Household appliance scheduling in a smart grid community

(A game theory based approach)

Apoorva Venkatesh, Narendra kumar Sampath kumar, Priyadharshini Gunaraj
Group Number: 26
Mentor: Arun Das

***Abstract*—"Smart grid" refers to a class of technology that has a computer based remote automation system that helps in controlling thousands of devices/appliances via two-way communication over wireless internet, cellular network or through smart meter network. Since its inception, it had a significant contribution to help balance between supply and demand, to shift the energy consuming workload from peak time to off-peak time for the purposes such as load balancing and monetary benefits. With IoT in place that transforms any appliance into a smart device, presenting an opportunity for the utilities to better manage the connected appliances and explore non-wire alternatives like renewable energy sources. The proposed model will consider the uncertainties with respect to operation time and energy consumption in household appliances which will be scheduled with time-varying pricing model and utilizes the renewable energy from PV panels during trip off in a smart grid community. A trip off occurs when the total demand of household appliances exceeds the load limit of the household. The uncertainties will be handled through several scheduling techniques and the model will be using game theory based scheduling for multiple users in a community. The model ensures reduced energy consumption, cost saving per user, increased algorithmic efficiency and reduced trip rate. Additionally, the model will learn the data history to help understand the energy consumption pattern in the smart community.**

***Index Terms*—**Smart Home, Uncertainties, Appliances, Scheduling, Dynamic Programming, Game Theory, Multi User

I. INTRODUCTION

Smart home has become one of the most researched topics in recent years. Smart Home has always had the potential to unleash unprecedented value of comfort and convenience as well as safety and security. The drive to develop technology can inspire grandiose visions that makes simple things worthwhile. A smart home generally is an automation system that manages the interconnected appliances. A smart grid is an electrical grid, a network of transmission lines that allows for two-way communication between utility to its customers or customer to customer within the community. A smart community consist of multiple smart homes/users and local area network serves communication among the users for information exchange such as energy consumption information [1] [2]. Scheduling the appliances in smart home is a challenging task, particularly if it involves in obtaining the maximal profit for the user as well as the smart community. The appliances' operation time and power levels are the major factor inducing the monetary cost of the user. Most of the Household appliance scheduling algorithms do not consider the uncertainties in appliance's frequency i.e. Variable Frequency Drive (VFD). The typical execution time of a task is determined assuming the task is scheduled to run at the default frequency. But the execution time might change based on the frequency with which the appliances run. For example, a micro-wave oven needs 10 minutes to cook a dish when operating at its nominal frequency

1.5GHz, it might need only 5 minutes when operating at 3GHz [3]. Most often there will be a limit on the total demand during a certain time interval. When the demand of household appliances exceeds the given load limit of the household, the power network trips out. The probability that the home power network trips out during a time interval is defined as trip rate. Due to uncertainties in household appliances' operating frequency, the scheduler should take these uncertainties into account while scheduling the appliances. The trip rate can be minimized, so it is desired for the user to set a trip rate constraint to some value (e.g. 0.5%).

II. RELATED WORKS

A solid research has been made on identifying the pricing model and scheduling in a multi user environment. J.D Bermúdez *et al* [5] investigated on a method to obtain accurate predictions using Holt-Winters model (an exponential smoothing method) from the dataset. A Bayesian forecasting approach to predict intervals ('α', 'β' and 'γ' values) is used which also incorporates the uncertainties which occur due to the smoothing unknowns. Denis Dondi *et al* [6] investigated a task scheduling algorithm which relies on an energy predictor to maximize the number of tasks executed considering solar power. The daily energy income is based on location, time and availability of resources. Moustafa Elshafei *et al* [7] worked on a similar dynamic programming algorithm for labor scheduling problem with a cost structure. The algorithm finds optimum work schedule which reduces total labor cost with work demand satisfied. Extensive research on game theoretic approach for scheduling in multi user environment was conducted. Scheduling based on game theory and mapping of tasks on processors to minimize the energy consumption is carried out in this work [8].

III. PRELIMS

Smart homes in recent years have deployed a Photovoltaic (PV) system to save energy cost. Typically, the smart communities will be installed with a centralized solar PV panel system. The energy that is being produced from the solar cells can be put into effective utilization while scheduling. This makes sure that the trip rate doesn't cross the threshold there by having the renewable solar power backup in the appliances having higher uncertainty. Dynamic pricing is an integral part of a smart grid. Dynamic pricing is referred as the price in real time which helps to lower peak electricity demand. The demand of electricity is likely to be based on several factors like weather, time, day of the week etc. One way to estimate the demand is by doing an analysis on historical demand and using a cost model to find out the overall cost incurred for scheduling the appliance in a day. The main contribution is summarized as follows.

- The model takes in uncertainty of the household appliance and reduces the power consumption and time duration by utilizing energy from solar. Solar is consumed from user's PV battery.
- The price of the electricity unit depends on the demand. We use Holt-Winters seasonal method, which gives smoothing parameters (Alpha–Level smoothing coefficient, Beta–Trend Smoothing coefficient, Gama–Seasonal smoothing coefficient). It is used to estimate the cost using quadratic cost function $C = \alpha P^2 + \beta P + \gamma$. For Analysis, we took data from CKAN data repository (Smart Grid Smart City(SGSC) project) [9]
- With the cost obtained for each appliance using quadratic cost function, we are doing a weighted Interval scheduling maximizing the profit. This returns the appliance schedule to the user.
- Game theory based Multi User Scheduling. Users in the community collaborate and compete to obtain good scheduling results. Nash equilibrium is attained when no player can increase the profit without changing the operations of others.
- Learn from the Smart grid community's dataset using Support Vector Machine. This data helped in learning about the smart grid community's power usage which in turn helped in connecting multiple smart grid communities, predicting the load ratio and estimating

the load reduction using renewable energy.

For the analysis purpose, customer trial data conducted as part of the Smart Grid Smart City (SGSC) project from CKAN data repository is used [10].

IV. PROBLEM DEFINITION

We are given a set of home appliance with the set of variable frequencies with which each appliance can run. Each home appliance must consume a certain amount of energy for a task to be completed. The duration of the run might vary based on the appliance frequency. We are given the capacity of PV panel installed in every smart home. The day is divided into K time intervals. The objective is to schedule the home appliances into some kth time interval for every user and apply game theory approach. The total monetary cost of every user in the community is minimized.

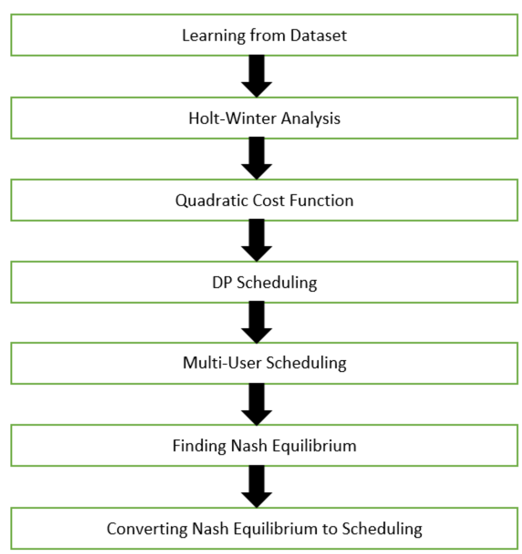
TABLE 1 APPLIANCES WITH HIGH UNCERTAINTY

Appliance ID	**Appliance Name**	**Min (kw)**	**Max(Kw)**
1	Dish Washer	1.2	1.5
2	Washing Machine	3.5	5.25
3	Ceiling Fan	0.25	0.75
4	Toaster	2	3
5	Microwave oven	4	6
6	Television	3	4
7	Iron	1	2
8	Vacuum cleaner	2	2.33
9	Air Conditioner	3	4.5
10	Hair Dryer	1.8	2.5
11	Water Filter	2.5	3.75
12	Light	1	1.66
13	Laptop	1	1.5

V. ALGORITHMIC FLOW

The overall algorithmic flow is as shown in Figure.1. First, the power consumed by an appliance is calculated using *(P = (S+E)*Reduced Duration)*, where the reduced duration is obtained through the inclusion of solar energy to the appliance with high variable frequency. The cost occurred for scheduling an appliance is obtained using the quadratic cost function. The quadratic cost function is decided based on the seasonal trends using Holt-Winters smoothing method. Once the quadratic cost function is fixed, a dynamic programming based scheduling is applied for one user. Similarly, it is computed for all the users in the community individually for timeframes T1…Ti. A game theory based approach is used to obtain the optimal schedule for all the users in the community. The algorithm shows that there exists a Nash equilibrium every time and it is PLS complete.

FIGURE 1 ALGORITHM DIAGRAM



VI. SYSTEM MODEL AND ARCHITECTURE

A. Holt-Winters seasonal method

The demand is usually estimated by using the data set history. The model applies a time series forecasting method: The Winters Method for forecasting the demand of electricity. we use this method to estimate the demand of the electricity in the community. For experiment, we have taken the data from CKAN data repository (Smart Grid Smart City(SGSC) project) and assumed to be yesteryear's dataset of the grid community. The data set contains 'n' different users' usage of 'k' different appliances with appliances having variable frequency. The power requirement for the appliance at every half an hour is listed in the dataset. The Holt-Winters method considers all three kinds of trends to forecast demand. The demand is predicted using the following equation.

$$F(k) = \alpha\, A(k)/c(k-N) + (1-\alpha)[F(k-1) + T(k-1)]$$

$$T(k) = \beta[F(k) - F(k-1)] + (1-\beta)T(K-1)$$

$$c(k) = \alpha\frac{A(k)}{F(k)} + (1-\alpha)c(K-N)$$

$$f(k+\tau) = [F(k) + \tau T(k)]c(k+\tau-N)$$

Where F(k) is the smoothed estimate, T(k) is the smoothed trend and c(k) is the seasonal factor. It is then compared with the actual demand A(k). τ is the forecast period which is taken to be 1 as the historical dataset considered is for a year. K is taken as 48 as the dataset provides information about the electricity demand for every half an hour and N = 12 (12 months in a year). The optimum smoothing constants are varied to get lowest mean square (RMS) which is given as

$$RMS = \frac{\sqrt{\sum[F(k) - A(k)]^2}}{K^2}$$

We use excel solver function to minimize the root mean square error considering the constraints of Alpha, beta and Gamma lying between 0 and 1. The alpha, beta and gamma values are calculated using the subsets of data taken from the CKAN data repository. Winters Method for Seasonality is applied with optimum smoothing constant α = 0.17, β = 0.08, γ = 0.01 (Table 2).

TABLE 2 SMOOTHING CONSTANTS OF THE DATASET

α	*β*	*γ*
0.19	0.1	0.03
0.2	0.5	0.04
0.17	***0.08***	***0.01***
0.2	0.12	0.09
0.18	0.09	0.02
0.22	0.15	0.05
0.2	0.1	0.03

The smoothing constants that is found above is used to estimate the dynamic pricing using quadratic cost function. Dynamic pricing model helps in reducing the monthly electricity bill and peak load. It would also help in reducing the supply side uncertainties and fluctuations. The power consumed for a user in a day is given by the equation

$$(P_i=(S_i+E_i)*D_{ir}$$

where S_i - Power consumed from the solar PV battery

E_i- Electricity consumed

D_{ir}- Reduced duration after introducing Solar power.

The quadratic cost function is used to find the cost of electricity using the smoothing constants. The cost of electricity for P_i power consumed by user *i*, for the timeframe k is given by

$$C_{P_i} = \alpha(P_i)^2 + \beta(P_i) + \gamma$$

The smoothing constants highly influence the quadratic cost function. With trial data conducted within day seasonality and within week seasonality resulted an average difference of 4-5% between the forecasted and actual data. The cost is calculated for every appliance and a new column of data containing the cost (C_{P_i}) is inserted along with the start time and end time of the appliances for user *i*.

B. Reduced Trip off rate

The addition of solar power to the appliances which has high frequency variation will reduce the trip off rate. Before scheduling the appliances, the solar power from the PV panel in every user's account is taken into consideration. Then the appliances are divided into three categories: High uncertainty in VFD, Medium uncertainty and low uncertainty. Based on the appliance duration with which it needs to be scheduled, the highly uncertain appliances and medium uncertain appliances are sorted per their power consumption. The appliances in the top of the list is given more priority in assigning solar power backup when the demand of the appliance exceeds the load limit. Here PV panel is taken as 7KWH Lithium-ion Solar PV system for analysis.

Trip rate constraint (T_r) = 0.5%

With solar power:

Appliance	Frequency uncertainty	Power Source	Trip off
1	3-5 KWH	Solar, Electric	No
2	4 KWH	Electric	No

Without solar power:

Appliance	Frequency uncertainty	Power Source	Trip off
1	3-5 KWH	Electric	Yes
2	4 KWH	Electric	No

C. *Dynamic Programming based single user Scheduling*

The appliances with the start time, end time along with their cost (C_{P_i}) is applied to Dynamic programming based scheduling. Initially the given appliances are sorted on non-decreasing end times. The profit for the appliance can be found from the difference between the cost with normal duration and cost with reduced duration (using renewable energy). For every appliance in the set (a1..an), find the appliance which incurs maximum profit to the schedule. This can be found by comparing the total profit when appliance Ai being added to the schedule set at the appropriate position using binary search and the existing total cost at that position. The appliance to be included should not conflict with the other appliance timings.

```
DP_based _Scheduler(Jobs)
    Sort ← Finish time of Jobs
    Table ←Job1.profit
    For m ← 2 to n
        Index ← Binarysearch(Jobs,m)
        Profit ← Profit+ Table[Index]
        Table[m] ← max(Profit, table[m-1])
    Return Table[n]
```

Since the appliances are sorted as per their finish time, it is guaranteed that the first appliance in the sorted order is always included in the scheduled result set. Suppose {a5, a7, a8, a12, a15} is an optimal solution, the start time of a7 must be after the finish time of a5. Since the finish time of a1 is earlier that of the finish time of a5, there will be no conflict between a1 and a7. Therefore, the activity set {a1, a7, a8, a12, a15} will also be an optimal solution. So once a1 is chosen, the problem of finding the optimal solution reduces to problem of finding the appliances that are compatible with a1 and providing minimal cost to the result set

D. *Problem solving approach for game theory:*

When scheduling has to be carried out for an individual user, there are many approaches which can be used such as greedy scheduling, dynamic programming scheduling etc. The problem of finding the optimal schedule between two users competing for the same resource can be modelled in game theory approach. Congestion models in game theory is a natural model for resource allocation in large networks such as the Internet. In such a model, each player is interested in a subset of resources and the cost of using that resource is dependent on the number of other players using the same resource. A congestion game consists of a base set of congestible elements E, n players, a finite set of strategies for each player which belongs to space of 2^E, cost of each resource is dependent on the number of users using that resource. Each user aims to choose a strategy such that his/her cost function $\sum c(i)$ is minimal. Consider the below payoff matrix for 2 players and 2 strategies.

TABLE 5 PAYOFF MATRIX

U1/U2	A	B
A	(C1,C2)	(C8,C3)

B	(C4,C5)	(C6,C7)

Here U1, U2 represents the users competing for the resources, A and B represents the different strategies used by each player. The strategies used by each player corresponds to the appliances for which he/she is competing for a given timeframe. Here c(i) represents the cost associated with using each of the different strategies by the player. This cost value is obtained from the Holt-Winter seasonal method as described above. From the payoff matrix we construct a potential function which is used to prove the existence of Nash equilibrium. The algorithm terminates on finding the Nash equilibrium which basically indicates that it is not possible for any user to reduce his cost without changing the solution of others.

E. Existence of Nash Equilibria and convergence:

Rosenthal's Analysis theorem states that,

Every congestion game admits a pure Nash Equilibrium.

Let 's' be the state of the game i.e.., any allocation of pure strategies. Let n (e,s) be the number of players using the resource 'e' in state 's'. The potential function for S is defined as $\emptyset = e \in E \sum k = 1 \, to \, n \sum C(i)$

Lemma: Let *s* be any state. Suppose we go from *s* to *s'* by changing the strategy of the user who decreases his cost function by $\delta>0$ then $\phi(s') = \phi(s) - \delta$

Proof: The potential function can be calculated by inserting the agents and summing up the cost associated with each user.

Agent *i* is the last player added into the potential function, then the potential associated with agent *i* corresponds to the cost of user *i* in state *s*.

When going from state *s* to *s'* the cost decreases by δ and the potential also decreases by a value of δ.

Suppose we start at any state *s* and iteratively decrease the potential by repeatedly applying the local improvement steps then the lemma shows that every such step decreases the potential by a unit. As potential can't drop below 0 we reach a pure Nash equilibrium in at most $\phi(s)$ steps. The Nash equilibrium can be found using a pseudo-polynomial time algorithm and it is PLS complete [10].

VII. SIMULATION RESULTS

TABLE.3 USER INPUT FOR SCHEDULING

User ID	Start Time	End Time	Appliance ID	Power from Electricity	Power from Solar	Total Cost	Total Profit
1	7	9	2	3.5	1.75	5.25	1.75
1	11	12	5	4	2	3	1
1	15	18	4	2	1	3	1
1	17	20	6	3	1	8	1.5
2	2	5	8	2	0.33	4.66	1.34
2	4	5	9	3	1.5	2.25	0.75
2	8	10	11	2.5	1.25	3.75	1.25
2	15	17	12	1	0.66	1.66	0.34
2	13	17	13	1	0.5	3	1

A sample from the dataset for two users is taken and simulated using dynamic programming interval scheduling and game theory approach is applied to obtain Nash equilibrium. The input is shown in Table 3. The appliance input is given to the Dynamic programming based algorithm and the results are shown in Table 4.a and Table 4.b.

TABLE.4.a DYNAMIC SCHEDULING RESULTS FOR USER 1

Appliance Id	Start time	End time	Cost	Profit
2	7	9	5.25	1.75
4	15	18	3	1
6	17	20	8	1.5

TABLE.4.b DYNAMIC SCHEDULING RESULTS FOR USER 2

Appliance Id	Start time	End time	Cost	Profit
8	2	5	4.66	1.34
11	8	10	3.75	1.25
13	13	17	3	1

The results are applied to game theory based approach for every Timeframe and user 1 and user 2 collaborate and compete for the resources (Timeframes). The timeframes are taken as T1 and T2 where T1 (12 am – 11.59am), T2 (12:00pm - 23:59pm) The payoff matrix is shown in Table 5.

TABLE 6 NASH EQUILIBRIUM

U1/U2	T1	T2
T1	(5.25,4.66)	(11,6.75)
T2	**(5.25,6.75)**	(11,6.75)

The Nash equilibrium is found to be at (5.25,6.75), so the User 1 will schedule his appliances that falls in timeframe 1 and User 2 will schedule the appliances that fall in timeframe 2.

VIII. CONCLUSION

Dynamic scheduling of various appliances for multiple users in a smart community is carried out. The multi-user scheduling is achieved using game theory technique. The smart community dataset is used to calculate the power consumption. The renewable solar energy is taken into consideration making sure that trip rate doesn't exceed the threshold and the overall cost is minimized. The uncertainty of appliances is handled by reducing the power consumption and time duration.

.

ACKNOWLEDGMENT

We are grateful to our professor Dr. Arunabha Sen and Teaching Assistant Arun Das for helping us finish our project "Scheduling household appliances in a smart grid community" within the given timeframe. This project would not be possible without the effort and cooperation from our group members' Apoorva Venkatesh, Narendra Kumar Sampath kumar, Priyadharshini Gunaraj. We also sincerely thank our professor Dr. Sen for taking the course CSE 551 Foundations of Algorithm.

.

REFERENCES

[1] Z. Liu and W. Huang, "The design of smart home system based on Wi-Fi", Proceedings of International Conference on Computational Problem-Solving, (ICCP), pp. 454-456, 2012..

[2] Z. Fan, P. Kulkarni, S. Gormus, C. Efthymiou, G. Kalogridis, M. Sooriyabandara,Z. Zhu, S. Lambotharan and W. H. Chin, "Smart Grid Communications: Overview of Research Challenges, Solutions, and Standardization Activities", IEEE Communications, Surveys & Tutorials, vol. 15, no. 1, pp. 21-38, First Quarter 2013.

[3] X. Chen, T. Wei and S. Hu, "Uncertainty-Aware Household Appliance Scheduling Considering Dynamic Electricity Pricing in Smart Home," in IEEE Transactions on Smart Grid, vol. 4, no. 2, pp. 932-941, June 2013.doi: 10.1109/TSG.2012.2226065

[4] N P -hardness of pure Nash equilibrium in Scheduling and Network Design Games, Elsevier Theoretical Computer Science 482 (2013) 86-95

[5] "J D Bermúdez", "J V Segura", "E Vercher", "E. J Oper ", "Bayesian forecasting with the Holt–Winters model", in Res Soc, 2011.

[6] Denis Dondi, Piero Zappi, Tajana Simunic Rosing, "A Scheduling Algorithm for Consistent Monitoring Results with Solar Powered High-Performance Wireless Embedded Systems", in IEEE, 2011.

[7] "Moustafa Elshafei", "Hesham K. Alfares", "A dynamic programming algorithm for days-off scheduling with sequence dependent labor costs" in Business Media, Springer Science, August 2007.

[8] "Sungjin Im", "Benjamin Moseley", "Kirk Pruhs", "Online Scheduling with General Cost Functions", in NSF grant CCF, 2012.

[9] Smart City Customer Trial data - CKAN BioCenit "http://biocenit-deq.urv.cat/dataset/energy-consumption-demo/resource/136b78d6-c66a-463a-958b-bfaa21e1b96d"

[10] Alex Fabrikant, Christos H. Papadimitriou, Kunal Talwar, The complexity of pure Nash equilibria, in: Proceedings of the 36th Annual ACM Symposium on Theory of Computing, STOC, 2004, pp. 604–612