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# Home Energy Management System Based on Genetic Algorithm for Load Scheduling: A Case Study Based on Real Life Consumption Data

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**Abstract:** This paper proposes a home energy management system able to achieve optimized load scheduling for the operation of appliances within a given household. The system, based on the genetic algorithm, provides recommendations for the user to improve the way the energy needs of the home are handled. These recommendations not only take into account the dynamic pricing of electricity, but also the optimization for solar energy usage as well as user comfort. Historical data regarding the times at which the appliances have been used is leveraged through a statistical method to integrate the user's preference into the algorithm. Based on real life appliance consumption data collected from a household in Morocco, three scenarios are established to assess the performance of the proposed system with each scenario having different parameters. Running the scenarios on the developed MATLAB script shows a cost saving of up to 63.48% as compared to a base scenario for a specific day. These results demonstrate that significant cost saving can be achieved while maintaining user comfort. The addition of supplementary shiftable loads (i.e., an electric vehicle) to the household as well as the limitations of such home energy management systems are discussed. The main contribution of this paper is the real data and including the user comfort as a metric in in the home energy management scheme.

**Keywords:** home energy management; load scheduling; genetic algorithm; user comfort



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## 1. Introduction

### *1.1. Setting the Stage*

One of the pressing challenges that countries are attempting to take on is achieving their energy independence. The main reason for this target is to ensure there is sufficient energy at all times for all sectors to operate smoothly. For Morocco, for example, peak hours demand is met by importing energy from neighboring countries. Energy reliance becomes an important parameter to keep in mind when considering the relationship with a particular country, as leaders would rather not put their energy security in jeopardy [1]. The need for a new and better way to handle energy on a national level is more crucial than ever. The aforementioned factors have been key catalysts in the progress of the research and development of what is referred to as smart grid (SG). The SG is an electric grid supported by a set of technologies which include but are not limited to automation, communication, and cybersecurity to mention a few. The SG is expected to be the key actor in a range of structural changes that are directly related to how energy is handled from day to day [2]. The main feature of the SG is a decentralization of the energy supply. The conventional grid operates in a way that puts the utility as a central dispenser of electricity that transmits energy based on the demand. SG not only enables the existence of a multitude of virtual power stations, but also provides the ability for bi-directional transmission of energy across the grid. Another crucial feature of SG is a reduced reliance on large-scale power plants and a wider ability to include small-scale otherwise known as distributed generation. This is of particular importance since small-scale power plants are mainly relying on renewable energy, which represents the way in which SG offers sustainable alternative [3]. A key aspect of SG, which this paper will rely on, is the active participation of individual homeowners in their energy consumption, thereby having an immediate impact on the energy demand. This involvement is reliant on what is referred to as demand response (DR). DR is an approach that involves responding to the global energy demand by attempting to manage and control the demand rather than relying on energy supply only [4]. This gives more importance to the involvement of individual house owners in following the adequate recommendations that lead to better energy consumption in their homes. Supporting homeowners with how they can better manage and schedule their appliances, electric vehicles (EV), and other miscellaneous loads becomes imperative in the DR approach. This conundrum of scheduling can be solved through optimization algorithms that proposes the most optimal way to run the loads in a household without impacting the users' comfort. This paper will rely on the genetic algorithm (GA) to provide an optimal schedule and demonstrate the impact on the energy efficiency of a particular household. The home energy management system (HEMS) is based on collected data of the energy consumption of the different loads present in this household. The use of actual acquired data will enable a more realistic use of the proposed algorithm.

Several researchers have previously tackled the matter of load scheduling in the residential sector. Two approaches to load scheduling, time-table and tree-based strategies, are investigated by Zupančič et al. [5], where a 17% improvement in terms of the cost objective is achieved. A HEMS based on linear programming is developed and discussed by El Makroum et al. [6] with varying loads being rescheduled to result in a 13.73% reduction in the electricity bill. Alıç et al. [7] developed a HEMS consisting of user discomfort models that enables a homeowner to achieve a balance between maintaining their comfort and saving on costs. Khorram et al. [8] investigated optimizing the energy consumption of an office building considering multiple user comfort parameters. Six scenarios based on individual appliance consumption show a decreased benefit to cost saving due to comfort consideration. Song et al. [9] introduced a novel approach to HEMS. Based on global user satisfaction, the simulation resulted in a 39.81% reduction in electricity expenditure. The inclusion of an electric vehicle (EV) and of an energy storage system (ESS) in a HEMS is investigated by Mohammad et al. [10]. A significant reduction in cost was achieved through binary particle swarm optimization, which was further reduced thanks to the ability to sell energy to the grid. Minhas et al. [11] explored using an EV for the purpose of energy storage in a HEMS, which achieves a 13% reduction in electricity cost at the expense of a yearly degradation of 0.013% in EV battery capacity loss. A GA based HEMS in the work of Liemthong et al. [12] manages the operation of an EV along with other loads in a household, achieving a daily improvement of 7.0185%. Fouladfar et al. [13] investigated the potential of EV in DR strategies, which resulted in an increased impact of DR by 17%. A novel algorithm merging both genetic algorithm and enhanced differential evolution is proposed in Albogamy et al. [14], with reduction rates ranging from 11.87% to 41.66% at the level of different parameters across two case studies. These pieces of research show that HEMS provide a positive impact despite varying parameters differing from one household to another.

### *1.2. Research Objective*

Following the analysis of the literature review, the contributions of this paper are three folds. The research gap presents itself in using higher frequencies of time series on which the loads operate, in leveraging real data to provide more support to the evidence, and in identifying approaches to user comfort that would have a more positive impact in encouraging homeowners to adopt HEMS and the subsequent recommendations. The research objective of this paper is to use real data to establish three distinct scenarios of load scheduling in a household. These scenarios will be optimized and then analyzed to address the aforementioned gap with the purpose of demonstrating and providing further evidence to the positive impact of HEMS. The goal would be to achieve great cost savings all the while maintaining an adequate level of user comfort. The remainder of this paper is organized as follows. Section 2 details the materials and methods involved in this paper. Section 3 shows and analyzes the results of the paper. Section 4 discusses and interprets the results.

## 2. Materials and Methods

### 2.1. Data Acquisition

The data used in this paper was collected through internet databases and hardware installations in a single house located in the region of Fés Meknes in Morocco. This house is inhabited by a family of four, two adults and two children. The tracked loads are detailed in Section 2.4. The hardware used involved smart plugs for appliances, and of smart clamps installed in the household's electrical box to track other forms of electricity consumption. The apparatus collects data and stores it on a cloud database provided by the manufacturer. For the purpose of the simulation, the data were extracted and stored in an excel workbook linked with the model on MATLAB. The acquired data came in the form of a set of load profiles of each individual appliance and other loads in the house at an interval of 5-min. The data acquisition spanning two years provided ample 24-h consumption profiles to work with, despite several gaps due to issues in maintenance. Using these data, a comparison can be established between the base load profile of the household, and the optimal load profile proposed. As household consumption data are not solely sufficient to perform the optimization, supplementary data were procured from online databases. Solar energy generation profile was extracted from the PVoutput database [15], while the electricity prices were extracted from the Australian Energy Market Operator (AEMO)'s website [16]. The decision to use AEMO's platform was made based on the 5-min resolution of the provided data, which could not be found for Morocco's electric utility company.

### 2.2. User Comfort

In this paper, the user comfort was not based on ambient temperature in the household, but rather on how the user's daily activities are impacted and how much input is needed from the user to fully adopt the HEMS. One of the challenges that face the widespread adoption of HEMS is the resistance from users to implement the recommendations of the system [17]. Whether it is due to indolence or incomprehension, the behavioral inertia of the user is important to consider for the diffusion of HEMS as a household pillar. To this end, the collected data from the household is leveraged further than to only provide consumption load profiles. According to Maibach [18], a large gap exists between people's attitude towards a behavior, and whether they would actually commit to performing it. For example, a homeowner can opt to install a HEMS to better manage their energy, but that does not necessarily mean that they will religiously follow each recommendation proposed by the systems. This research highlights the importance of making the changes easier for the user. Despite being aware that a particular behavior is in their best interest, people tend to be more likely to perform and commit to a simple straight forward behavior. Based on this, the assumption that the further a novel suggested behavior deviates from the normal, the less likely the user will be willing to adopt such recommendations. To further illustrate the idea, it is assumed that the user, who operates a certain load in the household consistently at 7:00 p.m. is more likely to follow a recommendation to operate the load at 7:15 p.m. than another recommendation at 5:00 a.m. Thus, user comfort for this paper refers to the likelihood of the user performing the behavior, and the amount of effort they would have to make to take the recommendation into account. The genetic algorithm thus not only optimizes for a lower electricity bill, but also minimizes this needed effort from the user perspective.

The way this is performed is through a user behavior profile (UBP) generated from the collected data. The core idea is that the more the user is to be kept comfortable and satisfied, the less wiggle room there should be for the optimization to schedule loads many hours away from the usual operation times. Based on the operation times of appliances over the span of six months, UBPs have been generated for every appliance. The method by which a UBP is generated is as follows. Usage profiles of an appliance are compiled into an array of 288 cells, each one representing a 5-min interval in a day. The result shows which times slots have seen the most initiations of the operation of a particular appliance.

In order to model the UBP as a penalty for the fitness function's calculation, a normalization of the data is performed through the z-score transform, where $ACP$ is the aggregated consumption profile, $\mu$ is the mean, and $\sigma$ represents the standard deviation:

$$Z - Score\ (ACP) = \frac{ACP - \mu}{\sigma} \tag{1}$$

So as to provide the user with further opportunity of involvement in the HEMS, the UBP is not used directly in the GA. Instead, the HEMS enables the user to modify how impactful the UBP will be to the optimization. This operation is performed through having the user set a rating, referred to as an appliance flexibility index (AFI) of how flexible they are in terms of operating loads far from the norm. The ratings are set between 0 and 10, with 0 representing absolutely no flexibility and 10 enabling the HEMS to perform the scheduling fully based on cost reduction. The user can either set a flexibility index for each individual appliance or set one AFI to be used for all loads. The generated UBPs are illustrated in Figure 1.

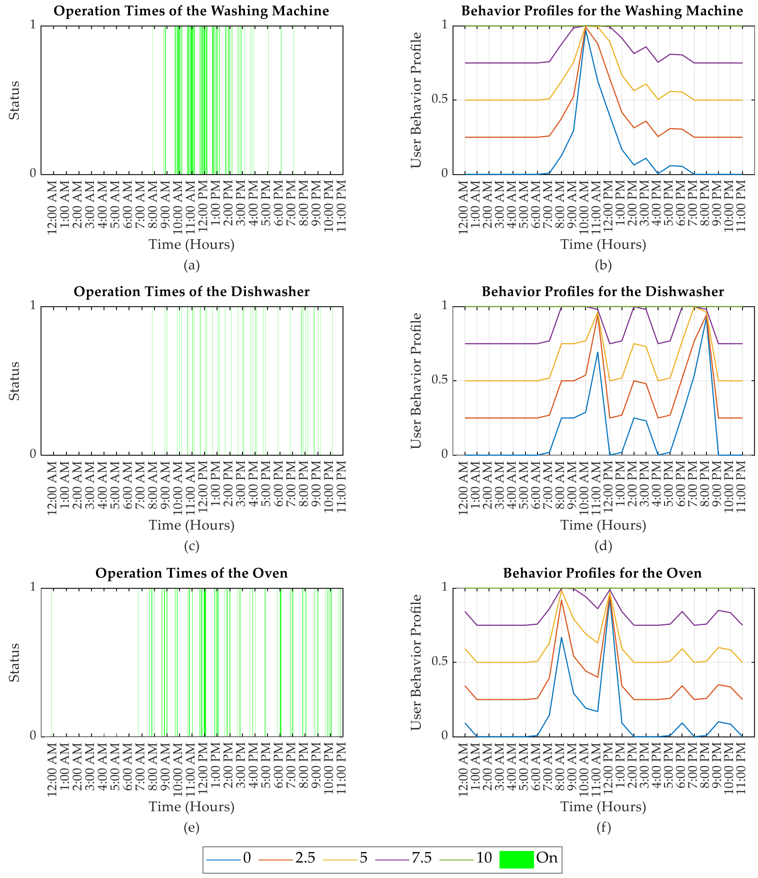


**Figure 1.** Operation times and behavior profiles for each shiftable appliance. (**a**) Operation times of the washing machine; (**b**) User behavior profile of the washing machine; (**c**) Operation times of the dishwasher; (**d**) User behavior profile of the dishwasher; (**e**) Operation times of the washing machine; (**f**) User behavior profile of the washing machine.

Tiles on the left side display the hours of the day where the appliance is more popularly used. The subsequently generated UBPs are shown on the tiles to the right. For example, pane (a) shows that the user generally operates the washing machine during the middle of the day. In pane (b), the UBP is generated based on the operation of the appliance and the flexibility index set by the user. The higher the index assigned, the flatter the curve of the profile gets, meaning that the impact of the penalties on different hours of the day is reduced.

*2.3. Genetic Algorithm*

This paper relies on GA to demonstrate the impact of load scheduling on a household. GA is a heuristic search-based algorithm that embodies the concept of "survival of the fittest". Inspired by natural evolution, it involves the generation of a large population of solutions, and the performing of genetic operations which enable the diversification of solutions [19]. The idea is to widen the pool of possible solutions and to improve the populations through multiple iterations of said operations. Though the GA is able to output the best solution out of the pool, it is not guaranteed to provide the most optimal solutions for the problem. However, given enough iterations and the right parameters, the algorithm is generally able to get sufficiently close to the best possible solution, or even achieve it [20]. While GA does not assure that the best solution will be found in polynomial time, it is capable of generating an adequate solution within a short space of time. This points to the NP hardness of this paper's optimization problem, which is characterized by a large amount of data required as input and the linear growth rate of these data [21].

These parameters are what motivated the use of GA for this paper, as this ability to extract a solution from a wide pool suits the uncertain nature of this problem and can easily incorporate and satisfy the constraints of said problem. While there exist many other heuristic and meta-heuristic optimization algorithms, the extensive research already performed based on GA as well as its availability on the MATLAB optimization toolbox have further supported the decision to use it. The next part defines the parameters needed to develop the algorithm. $N_{pop}$ is the number of solutions to be generated during the initialization. $It_{max}$ is the maximum number of iterations that the algorithm will go through before coming to a half. It is one of the different termination criteria that can be set for the algorithm. Alternatively, the termination could be set to stop when a specific fitness rating is achieved or when the population has converged. Meaning that the iteratively generated solutions are not of significant difference compared to the parent solution. $N_c$ is then number of crossovers to be performed, while another parameter is $\mu_m$ which is the mutation rate. The higher $\mu_m$ is, the more genes will be altered in the selected solution.

Figure 2 depicts the flowchart of the genetic algorithm and Algorithm 1 details the steps of its operation. The first step consists of initializing a population of solutions. Performed at random, the initialization generates a number of solutions equal to $N_{pop}$. The following step aims at evaluating the generated solutions through the fitness function (FF). The FF is a crucial piece of the algorithm, it is a mathematical equation that takes one of the solutions as inputs, and outputs a fitness score relative to how adequate the solution is. It is through this fitness score that the solutions are sorted and then kept or eliminated. The kept solutions go through what is called the crossover. Depending on the value assigned to $N_c$, an equivalent number of crossovers is done between the two selected parents. This crossover entails an exchange of a set number of genes between said solutions. The set of genes to be crossed over is relative to the type of crossover to be performed, whether it is a single-point crossover or a multi-point one. In order to further diversify the population of solution, a number of genes, relative to $\mu_m$, is altered within an individual solution. The penultimate step before verifying if the termination criteria are met is to evaluate the solutions another time. If the criteria are not yet satisfied, the algorithm starts another iteration and continues running until the termination criteria are satisfied. Subsequently, the final solution is outputted. The aforementioned steps are all detailed in the following pseudo-code.

**Algorithm 1** Genetic Algorithm

**Data:** Import Consumption Profiles, Solar Energy Generation, and Electricity Market Prices.
**Parameters:** $N_{var}$, $N_{pop}$, $It_{max}$, $N_c$, $\mu_m$
compute behavior profiles of appliances;
initialize genetic algorithm;
**while** termination criteria is not satisfied do
    evaluate solutions through FF;
    sort solutions by fitness;
    perform crossover;
    perform mutation;
    evaluate new solutions;
**end**

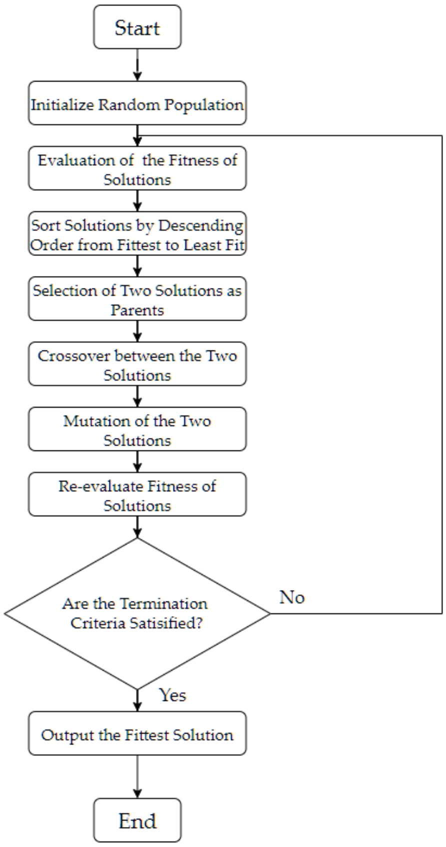


**Figure 2.** Flowchart of Genetic Algorithm.

### *2.4. Problem Formulation*

The load scheduling problem in this paper takes into account one day of the operation of appliances and loads in the household. The considered day starts at 12:00 a.m. and ends on the timeslot starting at 11:55 p.m. With a frequency of 5 min, the day is composed of 288 timeslots. $T$ represents the set of time slots in the considered day; it is defined by

$$T = \{1,\ 2,\ 3, \ldots,\ 288\} \quad (2)$$

The set of loads running that day is denoted $L$, and the loads are split between shiftable loads and non-shiftable loads as

$$L_{SH} = \{L_{WM},\ L_{DW},\ L_{OV},\ L_{EV}\}, \quad (3)$$

and

$$L_{NSH} = \{L_{RE},\ L_{CO},\ \ L_{HE},\ L_{TV},\ L_{FR}\}, \tag{4}$$

where $L_{SH}$ is the set of shiftable loads in the HEMS, consisting of $L_{WM}$ the load of the washing machine, $L_{DW}$ the load of the dishwasher, $L_{OV}$ the load of the oven, and $L_{EV}$ the load of the electric vehicle. $L_{NSH}$ is the set of non-shiftable loads, consisting of $L_{RE}$ the load of the refrigerator, $L_{CO}$ the load of the home computer, $L_{HE}$ the load of the heater, $L_{TV}$ the load of the television, and $L_{FR}$ the load of the freezer.

According to the collected data, each appliance has consumed a specific quantity of electricity on the considered date. The consumption of a given load is denoted as a vector $C_L$, and is defined by

$$C_L\ = [C_{WM},\ C_{DW},\ \ C_{OV},\ C_{EV}, C_{RE},\ C_{CO},\ \ C_{HE},\ C_{TV},\ C_{FR}] \tag{5}$$

where $C_T$ is the aggregated consumption of all loads in the household.

Let $t_L^s \in\ T$ and $t_L^e \in\ T$ be the start time slot of operation of a load and the end time slot respectively. So as to avoid the HEMS providing time slots that are erroneous, an equation that ensures the sequentiality of the periods of the start and end of the load is added. Thus,

$$t_L^s < t_L^e \qquad\qquad \forall t \in\ T \tag{6}$$

Let $n_T$ denote the number of time slots that an appliance needs for its cycle. (7) is imposed as a constraint to ensure that the difference between the suggested time slots is equivalent to the time needed to complete one cycle of the load. Thus,

$$t_L^e - t_L^s = n_T \qquad\qquad \forall t \in\ T \tag{7}$$

At any given time $T$, the load is either running and consuming energy, is idle and consuming very low quantities of electricity, or is unplugged and inactive. Due to the marginal amount of electricity consumed during the period in which an appliance is idle, only two possible states are considered for each load.

$$C = \begin{cases} L, & t \in \left[t_L^s, t_L^e\right] \\ 0, & t \in \left[t_1, t_L^s\right[ \cap \left]t_L^e, t_{288}\right] \end{cases} \qquad\qquad \forall t \in\ T \tag{8}$$

The total consumption of the household can be calculated as

$$C_{Total}\ = \sum_{t=1}^{288} C_L \qquad\qquad \forall t \in\ T \tag{9}$$

Let $P$ denote a vector of the dynamic pricing of electricity over the considered day; it is defined by

$$P = \{P_1,\ P_2,\ P_3, \ldots,\ P_{288}\} \tag{10}$$

where $P_i$ is the price of a kWh of electricity in the timeslot $t_i$.

Let $S$ denote a vector of solar energy generation over the considered day, it is defined by

$$S = \{S_1,\ S_2,\ S_3, \ldots,\ S_{288}\} \tag{11}$$

where $S_i$ is the quantity of kWh of electricity generated in the timeslot $\mathrm{t_i}$.

Let $B_L$ denote the set of generated UBPs defined by

$$B_L = \{B_{WM},\ B_{DW},\ \ B_{OV}\}, \tag{12}$$

where $B_{WM}$, $B_{DW}$, and $B_{OV}$ are the UBPs of the washing machine, the dishwasher, the oven respectively. In order to adequately reflect the impact of the UBP on the optimization problem, a utility function is implemented to the objective function. As utilized by

Alıç et al. [2], it provides a more accurate measure of how a solution is to impact the user's comfort.

The objective function for each appliance in scenario 1 can be formulated as follows:

$$min\ C_L \ = \sum_{t=1}^{288} \frac{C_i {P_i}^{1-B_i}}{1-B_i} \qquad \forall t \in \ T \tag{13}$$

where (13) is utilized to minimize the cost of operation of a given load. This is performed through incorporating the consumption needed for operating the load, the pricing of electricity, and the UBP of the load into the objective function with a formulation following the utility function.

For scenario 2, the objective function is:

$$max\ C_L \ = \sum_{t=1}^{288} \frac{C_i {S_i}^{1+\mathrm{B}_i}}{1+\ \mathrm{B}_i} \qquad \forall t \in \ T \tag{14}$$

where (14) is aimed at maximizing the usage with regards to the renewable energy generation profile during that day. It involves parameters that are identical to those of (13), except the pricing of electricality, which is replaced by the electricity generated. It is worth pointing out that $B_i$ is negated so as to adapt the UBP to the change in the objective function of the optimization.

This study is divided into three scenarios in which the impact of the HEMS will be assessed. All the scenarios will include all loads in $L_{SH}$ and $L_{NSH}$. The difference will be in the form by which energy is procured to the household. As for scenario 3, a more concrete example is illustrated. Rather than optimizing solely for renewable energy or for dynamic pricing, the algorithm merges both sources in this scenario for more optimal energy usage. Table 1 summarizes the scenarios.

**Table 1.** Summary of characteristics of the presented scenarios.

| Scenario | Energy Use | Characteristics |
|---|---|---|
| 1 | Grid Electricity | Purchasing from the grid at prices based on the Australian energy market |
| 2 | Solar Energy | Local photovoltaic field with a capacity of 2.75 kW |
| 3 | Grid and Solar | Reliance on both sources with prioritization of solar energy |

## 3. Results

The proposed HEMS was modeled on MATLAB R2022a with the addition of the optimization toolbox. The script was run on a laptop computer with Intel (R) Core (TM) i7-7700HQ CPU @ 2.80 GHz with four cores and eight processors, 12.0 GB RAM in times ranging between 22 and 28 s. As summarized in Table 1, this paper will base the simulation on the sections discussed in the methodology to generate scenarios of the operation of appliances in the household. So as to remain consistent with the format of the data, the simulation will be based on a 5-min resolution.

Table 2 displays the settings based on which the HEMS will be run. In order to illustrate a more realistic impact, three settings of behavior profiles will be considered for each scenario. The settings have been implemented with considerations related to the general perception of how the flexibility of a given appliance compares to the other. For example, in the moderate setting, it is assumed that the user would be very flexible in scheduling his washing machine and dishwasher, while their cooking habits would not enable much control at the level of the oven. Table 3 illustrates the considered flexibility ratings. While, in Figure 1, the UBP is set between 0 and 1, the flexibility index is not set according to the same ratio. The flexibility index is rather set on a scale from 0 to 10 so as to make the process of setting the ratings more user friendly. It is assumed that the user would be more comfortable with setting a rating of seven out of 10, rather than a rating of 0.7, for example.

**Table 2.** Parameters of the genetic algorithm in the simulation.

| Parameter | Value |
|---|---|
| $N_{pop}$ | 100 |
| $It_{max}$ | 100 |
| $N_c$ | 1 |
| $\mu_m$ | 0.1 |

**Table 3.** User Comfort settings for the considered scenarios.

| User Comfort Setting | Load | Flexibility Rating |
|---|---|---|
| Flexible | Washing Machine | 10 |
| | Dishwasher | 10 |
| | Oven | 10 |
| Moderate | Washing Machine | 9 |
| | Dishwasher | 7 |
| | Oven | 1 |
| Not Flexible | Washing Machine | 0 |
| | Dishwasher | 0 |
| | Oven | 0 |

### *3.1. Base Scenario*

Figure 3 illustrates the base scenario for the simulation. The blue shaded bars of consumption represent the shiftable loads managed by the HEMS, while the red shaded ones represent the non-shiftable loads. The selection of the day from which this load profile has been generated was made on the basis to follow the conventional load profile of an electrical grid where the consumption is very high at night, relatively moderate during the early afternoon, and low during the other times in the day. The similarity between the usual load profile of the grid and the selected load profile for the base scenario of the simulation is intended to enable a clearer comparison of the potential impact of load scheduling on peak shaving in the grid as a whole. The cost of electricity for the base scenario is calculated to be $1.72197. This cost was calculated by multiplying the consumption in each period of the day by the electricity price in the corresponding period, and then summing the total cost.

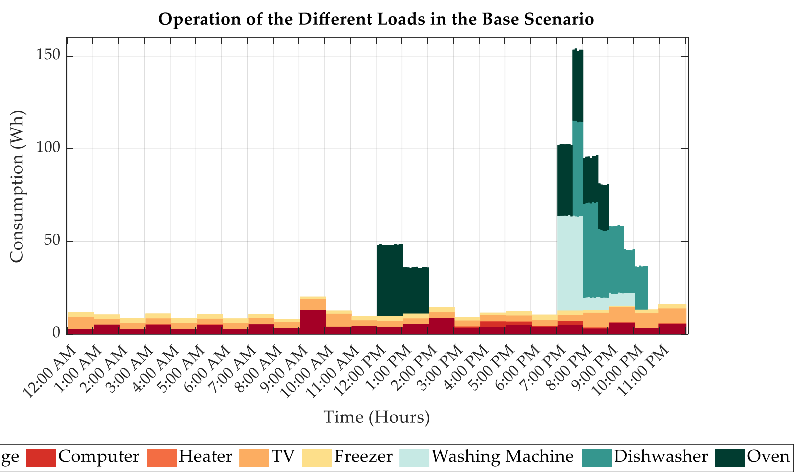


**Figure 3.** Base Scenario of the Chosen Day for the Simulation.

### 3.2. Scenario 1—Electrical Grid Only

In this scenario, the optimization will be concerned with reducing the daily cost of electricity for a household only drawing energy from the grid. The utilization of different flexibility settings is expected to impact the energy saving capabilities of the HEMS.

Figure 4 illustrates the load profiles resulting from running the simulation for scenario 1. Under the flexible setting, the HEMS was able to freely schedule the loads in the valleys of the dynamic pricing scheme. For the moderate setting, only the second operation of the oven was allocated to the peak. As for the strict setting, the dishwasher's cycle was allocated to the peak in addition to the oven's second run. The washing machine remained assigned in the middle of the day, which is due to its usual usage in the household being in the same time period. Table 4 summarizes the results of the simulation under scenario 1 under the different settings. The table also displays how much it cost to run the appliance during the specific time in which it was allocated, as well as the total cost including the non-shiftable loads. It also displays the percentage by which the optimization managed to reduce the cost of electricity for the selected day. The HEMS, under flexible setting, was able to achieve a cost reduction of 33.64 compared to the base cost. Though lower than the flexible setting, the moderate one was still able to achieve substantial reduction in cost. When it comes to the strict scenario, the cost saving capabilities of the HEMS are rendered almost ineffective, as only a 4.27% cost reduction was recorded. The generated scheduling of the appliances in the middle of the day indicates that a solar energy generation installation in this household is set to have a positive impact on the output of the HEMS.

**Table 4.** Result Summary for Scenario 1.

| Setting | Load | Operation Times | Cost ($) | Total Cost ($) | Cost Reduction (%) |
|---|---|---|---|---|---|
| Flexible | Washing Machine | [11:25 a.m. to 02:20 p.m.] | 0.07765 | 1.14256 | 33.64 |
| | Dishwasher | [11:25 a.m. to 02:15 p.m.] | 0.13478 | | |
| | Oven | [06:15 a.m. to 08:10 p.m.] | 0.10407 | | |
| | | [01:55 p.m. to 03:10 p.m.] | 0.09885 | | |
| Moderate | Washing Machine | [11:25 a.m. to 02:20 p.m.] | 0.07765 | 1.33317 | 22.58 |
| | Dishwasher | [12:05 p.m. to 02:55 p.m.] | 0.14606 | | |
| | Oven | [10:30 a.m. to 12:25 p.m.] | 0.08486 | | |
| | | [05:30 p.m. to 07:25 p.m.] | 0.29739 | | |
| Strict | Washing Machine | [09:40 a.m. to 12:35 p.m.] | 0.07966 | 1.64844 | 4.27 |
| | Dishwasher | [06:35 p.m. to 09:25 p.m.] | 0.45932 | | |
| | Oven | [10:30 a.m. to 12:25 p.m.] | 0.08486 | | |
| | | [05:30 p.m. to 07:25 p.m.] | 0.29739 | | |

### 3.3. Scenario 2—Solar Energy Only

In scenario 2, the HEMS will assume that the home is running solely on solar energy generation. An installation of 2.75 kW is considered for the studied home, with a battery capacity of 0.5 kW. An energy storage system is also considered in the HEMS. It charges during the early hours of solar energy generation, and discharges after the latter starts declining.

Figure 5 illustrates the load profiles resulting from running the simulation for scenario 2. Both the flexible and moderate settings allow to allocate the loads during the peak of solar energy generation. As for the strict setting, the loads are scheduled further in the afternoon, which is mainly due to the heightened impact of the user comfort setting.

In Table 5, the percentage of utilization of solar energy by the shiftable loads is calculated. High percentages are recorded across all settings, which is mainly due to the usual operation of the appliances of the household being concentrated in the middle of the day. The flexible settings achieved a percentage of usage of 88.85%, while the moderate setting was slightly lower at 87.13%, and the strict setting being the lowest at 86.62%. It is noticeable from the graphs that solar energy alone was not sufficient to cover all the loads.

The first cycle of the oven was constantly allocated outside solar energy usage. Thus, this points at the importance of using both electricity from the grid and solar energy to achieve a better operation for the household.

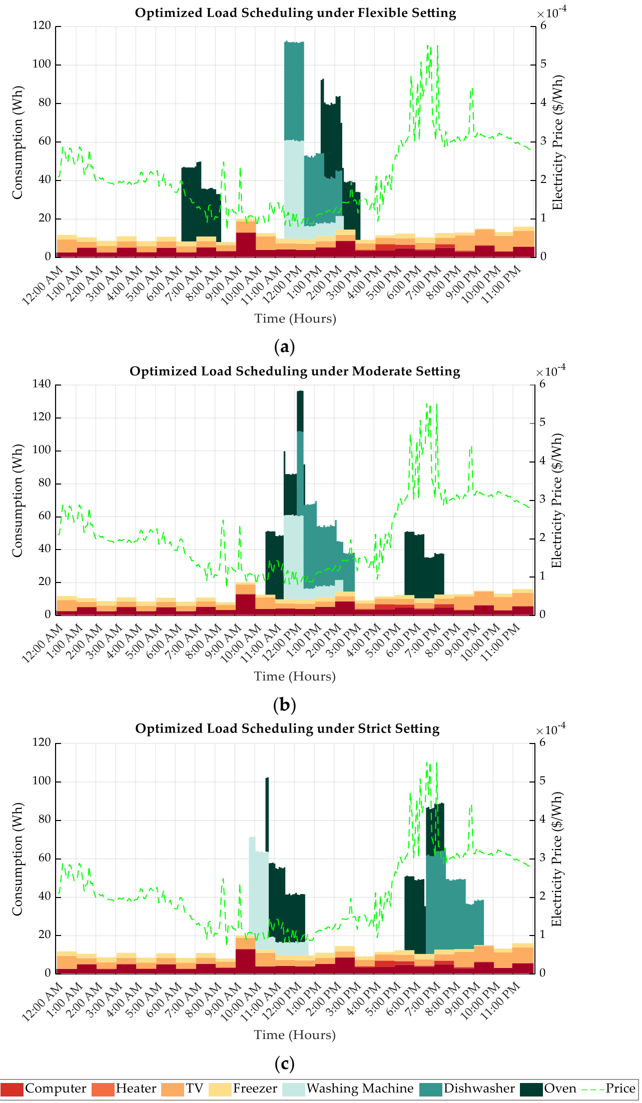


**Figure 4.** Resulting Load Profiles from Scenario 1. (**a**) Load Scheduling for the Flexible Setting; (**b**) Load Scheduling for the Moderate Setting; (**c**) Load Scheduling for the Strict Setting.

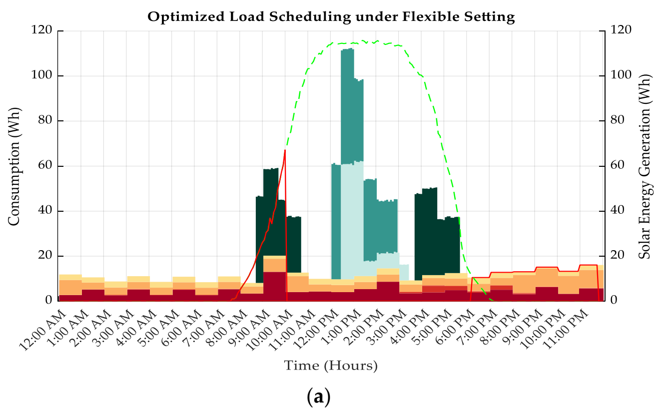


**Figure 5.** *Cont.*

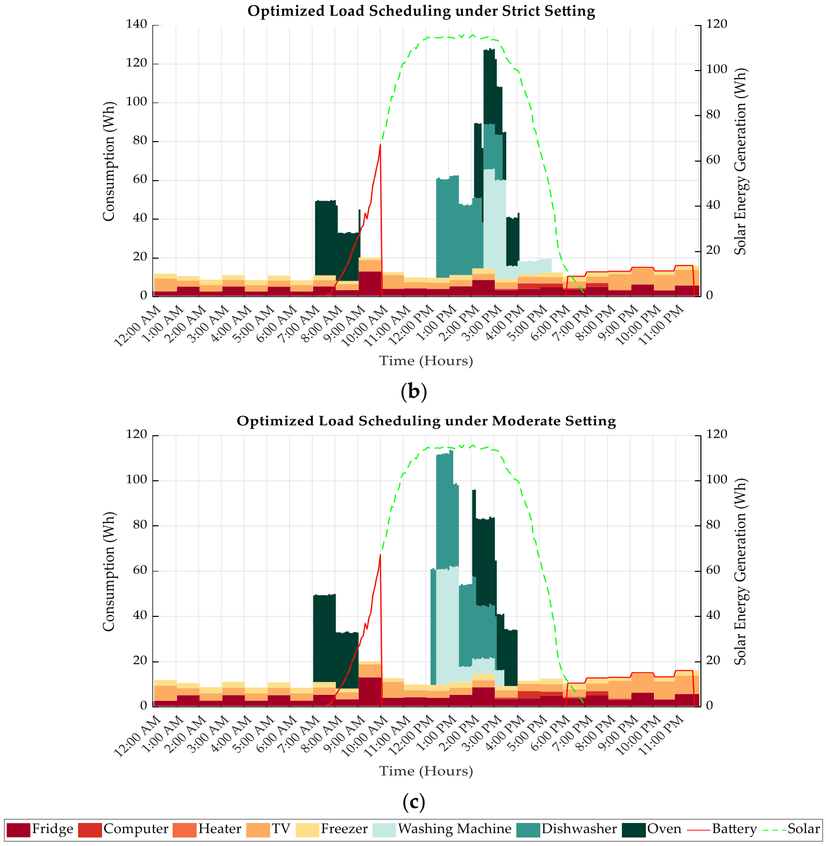


**Figure 5.** Resulting Load Profiles from Scenario 2. (**a**) Load Scheduling for the Flexible Setting; (**b**) Load Scheduling for the Moderate Setting; (**c**) Load Scheduling for the Strict Setting.

**Table 5.** Result Summary for Scenario 2.

| Setting | Load | Operation Times | Solar Energy Usage (%) |
|---|---|---|---|
| Flexible | Washing Machine<br>Dishwasher | [12:25 p.m. to 03:20 p.m.]<br>[12:00 p.m. to 02:50 p.m.] | 88.85 |
| | Oven | [08:35 a.m. to 10:35 a.m.]<br>[03:40 p.m. to 05:35 p.m.] | |
| Moderate | Washing Machine<br>Dishwasher | [12:25 a.m. to 03:20 p.m.]<br>[12:10 p.m. to 03:00 p.m.] | 87.13 |
| | Oven | [07:00 a.m. to 08:55 p.m.]<br>[02:00 p.m. to 03:15 p.m.] | |
| Strict | Washing Machine<br>Dishwasher | [02:30 p.m. to 05:25 p.m.]<br>[12:20 p.m. to 03:10 p.m.] | 86.62 |
| | Oven | [07:00 a.m. to 08:55 a.m.]<br>[02:00 p.m. to 03:15 p.m.] | |

### *3.4. Scenario 3—Use of Electricity and Solar*

In scenario 3, both the previous scenarios will be merged to assess the potential impact of combining dynamic pricing and a solar energy generation system. The latter considered in this scenario will be half the size of the one considered in scenario 2, to illustrate how a cheaper system of lower generation capacity can also have a positive impact.

Figure 6 illustrates the load profiles resulting from running the simulation for scenario 3. As the valley for the dynamic pricing slope is synchronous with the peak for solar energy generation, the scheduling of loads was globally assigned during the middle of the day.

The only noteworthy scheduling is that of the oven, which was unreasonable for the flexible setting (being set at 6:15 a.m.). However, it became more regulated when it came to the moderate and strict setting.

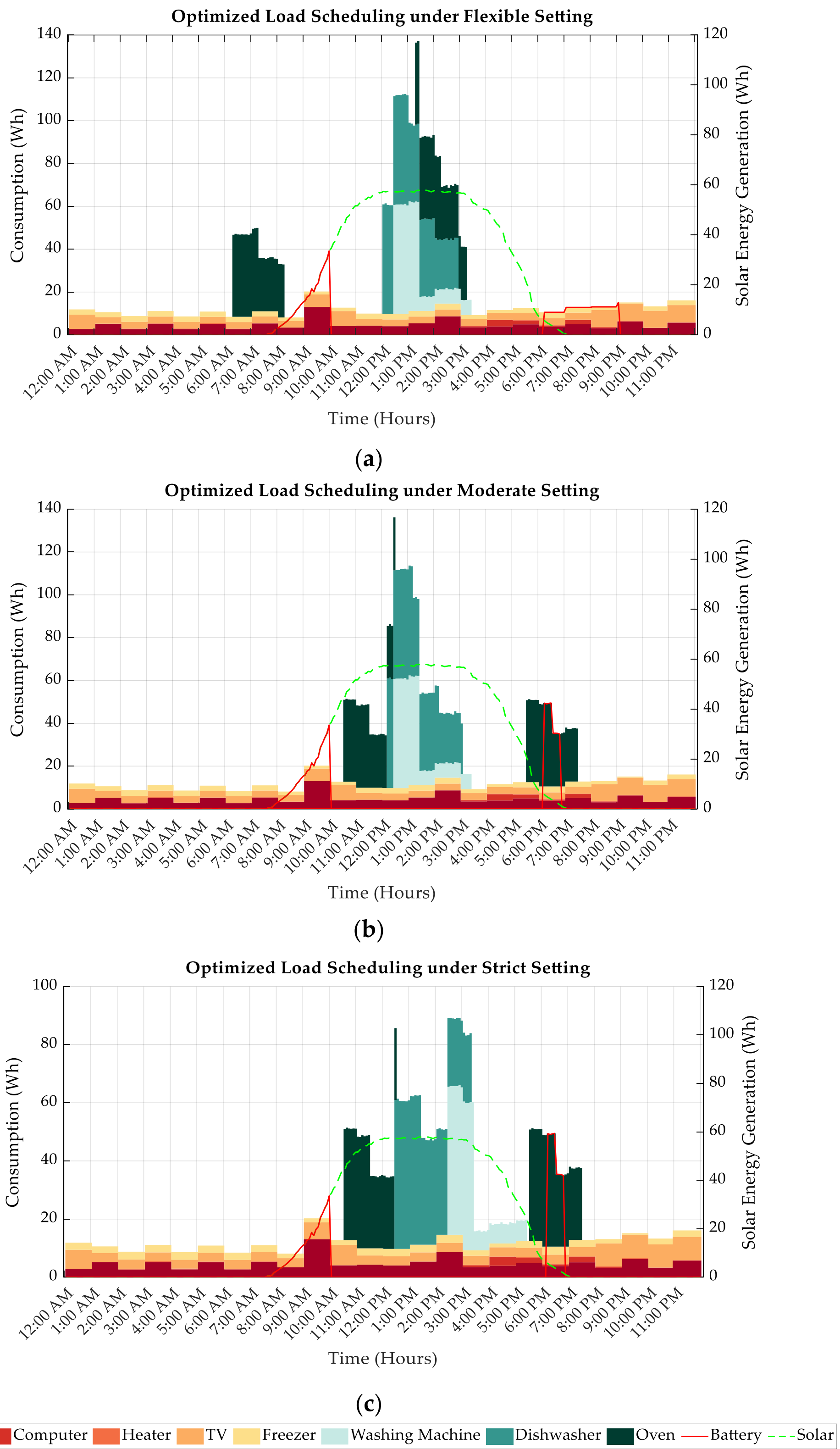


**Figure 6.** Resulting Load Profiles from Scenario 3. (**a**) Load Scheduling for the Flexible Setting; (**b**) Load Scheduling for the Moderate Setting; (**c**) Load Scheduling for the Strict Setting.

Table 6 summarizes the cost reduction achieved in scenario 3. The reduction is calculated based on comparing with the base cost which is $1.72197. The cost reductions achieved in this scenario are substantially higher than that of scenario 1. The flexible setting, being the one with the best results, achieved a cost reduction of 63.48%. As opposed to the trend displayed in the previous scenarios, the strict setting was not the one with the lowest impact. This setting achieved cost savings of 56.24%, while the reduction was limited to 55.36% for the moderate setting. This shows that despite having an inflexible scenario, important levels of cost reduction can be achieved. This is subject to the different parameters that the HEMS considers possible to adapt together in the operation of the household.

**Table 6.** Result Summary for Scenario 3.

| Setting | Load | Operation Times | Total Cost ($) | Cost Reduction (%) |
|---|---|---|---|---|
| Flexible | Washing Machine<br>Dishwasher | [12:25 p.m. to 03:20 p.m.]<br>[12:00 p.m. to 02:50 p.m.] | 0.62888 | 63.48 |
| | Oven | [06:15 a.m. to 08:10 p.m.]<br>[01:15 p.m. to 03:10 p.m.] | | |
| Moderate | Washing Machine<br>Dishwasher | [12:25 p.m. to 03:20 p.m.]<br>[12:10 p.m. to 03:00 p.m.] | 0.76825 | 55.36 |
| | Oven | [10:30 a.m. to 12:25 p.m.]<br>[05:30 p.m. to 07:25 p.m.] | | |
| Strict | Washing Machine<br>Dishwasher | [02:25 p.m. to 05:25 p.m.]<br>[12:25 p.m. to 03:15 p.m.] | 0.75354 | 56.24 |
| | Oven | [10:30 a.m. to 12:25 p.m.]<br>[05:30 p.m. to 07:25 p.m.] | | |

### *3.5. Supplementary Shiftable Loads*

It is important to ask the question of whether the HEMS is adaptable to changes that can happen to the household. Whether the user purchased a new appliance, or if they are exploring the ability to turn non-shiftable loads into shiftable ones, it is crucial to assess the ability of the HEMS to incorporate more loads. In order to analyze how this can be performed, the user is assumed to have very recently purchased an EV, with a home electric vehicle charging station (HEVCS). The recency of the purchase imposes the constraint that there is no historical data from which an UBP can be generated. As a temporary substitute to the UBP, the following assumption is made. The user of the EV uses the vehicle for the commute to his work, making it important for the car to be fully charged before 8:00 AM. In addition, it is assumed that the vehicle is not being charged at the workplace parking, and that once the user arrives home the battery is fully depleted. The charging is assumed to take about 8 h, for a battery capacity of 40 kWh.

Figure 7 illustrates the result of optimizing the scheduling of the EV for dynamic pricing, while Figure 8 does the same for solar energy generation. The restricted area filled in grey represents the hours of the day where the vehicle is unable to be charged due to the commute of the user. For both figures, it is noticeable that the best time for the charging is located during the restricted area. However, due to the constraint, the HEMS locates the next best time to charge the EV. In Figure 7, the load is scheduled during the first hours of the day, taking advantage of relatively average prices. In Figure 8, the load is allocated right after the end of the restraint, so as to take advantage of the last few time periods where solar energy is still being generated. The idea is for the HEMS to continue running in this manner, until enough time has passed for historical data to be collected regarding the charging times of the vehicle. Once that is achieved, a UBP specific for the user's daily life should be generated and utilized, enabling higher levels of user comfort.

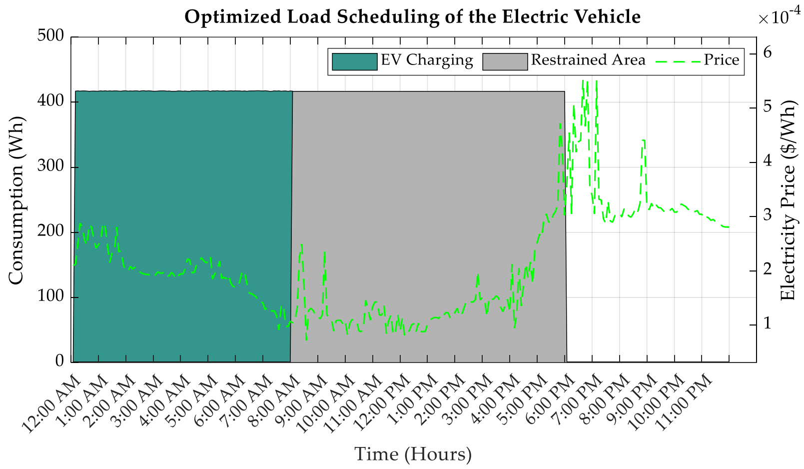


**Figure 7.** Load scheduling of the Charging of the EV under optimization for Price.

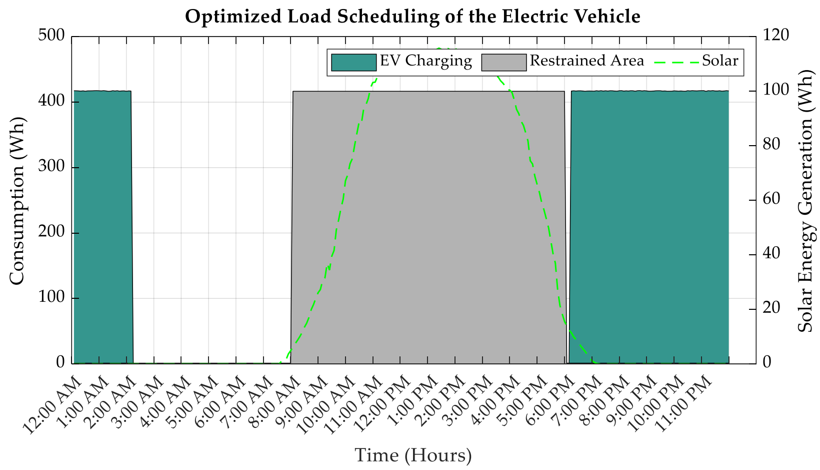


**Figure 8.** Load scheduling of the Charging of the EV under optimization for Solar Energy.

## 4. Discussion

Following the assessment of the potential impact of the HEMS through simulating three different scenarios, the cost saving ability of the system was highlighted. The first and perhaps most crucial part of the HEMS was generating the UBP for each shiftable load. Through z-score transform, historical data of the daily usage periods of the appliances were leveraged to optimize user comfort. The UBPs, in addition to a utility function, are utilized to establish the objective function. The base scenario illustrates a day of operation in which all appliances have been used, with an oven being operated twice throughout the day. Subsequently, the simulation has been run separately for each scenario, with three distinct flexibility settings for each one, and results have been compared with the cost in the base scenario. The first scenario, based solely on dynamic pricing, resulted in cost savings of 33.64%, 22.58%, and 4.27% for the flexible, moderate, and strict settings respectively. Utilizing renewable energy in the HEMS was the goal from running the second scenario. For every flexibility setting, relatively high solar energy usage (between 86% and 88%) was recorded. Following the analysis of the generated load scheduling, it has become noticeable that relying solely on solar energy generation and battery storage systems was not sufficient to fully handle the energy needs of the household. Scenario 3 serves as a solution to this disparity; where both sources have been used to entirely cover the needs of the home and where the capacity of the solar energy generation system has been halved. The goal from this change is to assess whether a cheaper investment in renewable energy is also able to produce important results. Scenario 3′s resulted in cost savings of 63.48%, 55.36%, and 56.24% for each setting from flexible to strict respectively. The reason behind such high levels of savings is related to all parameters for which the optimization is performed being aligned, meaning that this was achieved thanks to the prices being their lowest, solar generation being its highest, and UBPs having lower penalties during the same period, which was the middle of the day. The cost saving for scenario 3 was not only substantially higher across all flexibility settings, but the trend in the difference of savings across the different settings was also positively altered. As a matter of fact, the strict setting achieved better results than the moderate one, highlighting the fact that high levels of user comfort can be achieved all the while making important cost saving. The cost reduction of the strict setting turning out better than the moderate one is mainly thanks to the fact that the aforementioned alignment of the involved parameters made for the restriction of the UBPs to become less constraining on the problem. The final step of the simulation was to assess the ability of the HEMS to incorporate a new load. The particular challenge of such an approach lies in the unavailability of a UBP for the new load. Thus, a temporary profile is established based on assumptions on the user's preference for the operation of said load. The resulting load scheduling of this load, which is an EV home charging cycle, achieved scheduling that respects the temporary UBP all the while minimizing cost and maximizing solar energy usage.

Now that the potential impact of the HEMS has been thoroughly analyzed and shown to be positive, it is important to point at the possible limitations. While the simulation utilizes preexisting pricing dispatch data and solar energy generation profiles, the system in real life operation is intended to provide day-ahead recommendations for the usage. Thus, it would be crucial to accompany the HEMS with a highly accurate forecasting model that can provide profiles for the day for which the recommendations are to be made. Looking at matters from a broader perspective, it is important to pinpoint the potential points of improvement of the HEMS. Generally, these improvements not only serve the purpose of making the system perform better, but also contribute positively to more and more homeowners adopting similar systems. As the HEMS is in need of access to different types of data to ensure its operation, it is clear that the safety and privacy of this data to be airtight so as to not expose the user to cybersecurity threats. An important question to ask is related to the factors that are holding back a widespread use of such systems. Such factors can be divided into the micro level and the macro one. On a smaller, more local scale, the financial barrier of entry can be daunting to the homeowner. The latter can be willing to adopt a HEMS and its subsequent recommendations. However, the cost of the smart home apparatus, software, and further expenses needed can deter from making the initial investment. From a macro perspective, an efficient smart grid ecosystem is a pre-requisite to the smooth operation of HEMS. Although the latter could be deployed in a home that is part of a conventional electrical grid, its abilities are restricted, mainly due to a drastically lower resolution in electricity pricing. It is worth mentioning that the microgrid represent an ideal framework for an initial implementation of such HEMS, as one of its distinctive characteristics is its diverse energy generation sources as well as its well-defined boundaries, including adjustable loads [22].

## 5. Conclusions

Throughout this paper, the results of simulating a HEMS aiming to optimize energy costs and maintain user comfort have been illustrated and analyzed. The simulation incorporates three different scenarios, each with three distinct flexibility settings. The first scenario focuses on dynamic pricing and results in cost savings of 33.64%, 22.58%, and 4.27% for the flexible, moderate, and strict settings respectively. The second one depends solely on renewable energy usage, which was found to not be as sufficient to handle the needs of the home since only up to 88% of the household's needs could be covered. As for the third scenario, a combination of both sources was established to cover the needs of the household, resulting in an even higher cost reduction, reaching 63.48%, 55.36%, and 56.24% for each setting, respectively. Utilizing high-resolution real-life consumption data not only aided in illustrating the cost saving ability of HEMS, but also provided an interesting method of incorporating user comfort into the system. Avenues of future work stemming from this paper can involve a more thorough approach to user comfort, namely in the sense that it is not sufficient to assume the user's behavior is equivalent each day, but that the household's utilization of loads can differ between weekdays, weekends, and even holidays. As mentioned earlier, accompanying forecasting models are important for the concrete operation of a HEMS. Such models are preexisting aspects of the SG as they represent a crucial component to its ability to manage the load on the grid [23]. In future work, comparing the performance of the same HEMS under different optimization algorithms could be an adequate method to improve its performance.

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