

Genetic Algorithm-Based Residential Appliance Scheduling for Optimal Power Management

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ABSTRACT: Despite the numerous creations by man, the electric grid remains one of the most intricate and largest of physical systems ever made. Thus on the very outset it is wise, even expected, that creativity and continuous innovation be invested in it. Further, environmental concerns, exponential increase of energy consumption translating to problem of *peak* demand management are also among the factors that have necessitated need for clever use of electricity. Hence the prevalent electricity consumption behaviour, which does not mirror the current grid requirements, is reconsidered, with a view of making it an effective tool that can potentially offset need for physical expansion of the power grid. Drawing on the timely concept of the Smart Grid the role of consumers is reconceived through Demand Side Management (DSM). The main idea presented is deft domestic appliance scheduling to smoothen the demand curve, since domestic load takes up an appreciable portion of the total generated energy. The appliance scheduling algorithm is modelled and solved using a 1970s invention, Genetic Algorithm (GA). The results indeed show conscious use of electricity does utilise the grid painstakingly.

KEYWORDS: Smart Grid, Demand Side Management, Genetic Algorithm, appliance scheduling, smart meter

I. INTRODUCTION

Consumers' deliberate involvement in balancing the energy equation has not been aggressively sought, even after introduction of DSM in the 1970s. Utilities are still considering dear options in a bid to strike the delicate balance between generation and load. Consumers on the other hand have not been programmed to be energy savvy. Their electricity consumption behaviour is uninformed and non-participative with the power system [1] making energy management elusive. However, with numerous concerns in regard to energy, the role of consumers is increasingly being redefined. It is proper that the utility be in mutual business relationship with consumers for effective control and management.

One way to facilitate this participation is through monitoring of energy consumption of *domestic appliances*, by carrying out *appliance scheduling*. Household energy consumption takes a perceptible percentage of the total daily generated energy. Kenya for instance has had a 23.7% rise in the number of consumers connected to the national grid under the Rural Electrification Programme as at June 2012 [2]. A report from US Department of Energy indicates domestic consumption takes up 34.4% of the total electricity generated [3]. Further a report from Smart Grid News argues that household appliances take up 60 to 90 percent of residential electricity consumption in the U.S. depending on a particular account. Thus management of household energy consumption is crucial in saving energy and reducing peaks. Through appliance scheduling, valuable information on precisely how the demand profile changes is obtained. Therefore, *electrical appliance scheduling* is a major tool used in demand response. To ensure cooperation of consumers, *dynamic pricing* is integrated. Real Time Pricing (RTP) initially may be difficult to implement due to the

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 4, April 2017

rapidly changing electricity prices that requires unfailing sharp-wittedness of consumers to respond to load fluctuations on grid. Time of Use (TOU) tariff is suggested here as the best strategy to start with.

The key question is how to develop an optimal scheduling plan for domestic appliances. Further, it is also necessary to quantitatively understand the impact of appliance scheduling on demand profile, and by extension, on energy bills.

This paper is organized as follows: Section II briefly discusses related works. Section III details the technique for solving the appliance scheduling problem. Section IV presents experimental results and later section V makes the conclusion.

II. RELATED WORK

Energy optimization has increasingly become a popular area of research due to the fact that many countries are being forced to chart new ways of generating, transmitting, distributing and consuming electricity [4]. Household appliance scheduling is about coordinating usage of domestic electric appliances in a bid to fully utilize the grid, most notably by smoothening the demand profile. Various techniques have been proposed to solve this scheduling problem. Since certain aspects of this scheduling require unalloyed binary representation Mixed Integer Linear Programming (MILP) has been widely used. However, MILP does not satisfactorily incorporate the suppositional nature of demand. [5] proposes game theory to formulate energy consumption scheduling whereby players are the electricity consumers; their strategies being daily schedules of domestic appliances. DSM requires that electrical appliances be responsive through inclusion of communication technologies and embedded intelligence, the two fundamental ingredients of demand response [4]. In [6] a day-ahead variable peak pricing is proposed and the scheduling problem solved using the multiple knapsack method.

The proposed scheduling approach in this paper makes use of TOU tariff, whereby electricity prices are pre-determined by utility whose judgement is seasoned following lots of knowledge on grid trends. The scheduling problem is solved using G.A.

III. APPLIANCE SCHEDULING

A heuristic approach takes care of the stochastic nature of load. Genetic Algorithm is an acknowledged tool used to solve problems especially of minimizing and maximizing functions with several variables. Of importance is to understand exactly how the smart grid will be implemented in the existing grid. In this study focus is on the smart meter which is a great enabler of the smart grid. Key feature of the smart meter is the two-way communication between the utility and consumer. The smart grid also has the *electricity consumption scheduling feature* that will enable appliance scheduling. This attribute is also in the main energy meter at the energy source that feeds the consumers. The smart meter is able to communicate between the main meter and other smart meters connected to the main.

International Journal of Innovative Research in Science, Engineering and Technology

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Vol. 6, Issue 4, April 2017

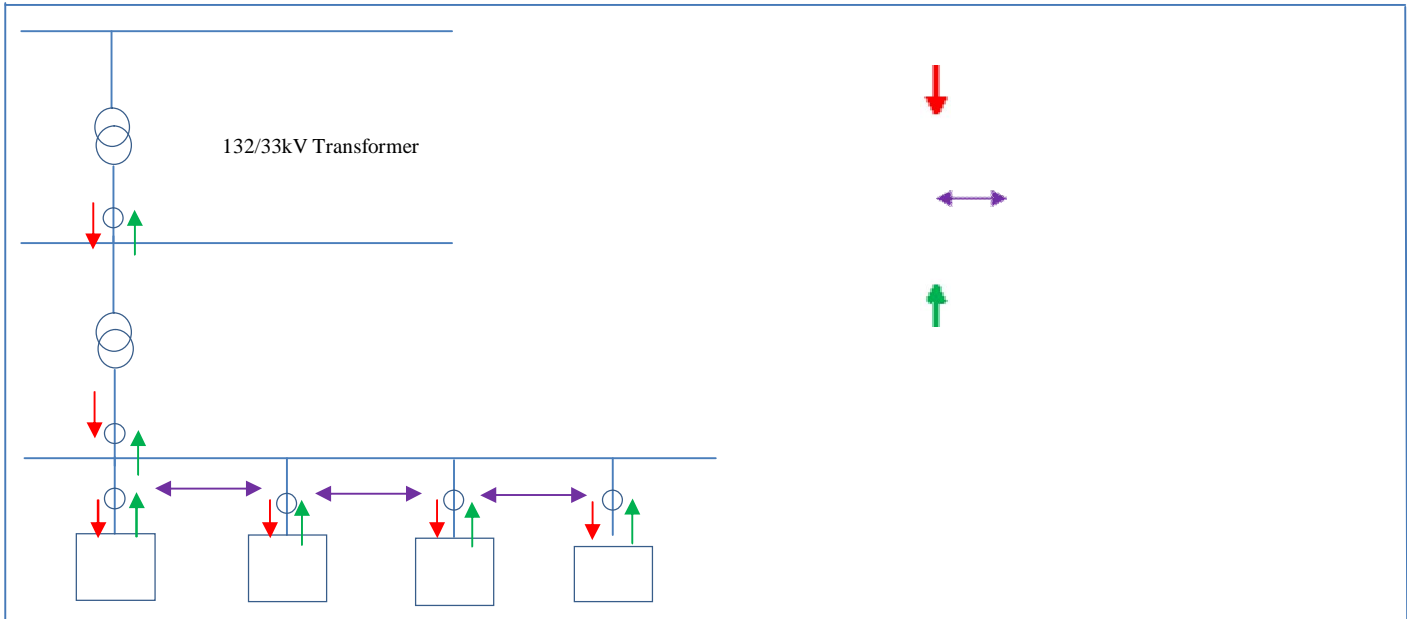


Fig.1 Two way communication of the Smart Meter

Figure 1 shows the placement of the smart meters in the grid and their characteristic two-way communication. Main smart meter in the distribution substation conveys grid information to connected consumer smart meters. Based on this information, the consumer meters are able to create a lean scheduling plan that is shared amongst other consumer meters, for any necessary readjustments. This is in a bid to prevent formation of new peaks. Final information is relayed back to the main meter for implementation.

Consider:

F consumers: $F = \{1, 2, \dots, F\}$

H time slots: $H = \{1, 2, \dots, 24\}$

D domestic appliances: $D = \{1, 2, \dots, D\}$

y_i is the schedule strategy of appliance i , hence $y_{i,j}$ is the energy consumption of appliance i of household j (KW); where $i \in D$ and $j \in F$.

The energy consumption of appliance i , should not exceed the maximum energy need [7]:

$$\alpha_{i,j} \leq y_{i,j} \leq \omega_{i,j} \quad (1)$$

The total energy at h -hour for consumer j is

$$l_j^h = \sum_{i=1}^D y_{i,j}, \text{ where } i \in D, j \in F, h \in H \quad (2)$$

Hence total energy for consumer j in a day is

$$\sum_{h=1}^{24} L_h = \sum_{i=1}^D y_{i,h} \quad (3)$$

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Equation (3) holds subject to the constraint that the consumer has a limit to which they can consume electricity in a day:

$$\sum_{h=1}^H L_h \leq P_{i,j}, \quad (4)$$

where $P_{i,j}$ is the preset energy allocation for consumer j , $j \in F$.

Energy Cost

Considering all the consumers connected to one energy source, total consumption cost is therefore obtained as follows:

$$\sum_{h=1}^H C_h (\sum_{j=1}^F \sum_{i=1}^D y_{i,j}) \quad \text{where} \quad (5)$$

$$C_h = (C_1, C_2, \dots, C_{24}) \quad (6)$$

Equation (6) shows that electricity price changes for different time slots in a day. The scheduling algorithm should minimize this cost, as expressed below:

$$\text{Minimize } C_T = \min \{ \sum_{h=1}^{24} C_h (\sum_{j=1}^F \sum_{i=1}^D y_{i,j}) \} \quad \forall j \in F, \forall i \in D \quad (7)$$

It is however probable that shifting load from peak period to non-peak times is likely to create new crests. A constraint is hence introduced to equation (7) in order to impede this scenario.

Thus energy cost is expressed as

$$\sum_{h=1}^H C_h (\sum_{j=1}^F \sum_{i=1}^D y_{i,j}) + \mu L_p \quad (8)$$

where L_p is the penalty parameter and μ is the weight on violation:

$$1 \leq \mu \leq 0 \quad \{ \mu=1 \text{ when there is significant convergence of consumer preference;} \\ \mu=0 \text{ when consumer load is evenly distributed} \}. \quad (9)$$

Genetic Algorithm

Number of appliances to be scheduled and their consumption levels are noted. Electricity price which changes for the different time slots in a day are known to consumers.

From these, we have a *population* of possible candidates. Selection of suitable candidates is done using *fitness-proportionate selection method*: chance for *recombination* is based on fitness of a particular schedule (schedule that gives minimal cost), obtained from the individual's fitness level divided by the population's average fitness value. Crossover type chosen is single-point crossover which though not as extensive as uniform crossover, ensures that the maximum information from the parent to offspring is preserved [8]. The consumer scheduling algorithm is as illustrated in flowchart below.

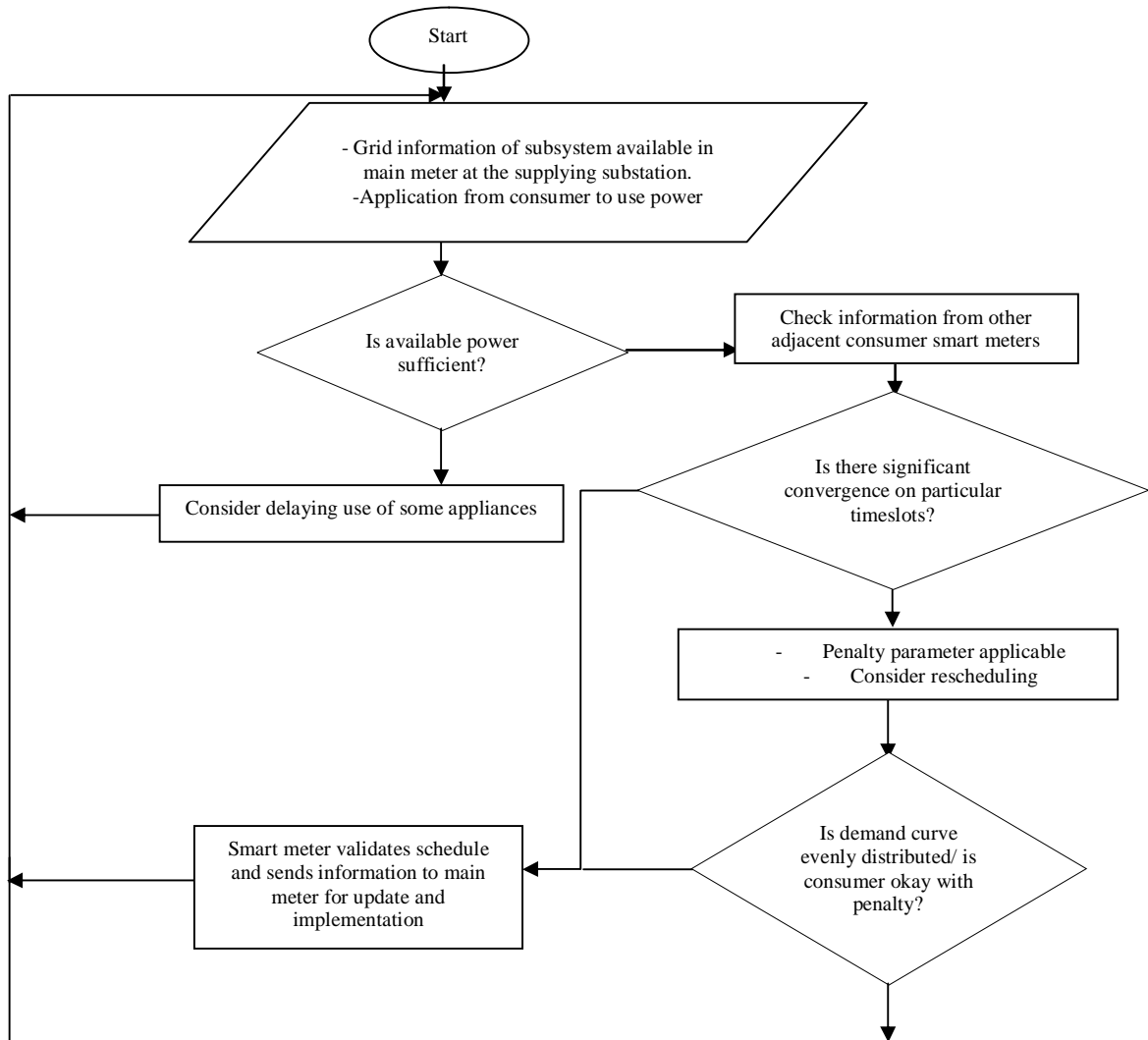


Fig.2 Flowchart showing Scheduling Algorithm

Figure 2 shows the precise representation of the scheduling algorithm taking into account the grid situation and consumer preferences. The algorithm guards against creation of new crests by first checking preferences of other consumers and readjusting accordingly. The final plan is sent to the main meter for update and implementation.

GA code is implemented in MATLAB. *Illustrative* computations are as follows:

Considering 1 utility, 7 set of appliances:

$$A = \{1, 2, \dots, 7\}$$

$C_h = (C_1, C_2, \dots, C_{24})$ cost of energy different for the different timeslots in a day.

and taking Ksh750.00 as the upper limit of energy spending for a particular appliance schedule.

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Table 1 Typical appliances scheduling scenario

No.	Appliance	Wattage (KW)	Time of Use	Energy KWh	Total cost	Modulation	Fitness%
1	Washing machine	0.70	9.00am-1.00pm	2.80	136.08	5.511	7.84
2	Oven	2.15	6.00pm – 10.00pm	8.60	712.94	1.052	1.50
3	Water pump	1.90	1.00am – 4.00am	5.70	58.14	12.899	18.34
4	Microwave	1.50	6.00am – 7.00am	1.50	24.90	30.120	42.83
5	Iron	1.00	7.00am-9.00am	2.00	84.20	8.907	12.67
6	Air conditioning	1.00	12.00pm-4.00pm	4.0	162.8	4.607	6.55
7	Dishwasher	1.50	11.00pm-3.00am	6.0	103.8	7.225	10.27

From the table, consumption of each appliance is known and time of use assigned to each appliance. Total energy cost of each appliance can be calculated basing on equation (6). In this case KSh. 750 is taken as the cost constraint for each appliance against which modulation is done to obtain fitness.

Chromosome representation can be of the form:

$$Schedule\ 1 = \left[a_3, a_1, a_4, a_5, a_7 \right] \tag{10}$$

$$Schedule\ 2 = \left[a_1, a_3, a_4, a_6, a_5 \right] \tag{11}$$

Further all possible schedule combinations are stored in *Consumer x Appliance* matrix i.e. *Nind x Lind*:

$$Chromosome = \begin{bmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,Lind} \\ a_{2,1} & a_{2,2} & \dots & a_{2,Lind} \\ \dots & \dots & \dots & \dots \\ a_{Nind,1} & a_{Nind,2} & \dots & a_{Nind,Lind} \end{bmatrix} \begin{matrix} Schedule\ 1 \\ Schedule\ 2 \\ \dots \\ Schedule\ Nind \end{matrix} \tag{12}$$

Fitness of each individual (schedule) is evaluated in order to determine probability of being chosen for crossover and mutation.

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IV. EXPERIMENTAL RESULTS

After crossover and mutation is done and the convergence criteria achieved, the chromosomes and further the phenotypes are decoded. Of uttermost interest are the energy cost function and objective function which define the problem statement. These will enable us to quantitatively see and analyse the impact of household appliance scheduling.

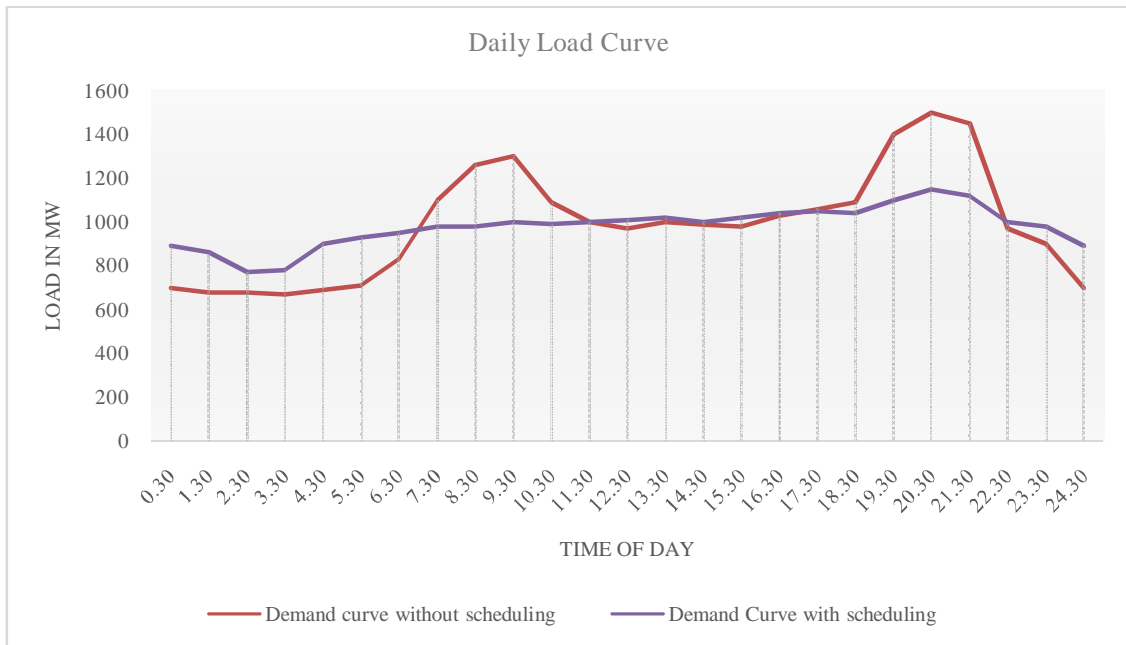


Fig.3 Demand curves

From the graph, grid utilization is efficient. For instance, usage of electricity at typically *non-peak* periods e.g. from 0030hours to 0630hours increases by about 23%. This increase in turn results in *decrease* in load at peak period from 1830hours to 2130hours by about 19% and period of 0630hours to 1130hours decreases by 10%. Consumers are able to save up to 32% of energy cost.

V. CONCLUSION

It is seen that fundamentally, the demand curve is evenly distributed throughout the day. This translates to a number of advantages among them reduction in electricity costs for both the consumer and utility – the utility is rarely forced to turn on the ‘peakers’ which are usually expensive and carbon emitters, while the consumer is not ‘punished’ for consuming electricity at critical times.

This implies that the grid capability is exploited and the consumer actually seen as a dynamic *resource* to be considered in the energy business.

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