Appliance Scheduling Optimisation Method Using Historical Data in Households with RES Generation and Battery Storage Systems

Martha Correa-Delval, Hongjian Sun, Peter C. Matthews
Department of Engineering
Durham University
Durham, United Kingdom
martha.t.correa-delval@durham.ac.uk

Wei-Yu Chiu
Department of Electrical Engineering
National Tsing Hua University
Hsinchu, Taiwan
chiuweiyu@gapp.nthu.edu.tw

***Abstract*—In recent years, the importance of reducing carbon dioxide (CO_2) emissions has increased. With the use of technologies such as artificial intelligence, we can improve the way households manage their energy use to decrease cost and carbon emissions. In this paper, we use the Spectral Entropy and Instantaneous Frequency-based Bidirectional Long Short Term Memory (SE-IF BiLSTM) method so the home energy management system (HEMS) can learn from historical data of energy usage, as well as the preferred energy consumption patterns for the user. With this data, a multi-objective optimisation problem (MOP) that considers cost, CO_2 emissions and discomfort is formulated to schedule appliances in different scenarios. These scenarios include households with battery storage systems and with or without renewable energy sources. We compared the results by using multi-objective immune algorithm where we found a 10.06% reduction in cost and 20.56% reduction in CO_2 emissions by using the proposed method.**

***Keywords*—appliance scheduling; home energy management systems; multi-objective optimisation**

I. Introduction

In 2019, the UK government passed a net-zero emission law, which aims to bring all greenhouse gas emissions to net-zero by 2050 [1]. While a big part of the energy produced comes from fossil fuels, there has been an increase in green energy sources. In 2021, we saw an increase of 23% and 14% in solar and wind energy generation, respectively [2]. This helps to balance the carbon dioxide (CO_2) emissions generated by the fossil fuels [3].

In recent years, traditional power grids have been transitioning to become smart grids, that enable bidirectional flows of both power and data.. This has allowed an increase in the adoption of renewable energy sources (RES) and battery storage systems (BSSs) in households [4].

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As we adopt new technologies and capabilities, new challenges arise for home energy management systems (HEMSs). With the increase of appliances used in households and the adoption of RES, there is a need to find an optimal way of managing them to reduce CO_2 emissions generated while also reducing the economical cost and discomfort for the users [5].

Appliance scheduling is a technique used to plan the use of household appliances at certain times that the HEMS finds appropriate. There are many researches in this area in the literature, focusing on reducing cost and discomfort. In [3], an appliance scheduling technique was developed to reduce cost under a real time pricing (RTP) scheme. In [6], Ali et al. developed techniques for reducing cost while also reducing user discomfort. In [7], Liu et al. developed a technique based on Deep Q-learning to perform the scheduling of the appliances. In [8], a mixed integer linear programming problem was formulated to schedule appliances on a day-ahead scenario considering different types of users.

In [9], a Sequential Forward Selection (SFS) method was used to identify appliances and then the results were evaluated with NSGA-II to find a pareto-optimal front. While most of the research found in the literature is based on user inputs for preferences for the scheduling, an approach without user input or extensive metering data has not been widely discussed. It is important to propose appliance scheduling even when minimal information is provided by the smart meter to the utility company. With the use of the SE-IF BiLSTM method developed in our preliminary work [10], we can robustly identify appliances in previous usage by the user without the need of any user input.

Compared with existing research, the main contributions of this paper are as follows:

- A novel appliance scheduling method is proposed that uses the previously developed SE-IF BiLSTM appliance classification method. This allows the HEMS to learn from historical data by accurately detecting and classifying appliances in order to schedule them in the future.
- A multi-objective optimisation problem is formulated that considers cost, CO_2 emissions and discomfort reduction

for the user when scheduling appliances in a household with RES generation and BSS.
- Comparison of results is provided to validate the multi-objective immune algorithm and multi-objective genetic algorithm.

II. System Model

A. Battery storage model

The battery storage model assumes the use of a Powervault 3 battery, which has a capacity of 4 kWh and a discharge rate of 2 kW. It is assumed that the battery is at its minimum level at the beginning of the day. The household battery storage level can be calculated with the following equations:

$$\mathrm{SOC}(0) = 0, \tag{1}$$

$$\mathrm{SOC}(t) = \mathrm{SOC}(t-1) + \Delta t \cdot P_{bat}(t), \quad t = 1...T, \tag{2}$$

where SOC represents the state of charge of the battery at time t, Δt represents the time interval and P_{bat} represents the power drawn by the battery at time t.

B. RES model

The original energy consumption information in the dataset is for houses in the south of England, and these houses do not include any type of RES generation. The RES model uses the information from the European solar radiation database Photovoltaic Geographical Information System of the European Commission [11] to calculate solar irradiation.

It is assumed that the house has 6 SunPower Maxeon 3 photovoltaic panels that have a solar efficiency of 0.212 at a slope of 35° and azimuth at 0°. Each panel is 1.046m by 1.69m in size, making a total area of 26.5161m^2. The power generation from solar panels can be given by [12]:

$$P_{PV}(t) = \eta \cdot E(t) \cdot A_c, \tag{3}$$

where P_{PV} is the power generated at time t, η is the solar efficiency, E is the solar irradiation received in W/m^2 at time t and A_c is the area of the panels.

C. Load consumption model

The load demand model uses the information from the UK DALE dataset [13], which is from an End-terrace house in Southern England. Depending on the month selected, the power consumption of the corresponding average aggregate power is obtained. The output of the model is $P_{load}(t)$, which is the base power load demanded at time t.

D. Appliance scheduling model

We use the dishwasher, washing machine and electric hob consumption data obtained from the pre-processing done to the load demand data, explained further in Section III.

By using the SE-IF BiLSTM method, we identify and classify the appliances in previous days to obtain their average consumption data and preferred usage times. These appliances do not have a constant power consumption, since their cycles demand different amounts of power at different times. We obtained the average length of duration of each of these appliances operations and average consumption per hour, to better simulate the variation in power during their operation.

TABLE I
APPLIANCE SETTINGS

Appliance	δ 1	T_{pref} 2	$T_{duration}$	Power rating (Watts)
Washing Machine	2	12:00	2h	150 - 650
Dishwasher	3	21:00	2h	520 - 910
Electric Hob	3	17:00	0.5h	1000

Let T_{start} be the time at which the optimisation algorithm schedules the appliance to start operations; we have:

$$0 \leq T_{start} \leq T - T_{duration}, \tag{4}$$

where $T_{duration}$ denotes the duration of the appliance usage.

To calculate the load used by the schedulable appliances at time t, we can use the following equation:

$$P_{load}^{app}(t) = \sum_{m=1}^{M} P_m(t), \tag{5}$$

where P_{load}^{app} is the sum of power used by the schedulable appliances at time t, M is the number of schedulable appliances and P_m represents the power load of appliance m.

To calculate the total scheduled load at time t, the system uses the following equation:

$$P_{load}^{SCH}(t) = P_{load}(t) + P_{load}^{app}(t), \tag{6}$$

where P_{load}^{SCH} represents the sum of the base load P_{load} and the load of all schedulable appliances P_{load}^{app}.

E. External power grid model

The household gets power supply from the external grid to fulfill the load demand, together with the use of the power generated by the photovoltaic panels and the power taken from the battery storage. To calculate the power taken from or sent to the grid at time t, the system uses the following equation:

$$P_{grid}(t) = P_{load}^{SCH}(t) - P_{PV}(t) + P_{bat}(t), \tag{7}$$

which also ensures that the load demand is always met.

F. Cost model and formulation

The cost model is based on the purchase and sale price information from previous years from the British Energy Trading and Transmission Agreements [14]. In this research, it is assumed that this information is the one that will be happening during the selected day to simulate. This model uses an Hourly Real Time Price structure, where the price of electricity varies on an hourly basis and remains constant during the entire hour duration. Costs are also calculated considering the current month or the one selected by the user. Finally, this model has 2 outputs: C_{sell} and C_{buy}, which represent the unit price of selling energy to the grid and buying energy from the grid, respectively. Using these values, we can calculate the cost of the electricity bill in British Pounds, denoted by the following equation:

$$Cost = \sum_{t=1}^{T} \Delta t \cdot P_{grid}(t) \cdot C_{grid}(t), \quad (8)$$

where C_{grid} can be given by

$$C_{grid}(t) = \begin{cases} C_{buy}(t), & \text{if } P_{grid}(t) \geq 0 \\ C_{sell}(t), & \text{otherwise} \end{cases} \quad (9)$$

G. CO_2 emissions model and formulation

The CO_2 model is based on the carbon emission intensity (CEI) data obtained from National Grid Group UK. We collected data from 2020 to calculate the hourly averages of the carbon emission intensity each month. This model outputs CEI_{buy}, which represents the intensity of the carbon emissions generated by purchasing electricity from the grid. Using these values, we then calculate the amount of CO_2 emitted in grams:

$$CO_2 = \sum_{t=1}^{T} \Delta t \cdot P_{grid}(t) \cdot \text{CEI}_{grid}(t) \quad (10)$$

where CEI_{grid} can be given by

$$\text{CEI}_{grid}(t) = \begin{cases} \text{CEI}_{buy}(t), & \text{if } P_{grid}(t) \geq 0 \\ 0, & \text{otherwise.} \end{cases} \quad (11)$$

H. User discomfort model and formulation

The user discomfort model is based on the data obtained from the SE-IF BiLSTM model [10]. The model learns the average starting time of the appliances in the previous days. The discomfort is calculated considering the time of use and the discomfort coefficient. The discomfort coefficient, denoted by δ, is calculated for each appliance, depending on how much its starting time varies during the analysed days by the SE-IF BiLSTM model. If the appliance is mostly used at the same time every time, it is assumed that using it at a different time would generate a significantly bigger discomfort than an appliance that has a varying preferred time of use. Lastly, the further away the starting time is from the preferred starting time, the more discomfort it generates for the user.

The system then calculates the total discomfort by using the following equation:

$$Disc = \sum_{m=1}^{M} \delta(m) \cdot [T_{start}(m) - T_{pref}(m)]^2 \quad (12)$$

where M is the number of schedulable appliances, $\delta(m)$ represents the discomfort coefficient of appliance m and $T_{pref}(m)$ represents the preferred starting time of appliance m. These settings can be found in Table I.

III. Methods

A. Multi-objective Problem Formulation

The first objective is to minimise the economical cost of the electricity used. The second objective is to minimise the amount of CO_2 produced. The third objective is to minimise the user discomfort when scheduling the schedulable appliances. The resulting multi-objective problem (MOP) can be formulated as:

$$\min_{P_{bat}, T_{start}^{m \in M}} \alpha \cdot Cost + \beta \cdot CO_2 + \gamma \cdot Disc \quad (13)$$

subject to (2), (4) and (7), where α, β and γ represent the weights of each cost function and $\alpha + \beta + \gamma = 1$.

B. Data acquisition and pre-processing

The appliance consumption data was obtained from the UK DALE (Domestic Appliance-Level Electricity) dataset [13], which consists of 1/6 Hz individual appliances and aggregate power readings. Data consists of UNIX timestamp and the power reading in Watts. Since the original data presents a reading every 6 seconds, we averaged the consumption per every minute for simplicity purposes.

C. SE-IF BiLSTM method for appliance classification

In [10], we developed the SE-IF BiLSTM appliance classification method, which allows us to train a BiLSTM neural network that is able to identify and classify appliances in historical data, as well as preferred usage times, by extracting features such as spectrogram frequency bands, Mel spectrogram, instantaneous frequency, spectral entropy and signal variation. In order to get the appliance consumption data for the SE-IF BiLSTM training, we used the individual data from the dataset. Considered appliances include three individual appliances: washing machine, dishwasher and electric hob. In order to train the neural network to identify the moments where multiple appliances are being used at the same time, we generated different combinations based on the individual appliances consumption data.

D. Multi-objective Immune Algorithm

The multi-objective immune algorithm (MOIA) [15] is an optimisation method inspired by the gene operations of the human body. It uses antibodies, which are points in the decision variable space. Each iteration, the dominated antibodies are removed, allowing non-dominated antibodies to mutate and diversify, generating more dominated antibodies which are removed too. After that, a condition is used to erase infeasible antibodies. This process repeats until it reaches the maximum number of iterations. At the end, approximate Pareto optimal solutions are obtained.

E. Multi-objective Genetic Algorithm

The multi-objective genetic algorithm (MOGA) is a metaheuristic optimisation method based on the natural selection system. It is widely used for complex optimisation and search problems. First, it generates a random population of values between the established limits. Second, it calculates the fitness of the individuals. If the stopping criterion is not met, it selects values as parents, which then crossover to produce children. These children mutate and their fitness is then again calculated, generating new population. This process is repeated until the stopping criterion is met [16].

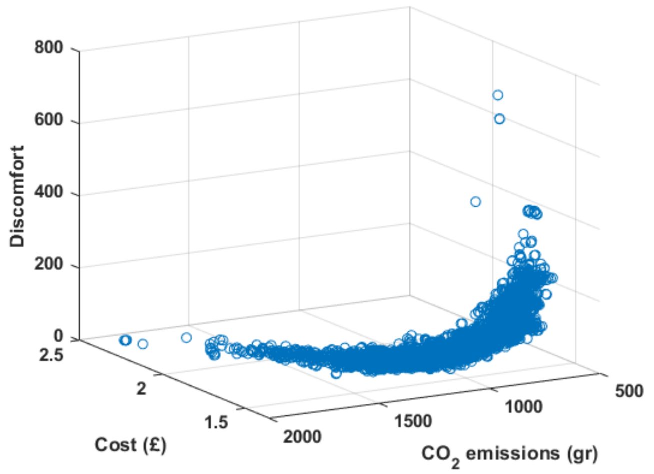

Fig. 1. Pareto Frontier evaluating cost, CO_2 emissions and discomfort, obtained after evaluating the MOIA.

F. Finding the best compromised solution

We used the gray relational analysis algorithm to find the best compromised solution of the Pareto Frontier (Fig. 1). This algorithm compares the gray relational coefficient, which is the similarity between each objective value of each solution and the best value of each objective [17].

IV. Results and Discussion

A. Simulation setup

For the simulations, we assume four different scenarios and three different cases. The parameteres used for the simulations can be found on Table II.

B. Simulation Scenarios

1) RES and Scheduling: In this scenario, the user uses RES power generation and power taken from the grid to meet the load demand. The user wants to schedule appliances in order to reduce the bill cost and CO_2 emissions.

2) RES and No Scheduling: In this scenario, like in the previous one, the user has access to RES power generation, but does not want to schedule any appliances, getting the most comfort.

3) No RES and Scheduling: In this scenario, the user does not have any kind of RES power generation, thus receiving all the needed power from the grid, but wants to schedule appliances in order to save money and produce less CO_2 emissions.

4) No RES and No Scheduling: In this scenario, like in the previous one, the user does not have RES power generation. But this time, the user does not want to schedule the appliances, seeking the most comfort by having them operate at their preferred times.

TABLE II
Simulation setup

Control parameter	Value
Location	50°50'16.8"N 0°08'13.2"W
Month	June
Time slots	24
Schedulable appliances	3
Solar Panels	6 SunPower Maxeon 3
Battery Max Capacity	4 kWh
Battery Max Charge/Discharge Rate	2 kW

C. Simulation cases

1) Case 1 based on cost minimisation: In this case, the user aims to minimise the economical cost of the electricity bills. When the prices are low, or when the RES generation is high, the battery is charged. At times of high generation, the user can sell energy back to the grid to aid minimise cost. When the prices are high during the day, the user can rely on the energy stored in the battery to meet the load demand. In Scenario 1, the algorithm schedules the appliances to start at 11 AM for the washing machine, 1 PM for the dishwasher and 12 PM for the electric hob, when the power generation is high.

2) Case 2 based on CO_2 emissions minimisation: In this case, the user aims to minimise the CO_2 emissions generated by their load. When the CEI is low or the RES generation is high, the system charges the battery. When the CEI is high, usually in the afternoon hours, the stored energy in the battery is used instead. In Scenario 1, the algorithm schedules the appliances to start at the same time as Case 1, with the difference that the system only starts charging the battery when the RES generation is high enough around noon.

3) Case 3 based on best compromised solution: In this case, the user aims for the best compromised solution among the three different objectives: Cost, CO_2 emissions and user discomfort. In Scenario 1, the algorithm schedules the appliances to start at 11 AM for the washing machine, 3 PM for the dishwasher and 2 PM for the electric hob, closer to the preferred start times. During early morning, most of the power is taken from the grid. In the late morning, midday and early afternoon, the power generated by the RES is sufficient to cover the base load and scheduled appliances, charge the battery and sell back to the grid. During the evenings, most of the remaining energy in the battery is used to meet the base load demand.

D. MOIA Results analysis

In Table III we find the results for all simulation scenarios. As expected, the scenarios with RES power generation present the lowest values in cost and CO_2 emissions. By having power coming from the solar panels, the user can save money because it covers the need to purchase electricity from the grid. They also generate power that can be sold back to the grid, reducing costs on the electricity bill while producing carbon-neutral electricity. In Figs. 2 and 3, we can see the load for Scenarios 1 and 3 respectively, contrasting the amount of power that is taken from the grid.

TABLE III
MOIA RESULTS COMPARISON

Scenario 1) RES - Scheduling			
Parameter	Case 1	Case 2	Case 3
Cost (£)	1.34	1.40	1.40
CO_2 emissions (grams)	793.55	676.46	718.72
Discomfort	269	269	137
Washing Machine (T_{start})	11	11	11
Dishwasher (T_{start})	13	13	15
Electric Hob (T_{start})	12	12	14
Scenario 2) RES - No Scheduling			
Parameter	Case 1	Case 2	Case 3
Cost (£)	1.49	1.59	1.55
CO_2 emissions (grams)	1034.64	851.64	861.58
Discomfort	0	0	0
Washing Machine (T_{start})	12	12	12
Dishwasher (T_{start})	21	21	21
Electric Hob (T_{start})	17	17	17
Scenario 3) No RES - Scheduling			
Parameter	Case 1	Case 2	Case 3
Cost (£)	6.16	6.54	6.34
CO_2 emissions (grams)	2862.11	2748.43	2814.63
Discomfort	1013	242	83
Washing Machine (T_{start})	13	13	10
Dishwasher (T_{start})	5	13	17
Electric Hob (T_{start})	8	13	14
Scenario 4) No RES - No Scheduling			
Parameter	Case 1	Case 2	Case 3
Cost (£)	6.26	6.68	6.54
CO_2 emissions (grams)	2878.64	2778.5	2782.31
Discomfort	0	0	0
Washing Machine (T_{start})	12	12	12
Dishwasher (T_{start})	21	21	21
Electric Hob (T_{start})	17	17	17

When comparing RES enabled scenarios (1 and 2), we can see that by scheduling appliances, we achieve lower costs in Cases 1 and 2 by 10.06% and 11.94% respectively. We also reduce the CO_2 emissions by 23.30% in Case 1 and by 20.56% in Case 2. When comparing Case 3, we get very similar costs on average, with a 9.67% reduction in cost and 16.58% in CO_2 emissions.

When comparing scheduling enabled scenarios (1 and 3), Scenario 1 presents a reduction of costs of 78.24% in Case 1, 78.59% in Case 2 and 77.9% in Case 3. We can also note a difference in CO_2 emissions of 72.27% in Case 1, 75.38% in Case 2 and 74.46% in Case 3. On the other hand, the discomfort values for Cases 2 and 3 are lower in Scenario 3 than in Scenario 1. In Fig. 4 we can see that this is achieved by storing energy in the battery during the morning, when the CEI is low, and scheduling the appliances at the lowest CEI time in the afternoon and evening, which are closer to the preferred starting times.

When comparing scenarios with no-scheduling (2 and 4), as expected, Scenario 2 presents a significant increase in money savings due to the use of RES power. In Case 1, we see savings of 76.19%, in Case 2 we get 76.19% and in Case 3 we get 76.29%. For CO_2 emissions, we achieve savings of 64.05% for Case 1, 69.34% for Case 2 and 69.03% for Case 3.

Finally, when comparing the scenarios with no-RES (3 and 4), we achieve lower values by scheduling, but the difference is not significant. We have money savings of 1.59% in Case 1, 2.09% in Case 2 and 3.05% in Case 3. When looking at CO_2 emissions savings, we have a reduction of 0.57% in Case 1, 4.5% in Case 2 and an increase of 1.14% in Case 3. With the considerable increase in discomfort when scheduling and the minimal decrease in costs and CO_2 emissions, the results of these experiments show that it might not be viable to the user to schedule their appliances in the no-RES scenarios.

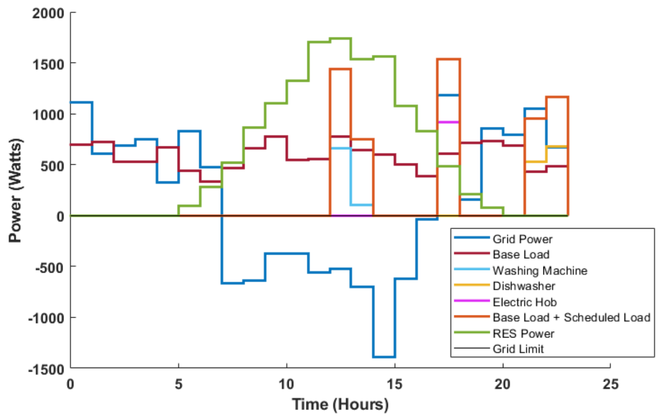

Fig. 2. Energy consumption for Case 3 in Scenario 1.

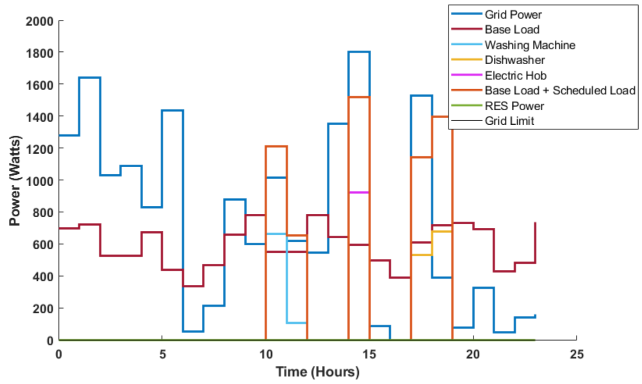

Fig. 3. Energy consumption for Case 3 in Scenario 3.

E. Algorithms comparison

We performed the same cases and scenarios for both MOIA and MOGA, with the same parameters as shown in Table II. In Fig. 5, we compare the results of Case 3 which is the Best Compromised Solution. We can see that the MOIA achieved lower results for cost in Scenarios 1, 2 and 3 and MOGA achieved lower results in Scenario 4. We can also see that MOIA achieved lower results for CO_2 emissions in Scenarios 1, 2 and 4, while MOGA achieved better results in Scenario 3. It is important to note that this being a compromised solution, it might not always benefit both aspects the most. In Scenario 3, we see MOIA achieving lower cost but higher emissions while in Scenario 4, we see the opposite.

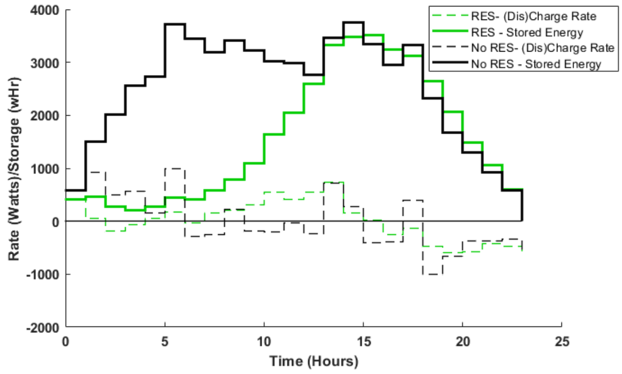

Fig. 4. Battery storage levels of Case 3 in Scenarios 1 and 3.

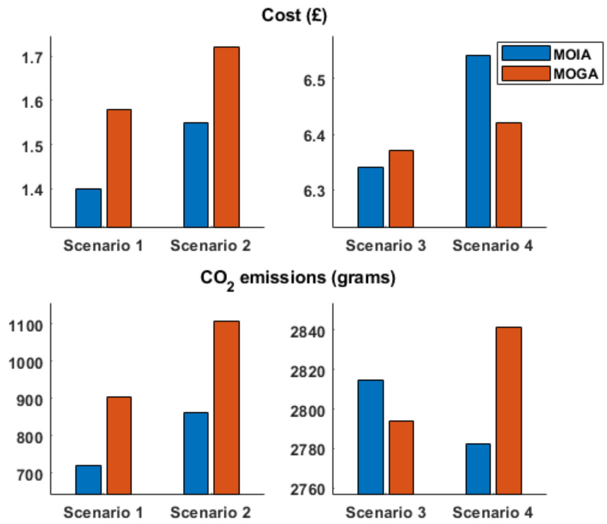

Fig. 5. Cost and CO_2 emissions comparison between MOGA and MOIA for Case 3.

V. Conclusion

This paper proposed a multi-objective optimisation model for scheduling appliances in homes with a battery energy storage system. Different scenarios were considered, such as RES enabled homes and scheduling preferences, while studying different cases, focusing on the priority goals for the user and considering user discomfort. An MOP was considered after modelling the system, which is then solved by the MOIA and the MOGA. These algorithms give a Pareto Frontier as a result, from which we obtained the best results for each case and scenario. The MOIA achieved better results than the MOGA in most scenarios and cases. The results show that the user can save the most money and reduce the most CO_2 emissions when scheduling appliances under a RES scenario, where we found a 10.06% reduction in cost and 20.56% reduction in CO_2 emissions when compared to a RES scenario without scheduling.

For future research, more appliances and different settings for the appliances will be considered.

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