Residential load control system based analytical optimization method for real residential data consumption

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Abstract: Peak load periods have a great impact for energy demand in smart grid. These times is directly related to the consumption of residential sector, thus utility need to add additional generation capacity during peak time to support the demand required. This paper proposes a demand response system for residential household. Analytical Method (AM) is used to optimize the load consumption based real data of typical residential home. The consumption data are measured using smart plugs that have been designed and implemented to communicate with household’s smart devices. The simulation results show the peak load was reduced by 37.64% and the energy consumption cost bill was reduced by 29.52%. The proposed method is compared with other optimization methods such as Bacterial Foraging Optimization (BFO), and Particle Swarm Optimization (PSO) to highlight the finding. The proposed approach indicated a greater saving period to produce the final results.

Keywords: BFO, Demand response, Load scheduling, PSO, Smart plug, ToU pricing.

1. Introduction

At present, brownout, outage, voltage fluctuations, and glitches are the customer's biggest concerns. The key task of the utility sector is to produce and distribute electricity provided for customers with low running costs [1], [2]. One of the most critical challenges for service providers is to meet the demand required from consumers during peak hours. The demand response of smart grid (SG) provides essential methods to manage the available generation capacity with demand required specially during peak period. DR becomes one of the main SG features [3], user-friendly, self-healing, bidirectional connectivity, efficient, sustainable, and enhanced operations efficiency [4]–[7]. The smart grid becomes a potential energy infrastructure that incorporates advanced knowledge, networking and connectivity, computer, and process technology [8], [9]. It helps to transfer power from bulk generation stations to provide customers with distribution plants to supply the electricity elegantly and effectively. The role of customers and service providers is exceptionally essential to all SG communication system components [10]. In recent years, the Internet of Things (IoT) creation has represented a broad means of communication for the sharing information [11], [12]. SG information is currently shared through the Internet with active customer and service provider involvement [13]. Regardless the type of communication protocol used by IoT devices, IoT devices should make their data obtainable to other side. This can be achieved by collecting the data and sending to the cloud or
web server [14]. The literary studies include various works that deal with the need for the customer’s load management using various types of optimization methods to resolve load planning issues in intelligent homes. In [15] a linear programming approach is used for optimal load management based on adaptive price levels for 10 electrical equipment. The results indicated a 31% reduction in their energy bill using Time of Use (ToU), while for the adaptive consumption level pricing scheme (ACLPS), the total bill cost reduced around 53%. In [16] a model containing central control to manage the customer load using linear mixed-integer programming method was introduced. Two scenarios were used, for the first scenario, the results showed a decrease of 68.6% and 54.4% in the second scenario. In [17] Gray Wolf Optimization (GWO) and Genetic Algorithm (GA) were used to obtain ideal scheduling in terms of lowering the cost of the bill. Seven scenarios were used for combination of real-time pricing (RTP) and Inclining Block Rates (IBR) pricing schemes. The results showed that GWO and GA reduced the cost of the electric bill by 6.6% and 4.3%, respectively. In [18] a residential energy management method was developed to track and manage residential loads. This method was built using the enhanced Binary Gray Wolf Accretive Satisfaction Algorithm (GWASA). This algorithm relies on four assumptions that permit the quantification of time and device-based preferences. A cost satisfaction index for each unit was extracted in order to be able to monitor the daily expenditures of the consumer and linked it to the satisfaction achieved. The result of the scenarios used was compared with the output of three other different algorithms, namely, Binary particle swarm optimization (BPSO), Binary Genetic Algorithm (BGA), Binary grey wolf optimizer (BGWO). The simulation results reveal that GWASA offers the lowest cost per unit satisfaction and maximum user comfort ratio of 74.89% in all scenarios.

In [19] presented a demand-side management (DSM) for residential load scheduling using an energy-management controller (EMC). Implementing a residential load scheduling EMC by utilizing different optimization algorithms such as BPSO, GA, and HGBPSO (Hybrid Genetic BPSO). The proposed EMC retains DSM by residential load scheduling under Day-ahead demand response (DR) program. The results indicate that HGBPSO-based EMC is superior to BPSO and GA-based EMC in reducing energy costs by 11.60%, peak to average ratio (PAR) by 20.53% and emissions of CO2, relative to 80%. In [20] introduces an optimum plan controller with a binary backtracking search algorithm (BBSA). The BBSA proposes to reduce the highest energy usage in DR by 33.84% on weekends and 30.4% monthly on weekdays. Also, the model monitors the equipment and hold the overall usage of residential energy below the given demand cap. In [21] a multi-agent system of centralized residential demand-side management (DSM) scheme is suggested. Multi-source is used to mitigate cost concern such as photovoltaic panels and energy storage devices, thus maximizing the time-shifting of appliances. The cost reduction is represented as an issue with Mixed Integer Linear Programming (MILP). The results indicate that a win-win scenario may be reached as consumer expectations are taken into consideration. These advantages provide savings and satisfaction to consumers.

These works are typically deal with residential load control strategies for optimal load scheduling. Most of the work discussed is about saving cost by reducing electrical loads in peak periods as much as possible. However, accurate consumption data collection is not considered. Furthermore, the time taken to reach the optimal load scheduling is not covered. This paper utilizes various optimization techniques for optimum cost reductions and for a minimal amount of time. Time-saving in the cost optimization and peak energy approach helped drive the rapid reaction of the price shift. The paper is organized as follows: Section 2 introduces the objective functions. Section 3 explains the proposed model and algorithm. While section 4 presents the smart plug and details of collected data. Section 5 discusses the results of simulation and analysis. Finally, the article is concluded in section 6.
2. Objective functions
Households are looking for a way to control their use and lower these prices. The method of controlling and regulating consumption needs to define the problem and create a viable model for its solution. The objective function is calculated according to the following:

$$\min C = \sum_{i=1}^{T} G_i \ast N_i \ast \Delta t$$  \hspace{1cm} (1)

Where $G_i$ represents the rate of the price per each time slot, and $N_i$ is the total load consumption during time slot $i$ in (kW). $\Delta t$ is the length of each time period (i.e., equal the selected sampling time divided by 60), while $T$ is the horizon and it is 24 hours. The overall consumption of all of the appliances $N$ can be calculated by:

$$N = \sum_{i=1}^{T} \sum_{j=1}^{D} (N_{ij} \ast \delta i)$$  \hspace{1cm} (2)

Where $D$ is the total number of the considered devices and $\delta i$ is a variable of two values (0, and 1). It is equal to 1 when the $i^{th}$ devise is on, otherwise it is off.

3. Optimization Methods
Proper optimization methods help redistribute the operation of household appliances to a suitable schedule at the lowest prices, and to avoid the peak load period as much as possible. In the following subsections, the proposed method is presented along with two other optimization methods for comparison purposes

3.1. Analytical method (AM)
The proposed AM method distributes household appliances loads during the permissible time periods for each appliance. The main steps of the AM processes can be described as follows:
Step 1: The household appliances are ordered randomly and the initial cost is calculated.
Step 2: The household appliances rearranged randomly. According to new arrangement, the allowable operating period of the appliances is tested taking into account each device actual working period.
Step 3: Using a sliding time window, the appliances are put to work in periods of as low as possible cost. Step 4: Calculate the cost of the total power per day.
Step 5: Isolate all appliances that work during the peak time durations.
Step 6: Slide the uptime for these devices back and forth to a non-peak period taking into account the permissible working time for each device.
Step 7: Save the lowest daily cost obtained with actual uptime for each device.
Step 8: Repeat steps 2-7 to a predetermined number of iterations or until the daily electricity cost approaches the minimum value.
A complete overview of the proposed approach is shown in Figure 1.

3.2. Bacterial Foraging Optimization
The Bacterial Foraging Optimization (BFO) is a recent addition to the family of natural optimization algorithms. The BFO algorithm is influenced by Escherichia coli’s social foraging behavior [22]. From its conception, BFO has brought scholars from numerous fields of expertise to the attention. The bacteria look for nutrients in the BFO algorithm and choose the right nutrients (solutions) to optimize their energies. The four stages of the BFO algorithm comprise chemotaxis, swimming, elimination-dispersal, and reproduction. BFO algorithm starts by initializing its parameters, after that, the initial state of the devices will be evaluated under the chemotaxis step, and then, the new location of bacterium will be calculated (solution matrix) [22]. The equation will mathematically describe the chemotaxis steps of a bacterium (3).

$$F^a(x + 1, y, z) = F^m(x, y, z) + W(a) \frac{\Delta(a)}{\Delta^2(a) + \Delta(a)}$$  \hspace{1cm} (3)
where $F^a(x, y, z)$ represents $a$-th bacterium at $x$-th chemotactic, $y$-th reproductive and $z$-th elimination-dispersal step. $W(a)$ is the step size taken in a random direction considered by the tumble, while $\Delta(m)$ denotes a vector in the random direction.

### 3.3. Particle swarm optimization method

Particle swarm optimization (PSO) method is one of the most popular optimization algorithms. This algorithm aims to deal with persistent optimization issues. The PSO algorithm is changed to a discrete structure due to the discrete nature of scheduling problem [23]. The following equations describe the operation of the PSO algorithm

\begin{align}
    V_l(t+1) &= s \ast V_l(t) + a_1 \ast b_1 \ast (p_s \ast p_B(t) - p_s(t)) + a_2 \ast b_2 \\
    &\ast (p_s \ast g_B(t) - p_s(t)) \\
    p_s(t+1) &= p_s(t) + V_l(t+1) 
\end{align}

Where $V_l$ is the particle velocity, $p_s$ is the current particle (solution), $p_B$ is the current fitness value and $g_B$ represents $p_B$ better particle value. Meanwhile, $b_1$ and $b_2$ are random value between $(0,1)$. $a_1$, $a_2$ are represent learning factors, and $s$ is referred to inertia weight.

![Figure 1. Flow chart describes the proposed (AM).](image)
4. Data collection

Most work gives the consumption data without mention the devices used to collect these data. In this paper, the consumption data obtained by using fabricated device (smart plug). The smart plug is intended to be connected to a home Wi-Fi network or home access point. Users may interact with each smart plug by using their smartphone or laptop to control the appliances. Figure 2 illustrates the diagram of the smart plug. The ESP 8266 microcontroller is used in the smart plug components, consisting of a controller and a Wi-Fi module, and reads data from the electricity consumption meter via a serial peripheral interface (SPI) port. Moreover, the smart plug has an electricity consumption meter (PZEM004v03) used to measure voltage, current, power, energy and power factor), a synchronous dynamic RAM (SDRAM) used to save data, relay (5V relay module) used to control connect/disconnect appliances depending on received signals (on/off) from microcontroller. The smart plug is used to calculate electrical quantities and store the data in an SDRAM. The data collected may be used to predict consumer expenditure and consumption schedules. One of the advantages of this device is that it can be used by central control unit or energy-management controller (EMC) to control the appliances. In addition, consumers can control and monitor their appliances remotely by using internet. Data have been collected containing 8 home appliances mentioned in Table 1. All data were obtained for typical house in Iraq-Baghdad within three months. In addition, the data obtained were compared with two other electrical measuring devices. The first device is (VC8045 multimeter), which has an error rate of (0.5%), (0.8%) for measuring voltage and current respectively [24]. The second device (DT9205A) has a voltage measurement error rate (0.5%) and a current measurement error rate (1.2%) [25]. The proposed smart plug used PZEM-004T V3.0 to obtain electrical measurements, which has an error rate of (0.5%) for both voltage and current measurement [26]. The practical accuracy rate of the proposed plug, VC8045 and DT9205A multimeters are as show in Table 2. To verify the correctness of the built device measurements, the readings measurements obtained from it (voltage and current) were compared with each of VC8045 and DT9205A multimeters measurements. Error rates for obtained data were explained as shown in Table 3 for temperature of accuracy guarantee is (24±5)°C.

Table 1. Home appliances.

| No. | Appliance name      |
|-----|---------------------|
| 1   | Washing Machine    |
| 2   | Micro Wave         |
| 3   | Oven               |
| 4   | Coal burner        |
| 5   | Air conditioner (1) |
| 6   | Air conditioner (2) |
| 7   | Water pump         |
| 8   | Heater             |
| 9   | Hair Dryer         |

Table 2. Error rate of the built device, VC8045 and DT9205A multimeters.

| Error Rate (%) | VC8045 [24] | DT9205A [25] | Built device [26] |
|----------------|-------------|--------------|--------------------|
| AC Voltage     | 0.5         | 0.5          | 0.5                |
| AC Current     | 0.8         | 1.2          | 0.5                |
Table 3. Actual accuracy rate of the implemented measuring device compared to VC8045 and DT9205A multimeters.

| Built device     | Error Rate (%) |
|------------------|----------------|
|                  | VC8045 | DT9205A |
| AC Voltage       | 0.1    | 0.11    |
| AC Current       | 0.3    | 0.5     |

5. Simulation results
The proposed analytical method is implemented using MATLAB software package. The collected data contains power values, starting (St) and ending times (Et) for each device, and the duration of time required for each device to complete its task. Table 4 shows the appliances data, for example, the oven is used once every day for 90 minutes, this implies that an 18-slot runtime is needed for this device (sampling period is 5 minutes per interval). Therefore, it needs about 18 slots from slot 150 (12:30) to slot 168 (14:00). The adopted pricing scheme is ToU [15], the off-peak hours are from 00:00-7:00, 11:00-18:00, and the peak period from 18:00 to 22:00. The tariff is 45.54 c / kWh for off-peak time, and 144.52 c / kWh for peak time as shown in Figure 3. Note that the pricing system adopted in Iraq is a block tariff, and it does not contain the necessary incentives to change consumption. In AM, the iteration continued until the output converges to a steady state as shown in Figure 4. The results of optimal load scheduling of AM for customer load are presented in Table 5. In this table, the fifth and sixth columns reflect standard cycles of service for electrical equipment without optimization methods. For instance, the Microwave needs 2 slots in the morning (10 minutes) and 2 slots in the evening (10 minutes). The optimum period plan for microwave with BFO begins at St = 80 (06:40) in the morning, ending at Et = 82 (06:50) in the morning, and started at St = 185 (15:25) in the evening, ending at Et = 187 (15:35). Meanwhile, appliances such as a Coal burner would operate for 4 slots...
once a day (20 mins), the baseline and the optimum time schedule duration using BFO method is from
the slot 226 (18:50) to the slot 230 (19:10). The results of the other devices are presented in Table 5.
Loads distribution for different optimization methods are shown in Figure 5. All optimization
methods, aim to redistribute the load while avoiding peak time to reduce the average energy costs. AM
produces optimum outcomes within the shortest operating period compared with other optimization
method. Comparison results for the peak load and the energy cost for a given optimal load are shown
in Table 6. Obtained cost reduction of AM of 29%, while both BFO and PSO reported a lower
reduction of 28%. As for the peak load, it was reduced by all means of optimization methods by 37%.

![Graph showing on-peak and off-peak cost rate](image)

**Figure 3.** On-peak and Off-peak cost rate

![Graph showing optimal cost of consumption using Analytical method](image)

**Figure 4.** Optimal cost of consumption using Analytical method
Table 4. Appliances data.

| No. | Device name          | Power rate (W) | Period (slot/day) | St (slot) | Et (slot) |
|-----|----------------------|----------------|-------------------|-----------|-----------|
| 1   | Washing Machine      | 480            | 12                | 204       | 252       |
| 2   | Micro Wave           | 973            | 2                 | 179       | 190       |
|     | Micro Wave           | 973            | 2                 | 75        | 84        |
| 3   | Oven                 | 1921           | 18                | 137       | 192       |
| 4   | Coal burner          | 324            | 4                 | 218       | 233       |
| 5   | Air conditioner (1)  | 1245           | 30                | 180       | 240       |
|     | Air conditioner (1)  | 1245           | 33                | 240       | 288       |
|     | Air conditioner (2)  | 1245           | 67                | 1         | 84        |
| 6   | Water pump           | 365            | 24                | 1         | 288       |
| 7   | Heater               | 1280           | 3                 | 72        | 84        |
|     | Heater               | 1280           | 3                 | 189       | 201       |
|     | Heater               | 1280           | 3                 | 256       | 267       |
| 8   | Hair Dryer           | 1635           | 4                 | 220       | 234       |

Table 5. Optimal and baseline appliances scheduling

| No. | Appliances name       | Power rate (W) | Duration (slot/day) | normal operating periods | BFO | PSO | AM |
|-----|-----------------------|----------------|---------------------|--------------------------|-----|-----|----|
|     |                       |                |                     | St (slot) | Et (slot) | St (slot) | Et (slot) | St (slot) | Et (slot) |
| 1   | Washing Machine       | 480            | 12                  | 222        | 233        | 205        | 216        | 204        | 215        | 205        | 216        |
| 2   | Micro Wave            | 973            | 2                   | 182        | 183        | 185        | 186        | 185        | 186        | 179        | 180        |
|     | Micro Wave            | 973            | 2                   | 80         | 81         | 80         | 81         | 82         | 83         | 75         | 76         |
| 3   | Oven                  | 1921           | 18                  | 150        | 167        | 160        | 177        | 156        | 173        | 137        | 154        |
| 4   | Coal burner           | 324            | 4                   | 224        | 227        | 226        | 229        | 229        | 232        | 218        | 221        |
| 5   | Air conditioner (1)   | 1245           | 30                  | 198        | 227        | 185        | 214        | 181        | 210        | 180        | 209        |
|     | Air conditioner (1)   | 1245           | 33                  | 249        | 281        | 255        | 287        | 255        | 287        | 256        | 288        |
|     | Air conditioner (2)   | 1245           | 67                  | 5          | 71         | 1          | 67         | 14         | 80         | 1          | 67         |
| 6   | Water pump            | 365            | 24                  | 222        | 245        | 1          | 24         | 165        | 188        | 155        | 178        |
| 7   | Heater                | 1280           | 3                   | 75         | 77         | 75         | 77         | 81         | 83         | 72         | 74         |
|     | Heater                | 1280           | 3                   | 192        | 194        | 196        | 198        | 197        | 199        | 189        | 191        |
|     | Heater                | 1280           | 3                   | 261        | 263        | 264        | 266        | 264        | 266        | 264        | 266        |
| 8   | Hair Dryer            | 1635           | 4                   | 227        | 230        | 221        | 224        | 224        | 227        | 222        | 225        |

Average execution time (sec) 0.1843 0.0205 0.01996
Table 6. Obtained energy and cost results

| DR Scheme | Optimization Method | Sampling time (min.) | Total energy (kWh) | Peak consumption (kW) | Total cost (R) | Cost reduction (%) | Peak reduction (%) |
|-----------|---------------------|----------------------|--------------------|-----------------------|---------------|--------------------|--------------------|
| Before scheduling | -                  | -                    | 19.52              | 4.049                 | 13.72         | -                  | -                  |
| ToU       | BFO                | 5                    | 19.52              | 2.525                 | 9.8           | 28.57              | 37.64              |
| ToU       | PSO                | 5                    | 19.52              | 2.525                 | 9.8           | 28.57              | 37.64              |
| ToU       | AM                 | 5                    | 19.52              | 2.525                 | 9.67          | 29.52              | 37.64              |

a- Load distribution using BFO.

b- Load distribution using PSO.
6. Conclusion
In this research, an analytical approach was used to redistribute the residential load for smart houses based on ToU price rate. The results show that the electricity bill decreased by 29% and the peak load of total demand is reduced by about 37%. The proposed method assists in decreasing the disparity of electricity used by redistributing electrical equipment loads to bypass peak hours, and minimizing environmental emissions as a consequence of improved energy demand to cover peak loads.

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