Residential Load Scheduling Based Analytical Optimization Method

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Abstract: Peak load periods in smart grids significantly affect the energy stability produced by energy suppliers. One of the important factors that distinctly affects the load during these periods is the household energy consumption. Thus, managing and improving energy demand for smart home appliances can effectively reduce the peak loads which represents a major challenge. This paper introduces a dynamic Analytical optimization Method (AM) to find the optimum managing for residential energy load. The results showed that the maximum load of total demand is decreased by 35%, as well as, the energy consumption cost bill is decreased by 44%. The results of proposed method are compared with two widely used optimization methods; Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). Although the results of the proposed method showed a superior time saving for achieving the final results.

Keywords: Demand response, Genetic Algorithm, Load scheduling, PSO, ToU pricing.

1. Introduction:
Smart Grid provides numerous possibilities for customers to truly save energy, cost, and for utility to work the grid in a far more efficient, effective, and reliable way. Availability of energy supply is a key factor to support the increasing in the energy demand. Completely growing energy consumption, significant losses while transmitting and distributing energy make necessity of energy saving. Nowadays producing effective energy management systems is one of the world’s most prospective [1], [2]. Residential electrical energy consumption ranges from 20% to 40% of the total energy in the world [3]–[5]. Utility companies are required to provide energy to users continuously all over the day even during peak demand [6], [7]. Moreover, information and communication technologies have been used to connect all home appliances in a home area network (HAN) which provides easy monitoring and smart control. This provides a great opportunity to schedule operation of home appliances to get the least energy consumed during peak time [8]–[11]. However, customers cannot be managing all the smart home devices. Thus, a dynamic load scheduling system is an effective solution to get optimal load scheduling for cost and energy saving [12], [13]. Present literary works include numerous studies on the need to deal with consumer load scheduling using various types of optimization methods through which load scheduling problems can be addressed in smart homes. In [14], mixed integer nonlinear programming was proposed to determine the optimal scheduling of household electrical appliances using time of use pricing rates (ToU), which reduced energy costs and provided an incentive to the consumer during peak times. The price difference between peak and off-peak times and the flexibility of shiftable appliances are the most important factors that affecting cost reduction. The cost of energy has been reduced in this research by 25%. In [15] a correct mixed linear
programming was proposed to achieve a balance in electrical energy consumption and reduce the electricity bill for the user, this method was applied for multiple scenarios for six homes, each with a set of pre-defined electrical appliances in the Czech Republic. The cost of energy has been reduced by 3% up to 16% [16]. A mixed linear programming is proposed to solve the problem of scheduling household electrical appliances to reduce the cost of electrical energy and reduce the maximum peak load. Seven electrical devices were used from different shiftable types of loads. The photovoltaic panels have been used in this paper as devices that produce electrical energy, as the proposed integer method helps to reduce the cost of the electricity bill and export the additional energy to the national grid. In [17] the linear programming method was used by the researcher using the time of use pricing rate and the adaptive consumption level pricing plan for ten electrical devices and the results showed a 31% decrease in the electricity bill using ToU either using the adaptive consumption level pricing plan the electricity bill decreased by 53%. In [18] the PSO and GA optimization algorithms were used to obtain appropriate scheduling for household electrical appliances and to reduce the electrical bill. Simulated results showed that the most significant reduction obtained using the PSO and GA method with an acceptable load curve. In [19] three types of optimization methods were used, namely GA, Ant Colony Optimization (ACO) algorithm and Binary PSO algorithm (BPSO) and thirteen household electrical devices were used. The results showed that the reduction in the electric bill reached 48.79% by using GA and 28.26% using ACO and 40.43% using BPSO. In [20] a model was proposed containing energy resources, generators, smart devices and a central console, and the components were connected to each other by the network. The central control is controlled by the mixed integer linear programming system, where more than two scenarios were used in this research, and the results showed a reduction in the cost in the first scenario by 68.6% and in the second scenario by 54.4%. In [21] a home energy management system was suggested using the correct mixed linear programming to schedule household electrical appliance operating times that reduces energy costs while maintaining a high level of user comfort. Electric vehicles and renewable batteries were used to provide energy in this research.

These works are generally related to load modelling and optimization methods for rescheduling consumer load. Most of presented work focus on cost saving and peak load reduction regardless the time taken for this task. This paper uses different optimization methods for optimal cost and energy saving as well as for minimum time period. Time saving in obtaining optimal solution for cost and peak energy helped to drive fast response for price change. The methods used in this paper is compared in terms of the time required to implement each method. The paper is structured as follows: Section 2 describes objective functions. Proposed model and algorithm are presented in section 3. Section 4 discusses the simulation results and analysis. Finally, the article is concluded in section 5.

2. Objective functions:

The increasing demand for electrical energy consumption in an irregular manner leads to high costs, so families strive to regulate their consumption in a manner that reduces these costs. The process of managing and regulating consumption requires defining the problem and developing an appropriate model for solving it. In this work a time sample rate (Δt) of 5 min with an examination period of 24 hours are considered. Thus, the total time slots (T) are 288 slots for each day. The objective function can be accomplished as follows:

$$\min H_c = \sum_{t=1}^{T} R_i \times P_i \times \Delta t$$

(1)

Where \(R_i\) is the pricing rate for each time slot \(i\), and \(P_i\) is the total consumption of all consumer’s load during time slot \(i\). The total consumption of all appliances \(P_i\) can be calculated by:

$$P = \sum_{i=1}^{T} \sum_{j=1}^{N} (p_{i,j} \times \delta i)$$

(2)
Where \( p \) refers to consumption of the \( i \)th devise, \( N \) is the number of all devices and \( \delta_i \) is a two values variable, it equals 1 at the time period in which the \( i \)th devise is on, and equal to 0 when the device is off, (outside the suggested time period for operating that device).

3. Optimization Methods

To solve the objective function, an optimization method should be used to provide optimal load scheduling for minimum customer cost as well as reducing the peak load.

3.1. Analytical method (AM)

The proposed AM redistributes electrical loads according to the time periods allowed to operate each electrical device and the actual operating times of that device, which leads to a reduction in the cost of the electric bill. The main steps of the AM method can be explained as follows: 1) Electrical appliances are randomly arranged and calculate initial cost. 2) The electrical devices are randomly rearranged and according to this arrangement, the permissible operating period of the device is examined taking into account the actual working period of each device. 3) Using time sliding window, the device is placed to work in a time whose cost is as low as possible. 4) Calculate the total electricity cost per day. This cost is based on the electricity pricing schema shown in Figure 1. 5) Search and isolate all devices that operate during the peak period. 6) Slide the operation time of these devices back/forth to the off-peak period taking into account the allowed operating period of each device. 7) Save The lowest obtained daily cost with the actual operating periods of each device. 8) Repeat steps 2-8 to a pre-specified number of iteration or till the daily electricity cost converged to a minimum value as possible as it can be. The detail description of the proposed method is as shown in the flowchart of Figure 2.

![Figure 1. On-peak and Off-peak cost rate [14]](image)

3.2. Comparative methods

To evaluate and compare the performance of the proposed analytical method two other well-known optimization methods have been used. The first method is Generic Algorithm (GA). GA is one of the most effective algorithms between all heuristic algorithms, GA used to schedule home appliances [22]. Appliances are scheduled based on user request. The goal of GA's work is to achieve the minimum cost of an electric bill. The second method is the particle swarm optimization method (PSO). PSO is one of the most popular swarm based optimization algorithms. This algorithm is intended to deal with the ceaseless enhancement issues. PSO algorithm is altered into a discrete structure because of the discrete nature of scheduling problem [23]. PSO can be described by:
\[ \text{Vel}(t+1) = w \times \text{Vel}(t) + c_1 \times r_1 \times (\text{pos. pBest}(t) - \text{pos}(t)) + c_2 \times r_2 \times (\text{pos. gBest}(t) - \text{pos}(t)) \]  

(3)

\[ \text{pos}(t+1) = \text{pos}(t) + \text{Vel}(t+1) \]  

(4)

Where Vel is the particle velocity, pos is the current particle (solution). Pbest and gbest are defined where pbest represents the current fitness value and gbest represents the better particle of the pBest value. r1 and r2 are random number between (0,1). c1, c2 are learning factors. w is inertia weight.

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**Figure 2.** Flow chart illustrates the proposed Analytical Method (AM).
4. Case Study:
In this work, the consumption data has been adopted from [14]. The data were collected for typical household in South Africa which contain 10 home appliances is shown in Table 1. The data includes the power rates, starting and ending time for each device $S_t$ and $E_t$ respectively, and the required duration of operation for each device represented by number of slot time per day. All these data were collected within one month. For further clarification to the data of Table 1, the device Microwave/Oven, as an example, is scheduled to run once a day for a period of 10 minutes. This means that this device requires operational duration of 2 slots (where the time of sampling is 5 minutes/slot). These 2 slots are considered to be between time slot 216 (18:00) and time slot 228 (19:00). The On-peak hours and the Off-peak hours is as shown in Figure 1. Where the On-peak hours represents the highest electricity demands, with highest cost rate, meanwhile, the cost rate of the Off-peak hours are the lowest. In this figure, the Off-peak hours are: 00:00 - 7:00, 11:00 - 18:00, and 22:00 – 24:00 the used ToU tariff is 45.54 c/kWh, while the On-peak hours are: 7:00 – 11:00, and 18:00 – 22:00 a tariff of 144.52 c/kWh was used.

5. Simulation results
In this paper, the proposed analytical method is applied for optimal load scheduling using MATLAB software package. The proposed method is based on analytic technique looking for best consumption cost. The iteration is continued until the output is converged to a steady state as shown in Figure 3. The obtained results using AM method for optimal load scheduling were compared with the optimization results of each of GA and PSO as shown in Table 2. This table includes the optimal timings for starting and ending each appliance depending on the mentioned methods. Note that the fifth and sixth columns of Table 2 represent the normal operating periods for electrical appliances without using optimization methods. For example, the duration time of a Kettle has 2 slots (10 min) in the morning and 2 slots (10 min) in the evening. According to [17], the best time is determined to be at $S_t = 77$ (06:25) to $E_t = 79$ (06:35) and at $S_t = 220$ (18:20) to $E_t = 222$ (18:30), respectively. The obtained optimal time scheduling for the Kettle using GA is starting from $S_t = 70$ (05:50) to $E_t = 72$ (06:00) in the morning and at $S_t = 216$ (18:00) to $E_t = 218$ (18:10) in the evening. Meanwhile, appliance as microwave, needs to work once a day for 2 slots (10 min), the baseline and the optimal scheduling time obtained by all of the comparative methods are the same, starting from slot 216 (18:00) to slot 218 (18:10). The results of the remaining appliances are as depicted in Table 2. The simulation results of total energy consumption for the comparative methods with the normal consumption rate are shown in Figure 4. According to figure, all optimization methods attempt to redistribute the load while avoiding peak time as much as possible to reduce the average cost of energy. The analytical method provides optimal results within shortest execution time compared to the other comparative methods as depicted in Table 2.

On the other side, the obtained results of total cost and consumed energy using the above mentioned methods were compared with the results presented in [14] and [17]. This comparison includes the peak consumption, total cost, cost reduction, peak reduction, and the time required to implement each method as shown in Table 3. The analytical method achieved a significant cost reduction of 44% compared to 25% in [14] and 31% in [17]. Moreover, the peak energy decreases to 35% in each of the optimization methods used in this paper as well as in the technique used in [17], meanwhile the peak load reduction in [14] is 20% using the same data.
Figure 3. Optimal consumption cost using AM

Table 1. Appliances data [17].

| No. | Appliances name       | Power rate (W) | Duration (slot/day) | St (slot) | Et (slot) |
|-----|-----------------------|----------------|---------------------|-----------|-----------|
| 1   | Microwave/Oven        | 1230           | 2                   | 216       | 228       |
| 2   | Steam Iron            | 1235           | 10                  | 192       | 252       |
| 3   | Electrical water heater | 2600         | 24                  | 48        | 98        |
|     |                       |                |                     | 24        | 192       | 264       |
| 4   | Kettle                | 1900           | 2                   | 66        | 90        |
|     |                       |                |                     | 2         | 212       | 240       |
| 5   | Toaster               | 1010           | 2                   | 60        | 84        |
| 6   | Dishwasher            | 2500           | 30                  | 240       | 288       |
| 7   | Tumble dryer          | 3300           | 6                   | 192       | 244       |
| 8   | Stove                 | 3000           | 6                   | 60        | 84        |
|     |                       |                |                     | 10        | 192       | 240       |
| 9   | Vacuum cleaner        | 1200           | 6                   | 96        | 124       |
| 10  | Washing machine       | 3000           | 9                   | 192       | 264       |
Table 2. Optimal and baseline appliances scheduling

| No. | Appliances name            | Power rate (W) | Duration (slot/day) | normal operating periods | GA St (slot) | GA Et (slot) | PSO St (slot) | PSO Et (slot) | AM St (slot) | AM Et (slot) |
|-----|---------------------------|----------------|---------------------|--------------------------|--------------|--------------|--------------|--------------|--------------|--------------|
| 1   | Microwave/ Oven           | 1230           | 2                   | 216 218                  | 216 218      | 216 218      | 216 218      | 216 218      |              |              |
| 2   | Steam Iron                | 1235           | 10                  | 201 211                  | 198 208      | 200 210      | 192 202      |              |              |              |
| 3   | Electrical water heater   | 2600           | 24                  | 47 71                    | 61 85        | 58 82        | 61 85        |              |              |              |
| 4   | Kettle                    | 1900           | 2                   | 77 79                    | 70 72        | 66 68        | 68 70        |              |              |              |
| 5   | Toaster                   | 1010           | 2                   | 61 63                    | 68 70        | 60 62        | 66 68        |              |              |              |
| 6   | Dishwasher                | 2500           | 30                  | 240 270                  | 258 288      | 258 288      | 258 288      |              |              |              |
| 7   | Tumble dryer              | 3300           | 6                   | 230 236                  | 192 198      | 211 217      | 202 208      |              |              |              |
| 8   | Stove                     | 3000           | 6                   | 73 79                    | 63 69        | 78 84        | 60 66        |              |              |              |
| 9   | Vacuum cleaner            | 1200           | 6                   | 107 113                  | 116 122      | 102 108      | 202 208      |              |              |              |
| 10  | Washing machine           | 3000           | 9                   | 213 222                  | 198 207      | 192 201      | 208 217      |              |              |              |

Average implementation time (sec) 1.91 0.09 0.03
### Table 3. Optimized cost and energy results

| DR Scheme             | Optimization Method | Sampling time (min.) | Total energy (kW h) | Peak consumption (kW) | Total cost (R) | Cost reduction (%) | Peak reduction (%) |
|-----------------------|---------------------|----------------------|---------------------|-----------------------|----------------|--------------------|-------------------|
| Before scheduling     | -                   | -                    | 27.18               | 10.5                  | 25.37          | -                  | -                 |
| Setlhaolo’s Model[14] | ToU                 | Mixed integer programming (AIMMS software) | 10                  | 27.18                 | 8.4            | 18.80              | 25                | 20                |
| DRLS Model [17]       | ToU                 | Linear programming (iterative program) | 5                   | 27.18                 | 6.8            | 17.38              | 31                | 35                |
|                       | ToU                 | GA                   | 5                   | 27.18                 | 6.8            | 14.46              | 43                | 35                |
|                       | ToU                 | PSO                  | 5                   | 27.18                 | 6.8            | 14.46              | 43                | 35                |
|                       | ToU                 | AM                   | 5                   | 27.18                 | 6.8            | 14.2               | 44                | 35                |
Figure 4. Total customer consumption with normal consumption rate before scheduling. (a) Consumption using GA, (b) Consumption using PSO, (c) Consumption using AM.
6. Conclusion:

In this paper, an analytical method has been used to schedule the electrical energy for smart homes based on ToU pricing rate in a smart grid environment. Using different demand conditions for electrical energy, results show that the proposed algorithm reduces the electricity fee about 44%, as well as reduces the maximum load of total demand about 35%. The proposed schedules are contributed to reduce the variance in the consumed energy by redistributing loads of electrical appliances to avoid peak times, which is reflected in reducing the cost of the user's bill, moreover reduces the air pollution that may occur as a result of increasing energy production to cover the peak loads. In addition, this work contributes to improve the work of these smart devices through working online due to the rapid response to the load analysis and the suggestion of timelines through which to turn on and off the electrical devices according to the conditions set by the user, which leads to a reduction in the cost of the electric bill.

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