average cost as compared to not using any scheduling method.

Historical energy consumption data [4] was also employed by Adika et al. [5]. In their implementation, historical data was translated into hourly appliance time usage probabilities which was then used to model customer's electricity demand pattern. Using these probability models, they defined a DSM model, which also considered fluctuating energy prices, to determine a suitable demand response. The authors noted that applying dynamic pricing on traditional consumers (i.e., the customers who do not have a scheduling method for demand response) increased their electricity bills. They observed that the flat rate tariff scheme was 6.7% cheaper than the dynamic pricing for traditional consumers. They also presented a comparison between households with demand response and traditional households under dynamic pricing. The results revealed that the households with demand response resulted in 10.92% savings in electricity bills.

Many innovative smart home appliance scheduling methods are also available which do not make use of historical data in order to determine electricity consumption pattern. These methods leverage user-defined appliance schedule as constraints for their scheduling algorithms. Some of these algorithms are *mixed integer linear programming (MILP)* [6], fuzzy goal programming [7] and stochastic scheduling [8]. Sou et al. [6] and Bu et al. [7] used similar approaches based on MILP formulation with discrete time-slots. Bu et al. [7] also incorporated fuzzy goal programming to their model which transformed user time preferences from rigid constraints to soft violation penalty objectives. Chen et al. [8] defined a stochastic scheduling algorithm using user defined appliance schedule. Their energy consumption scheduling scheme achieved up to 41% reduction in electricity bills when compared to the traditional appliance operation without scheduling. These user defined appliance schedule techniques, although more flexible, do not provide a good estimate of overall electricity consumption pattern.

In this paper, we leverage concepts similar to those used by Sou et al. [6] and Bu et al. [7]. However, in contrast to the aforementioned works, we propose a smart grid architecture which communicates with a smart scheduler in a home/building to select the appropriate energy source for a household while giving high priority to green energy sources, and then performs appliance scheduling to minimize electricity cost. We discretize the scheduling period into a prescribed number of uniform time-slots and employ a greedy algorithm to determine preferred energy sources for each time-slot. Our greedy approach uses historical data [9] to extract electricity consumption pattern of a common household. We use a Boltzmann machine neural network to minimize the cost of electricity consumption in our appliance schedule methodology.

III. Methodology

Our appliance scheduling methodology leverages a smart grid architecture and consists of two distinct phases: energy source determination and appliance scheduling using neural networks. Before describing the phases, we first discuss the proposed smart grid architecture.

A. Proposed Smart Grid Architecture

Figure 1 depicts our proposed smart grid architecture. We use this architecture as a model for describing our demand side management scheme. The architecture model consists of a central smart grid which supplies electricity generated from various green (wind, hydro and nuclear) and non-green (coal and diesel) energy sources to consumers. In addition, households may also have energy sources associated with them which is stored in a privately owned grid. There are

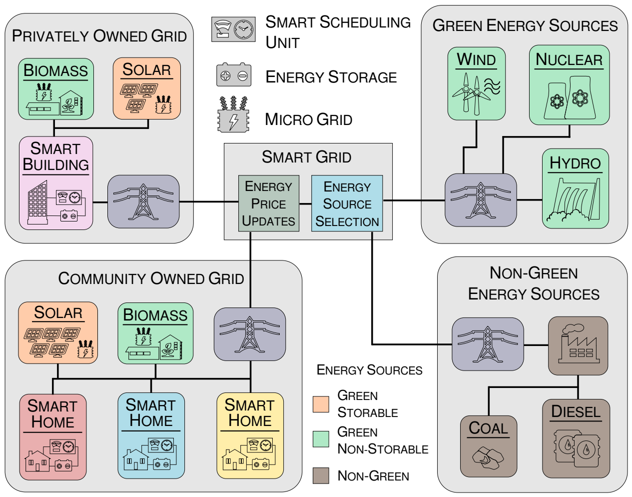

Fig. 1. Proposed smart grid architecture.

also community owned grids and energy produced from these grids is proportionally distributed according to household's electricity usage. We consider households to be the primary consumer of electrical energy in our model.

The smart grid maintains pricing and availability information for different energy sources used for electricity generation. This information is crucial to implement our proposed demand side management scheme. The smart grid communicates this information to smart scheduling units placed at every smart home/building connected to the smart grid. The smart scheduling units implement the scheduling algorithm used for demand side management.

The smart scheduling unit analyzes historical records of electrical device/appliance usage in a home/building to create electricity consumption profiles. The scheduling unit uses these records along with the pricing and availability information for different energy sources communicated by the smart grid in order to determine an optimal device/appliance schedule for the home/building.

Our proposed appliance scheduling methodology for the smart scheduling units prioritizes green energy sources for satisfying electricity demand. The methodology's primary objective is to determine an appliance schedule that decreases reliance on non-green energy sources for electricity generation while keeping consumer costs minimum. The proposed smart grid architecture model and appliance scheduling methodology thus benefits consumers as well as the environment.

B. Symbols

Our methodology separates appliances ($\mathcal{A}$) into two broad categories – schedulable (s) and non-schedulable (n). Energy sources ($\mathcal{S}$) are categorized into three types: green storable energy (G), green non-storable energy ($\mathcal{G}$), and non-green energy (N). We use η_A to denote the number of appliances of category $\mathcal{A}$ in a household. We denote an individual appliance – z^{th} appliance, of category $\mathcal{A}$ as $\mathcal{A}(z)$. We use $V_\mathcal{S}$ to represent the total amount of energy sources of type $\mathcal{S}$ available in the scheduling period.

We use historical electricity consumption data to extract electricity usage pattern. Let P be the total number of scheduling periods for which historical data is available. Each scheduling period is discretized into T number of uniform time-slots; t denotes the t^{th} time-slot of a scheduling period.

Let $e^t_\mathcal{A}$ be the electricity demand of all the appliances in category $\mathcal{A}$ in the t^{th} time-slot. $E_\mathcal{A}$ denotes a collection of electricity demands of all appliances in category $\mathcal{A}$ over one scheduling period and $E^P_\mathcal{A}$ denotes $E_\mathcal{A}$ collected over P scheduling periods. $r^t_\mathcal{S}$ denotes the amount of energy sources of type $\mathcal{S}$ allocated to the t^{th} time-slot and $R_\mathcal{S}$ is the collection of $r^t_\mathcal{S}$ allocated over a scheduling period. $c^t_\mathcal{S}$ represents the price of energy sources, $\mathcal{S}$, in different time-slots, t, over the scheduling period.

C. Methodology Phases

Phase I: Energy Source Determination: Algorithm 1 presents the steps involved in the first phase of our appliance scheduling methodology associated with the proposed smart grid architecture. This algorithm is used to assign energy sources to all T time-slots in a scheduling period. The algorithm uses historical data of electricity usage of all appliances in a time-slot t.

Once the electricity consumption pattern is available, the prices of non-green energy sources in each time-slot, c^t_N , is analyzed. This is done by sorting the price values c^t_N in descending order while preserving the index information for the time-slots in another array I. For example, if the 5^{th} time-slot has the highest price of non-green energy over the entire scheduling period then the 1^{st} value in the array I is 5.

For the time-slots having the highest price of non-green energy, energy sources are assigned from the available green storable energy, V_G. If we have more than one green storable energy source, then, preference is given to the one having lower cost. This is repeated till V_G is depleted to a certain threshold value Th.

For the time-slots whose electricity demand is not fulfilled by green storable energy, green non-storable and non-green energy sources are used. The choice between these two energy sources is made based on their price in the time-slot under consideration. If the price of green non-storable energy, $c^t_\mathcal{G}$ is lower than the price of non-green energy, c^t_N, in the t^{th} time-slot, then, the green non-storable energy is used to meet electricity demand of that time-slot otherwise the non-green energy is used. Here, it is assumed that the green stored energy source (G) assigned to each time-slot t is used for all non-schedulable appliances (n). Only for the schedulable appliances, green non-stored ($\mathcal{G}$) and non-green (N) sources are considered. Hence, our proposed appliance scheduling approach uses only green non-stored ($\mathcal{G}$) and non-green (N) sources.

Phase II: Appliance Scheduling using Boltzmann Machine Neural Network: The second phase of the methodology uses Boltzmann machine neural network for appliance scheduling. In this phase, we use a neural network model where neurons are arranged in a form of two-dimensional grid. The grid

Algorithm 1 Hourly energy source allocation using greedy strategy

Input: E_n^P - collection of electricity usage profiles of all appliances for all time-slots
V_G - total amount of green storable energy available in a scheduling period from different sources
$c_{\mathcal{S}}^t$ - price of energy sources $\mathcal{S}$ in different time-slots
Output: R_G - collection of green and storable energy source allocations in a scheduling period
$R_{\mathcal{G}}$ - collection of green and non-storable energy source allocations in a scheduling period
R_N - collection of non-green energy source allocations in a scheduling period

```
SortDecreasing(c_N^t, I)
k = 1
repeat
  if V_G ≥ μ(e_n^{I_k}) then
    r_G^{I_k} = μ(e_n^{I_k})
    V_G = V_G − μ(e_n^{I_k})
  end if
  k = k + 1
until V_G > Th or k = T
for t ← 1 to T do
  if r_G^t ≠ μ(e_n^t) then
    if c_𝒢^t < c_N^t then
      r_𝒢^t = μ(e_n^t)
    else
      r_N^t = μ(e_n^t)
    end if
  end if
end for
```

dimensions are the number of time-slots t^x in scheduling period, T, and the total number of schedulable devices in household, η_s. Each neuron in the grid has two types of connections: an input connection and weighted connections with all other neurons in the grid. Each neuron also has a binary state variable associated with it which represents whether the neuron is in ON state or OFF state. Let m_{uv} $\forall$ $u \in \{1, 2, \cdots, \eta_s\}$ and $\forall$ $v \in \{1, 2, \cdots, T\}$ represent each neuron in the two dimensional grid. i_{uv} is the input to the neuron m_{uv} which is given by $e_{s(u)} \cdot min[c_N^v, c_{\mathcal{G}}^v]$, where $e_{s(u)}$ is the energy demand of the u^{th} schedulable appliance and $min[c_N^v, c_{\mathcal{G}}^v]$ returns the smaller of the two values c_N^v and $c_{\mathcal{G}}^v$.

Let $w_{uv,xy}$ $\forall$ $u, x \in \{1, 2, \cdots, \eta_s\}$ and $\forall$ $v, y \in \{1, 2, \cdots, T\}$ be the weight of the connection between the neurons m_{uv} and m_{xy} in the neural network grid. The weight between neurons in each row, m_{uv} and m_{uy} with $v \neq y$, is A and between neurons in each column, m_{uv} and m_{xv} with $u \neq x$, is B. Here, A and B are large negative numbers which signify that each schedulable appliance is ON only once during the scheduling period and in each time-slot only one appliance is ON. We clarify that our methodology can be

Algorithm 2 Appliance scheduling using Boltzmann machine neural network

Input: $c_{\mathcal{S}}^t$ - price of energy sources $\mathcal{S}$ in different time-slots
e_s - energy demand of each individual schedulable appliance
Output: λ_{uv} - optimal schedule for appliance operation
$R_{\mathcal{G}}$ - collection of green and non-storable energy source allocations in a scheduling period
R_N - collection of non-green energy source allocations in a scheduling period

```
θ = 1
for u ← 1 to η_s do
  for v ← 1 to T do
    for x ← 1 to η_s do
      for y ← 1 to T do
        if u = x and v ≠ y then
          w_{uv,xy} = A
        else if v = y and u ≠ x then
          w_{uv,xy} = B
        else
          w_{uv,xy} = 0
        end if
      end for
    end for
    i_{uv} = e_{s(u)} · min[c_N^v, c_𝒢^v]
    λ_{uv} = 0
  end for
end for
repeat
  repeat
    Select a random neuron m_{xy}
    for u ← 1 to η_s do
      for v ← 1 to T do
        ξ = i_{uv} + Σ λ_{uv} · w_{uv,xy}
      end for
    end for
    P = 1 / (1 + e^{−ξ/θ})
    if ξ > τ then
      Switch state of m_{xy}
    else
      Switch state of m_{xy} with probability P
    end if
    ς = ς + 1
  until ς > ς_max
  θ = α · θ
until θ < θ_min
for u ← 1 to η_s do
  for v ← 1 to T do
    if λ_{uv} = 1 then
      if c_N^v < c_𝒢^v then
        r_N^v = e_{s(u)}
      else
        r_𝒢^v = e_{s(u)}
      end if
    end if
  end for
end for
```

TABLE I
ENERGY DEMAND OF EVERYDAY HOUSEHOLD APPLIANCES.

Appliance	Energy(kWh)
Dishwasher	0.50
Laundry	2.30
Oven	6.00
Water Heating	12.00
Sweep Pump	0.56

TABLE II
MINIMUM AND MAXIMUM PRICES OF ENERGY SOURCES.

Energy Source	Type	Min. Price ($\$/kWh$)	Max. Price ($\$/kWh$)
Coal	N	0.087	0.119
Advanced Nuclear	$\mathcal{G}$	0.092	0.101
Biomass	G	0.090	0.117
Solar PV	G	0.098	0.193

applied for different working needs of appliances by adjusting the granularity of the scheduling period. Weight between all other neurons is set to zero.

Let λ_{uv} be the binary state variable of the neuron m_{uv}. λ_{uv} takes on a value of either 0 or 1 which represents the neuron as either ON or OFF respectively. If λ_{uv} is 1 (ON) for a particular u and v, then, it implies that appliance u is scheduled to operate in the v^{th} time-slot. The large negative neuron weight connections between each row and column ensure that at any given instance of the neural network grid, only one neuron is active in each row and column.

Algorithm 2 presents the steps involved in the second phase of our appliance scheduling methodology. The algorithm first initializes the neural network by defining the states of the neurons λ_{uv}, weight of the connection between neurons $w_{uv,xy}$ as well as input connections to the neurons i_{uv}. Once the initial state of the neural network is defined, simulated annealing based Boltzmann machine relaxation technique is applied to advance the network to a low-energy stable state. This technique is implemented using two loops. The outer loop controls the annealing schedule of the system by decreasing the value of temperature, θ, in each iteration. The inner loop is repeated for a specified number of times, ς_{max}, such that almost all the neurons are randomly selected in the inner loop. The temperature decrease is controlled by a cooling factor α which is selected such that the cooling process is slow. The slow cooling process ensures that the network has a high probability of reaching an optimal configuration. The inner loop performs a randomized local search of the neural network and updates the state of neurons based on their excitation, ξ. A neuron's excitation ξ is a sum of the neuron's input connection i and weights w on all other connections which are in ON state. Updates to the state of neurons of the network are probability based and are dictated by Glauber dynamics, a function of excitation ξ and temperature θ of the system, as presented in Algorithm 2.

IV. EVALUATION RESULTS

We tested our methodology using five schedulable household appliances. Table I shows the devices and their

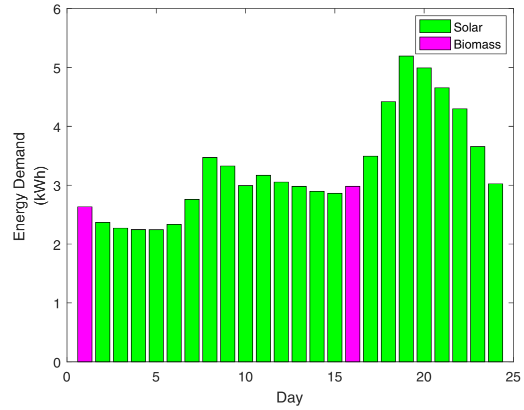

Fig. 2. Energy source allocation for non-schedulable appliances.

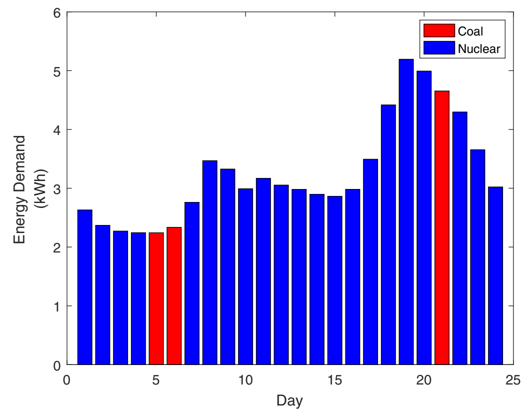

Fig. 3. Energy source allocation for schedulable appliances.

estimated energy demands per hour of operation [10]. Table II shows the minimum and maximum prices of five energy sources [11] considered for testing our algorithm. To get hourly fluctuation of prices, we assume that the price fluctuates randomly between the minimum and maximum limit. For historical electricity consumption data necessary for the first phase of the methodology, we use hourly energy consumption data for Anchorage, Alaska available from [9]. Figure 2 shows the hourly energy source allocation for the non-schedulable appliances (i.e., appliances that cannot be scheduled based on their demand profile determined for the data obtained from [10]) as arbitrated by our proposed greedy algorithm. From the figure, it can be seen that the biomass energy is allocated only in two time-slots. This is because, although the cost of biomass energy is comparatively lesser than solar energy, the biomass energy is not sufficiently available to be allocated in all phases. Hence, biomass energy is allocated only in those phases where its hourly cost is lower than solar energy.

Figure 3 represents the energy source allocation for schedulable appliances. Figure 2 and Figure 3 collectively represent the energy sources assigned in a particular time-slot. For instance, both solar and coal energy are allotted in time-slot 5. In this time-slot, solar energy is used for the non-schedulable appliances whereas coal is used for the schedulable appliances. Consequently, although coal is selected for this time-slot, it will be used only if some

TABLE III
APPLIANCE ASSIGNMENT ON HOURLY BASIS.

Appliances	**Time-slots**																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Dishwasher	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Laundry	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Oven	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Water Heating	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sweep Pump	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

appliance is scheduled in this time-slot according to our proposed Boltzmann machine neural network. For example, Figure 3 states that coal is selected as the energy source for time-slots 5, 6 and 21, however, Table III indicates that water heating pump and sweep pump are scheduled in time-slots 5 and 6 whereas none of the appliances is scheduled in time-slot 21. Hence, the use of coal, which is a non-green energy source, is minimized throughout the day by our proposed methodology.

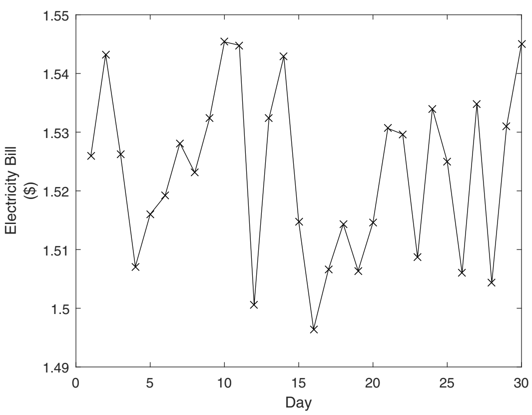

Fig. 4. Daily electricity bill for schedulable appliances.

Table III shows the operational time-slots for each appliance. In the table, each column represents a time-slot and each row represents the appliance to be scheduled. A 1 entry at the intersection of a row and column represents the ON state of the appliance while 0 represents OFF state. Each schedulable appliance operates only in one time-slot and each time-slot can have a maximum of 1 schedulable appliances such that each row has a single 1 entry and each column has a single 1 entry. Figure 4 shows the daily electricity bill for schedulable appliances obtained from Algorithm 2 for a period of 30 days. This electricity bill is the minimum bill for running these schedulable appliances. The figure indicates that there is very little variation in electricity bill throughout the 30 day period as minimum price of electricity has a fixed value for each energy source, and our proposed methodology schedules appliances only when the electricity price is minimum. These results verify the effectiveness of our proposed methodology in minimizing the electricity cost.

V. Conclusion

The use of renewable energy is expected to grow in future due to environmental concerns, however, conventional energy sources will still be used due to their low cost. Regardless of the electricity generation sources, consumers desire to minimize the total electricity bill. In this paper, we have proposed a methodology that promotes green environment by prioritizing the usage of renewable energy sources and also minimizes the electricity cost for the consumers. Our proposed methodology consists of two phases. In the first phase, we use a greedy strategy to determine the appropriate energy source to be used. In the second phase, we apply Boltzmann's neural network algorithm to schedule appliances to minimize the total energy cost. Results verify the effectiveness of our proposed methodology in minimizing the electricity cost. In future, we expect to extend our work to consider appliances with different operating phases and priorities. Moreover, we also expect to estimate the future energy demand of different energy sources given their current usage trends.

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