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Corresponding Author	Family Name	**Papakyriakou**
	Particle	
	Given Name	**Thalis**
	Prefix	
	Suffix	
	Role	
	Division	
	Organization	Frederick Research Center
	Address	Nicosia, Cyprus
	Division	
	Organization	Frederick University
	Address	Nicosia, Cyprus
	Email	res.pt@frederick.ac.cy
	ORCID	http://orcid.org/0009-0008-0176-1713
Author	Family Name	**Pamboris**
	Particle	
	Given Name	**Andreas**
	Prefix	
	Suffix	
	Role	
	Division	
	Organization	Frederick Research Center
	Address	Nicosia, Cyprus
	Division	
	Organization	Frederick University
	Address	Nicosia, Cyprus
	Email	res.ap@frederick.ac.cy
	ORCID	http://orcid.org/0000-0002-4877-6663
Author	Family Name	**Konstantinidis**
	Particle	
	Given Name	**Andreas**
	Prefix	
	Suffix	
	Role	
	Division	

Organization	Frederick Research Center
Address	Nicosia, Cyprus
Division	
Organization	Frederick University
Address	Nicosia, Cyprus
Email	com.ca@frederick.ac.cy
ORCID	http://orcid.org/0000-0001-5370-8692

Abstract

The European Green Deal has set ambitious short-term targets for reducing CO_2 emissions and achieving climate neutrality. In communal living spaces, the associated challenges involve the exploitation of energy from renewable sources in order to reduce indirect CO_2 emissions caused by grid electricity consumption, and the satisfaction of the residents, with their individual appliance-scheduling preferences that often conflict with their objective of minimizing associated billing charges. This paper tackles this multi-objective optimization problem by proposing a multi-objective evolutionary algorithm based on decomposition with decision making. The algorithm produces a set of optimal trade-offs between maximizing the satisfaction of resident appliance-scheduling preferences and minimizing their billing charges, with decision making opting for the trade-off offering minimal deviation from the use of green energy, consequently limiting the CO_2 footprint. Our experimental evaluation, based on the energy consumption patterns of 10 UK households as recorded in the REFIT public dataset, demonstrates that the proposed approach clearly outperforms alternative state-of-the-art approaches.

Keywords (separated by '-'): multi-objective - evolutionary - energy efficiency

Author Proof

Resident-Oriented Green Energy Optimization Using a Multi-objective Evolutionary Algorithm

Thalis Papakyriakou[1,2](✉), Andreas Pamboris[1,2], and Andreas Konstantinidis[1,2]

[1] Frederick Research Center, Nicosia, Cyprus
{res.pt,res.ap,com.ca}@frederick.ac.cy
[2] Frederick University, Nicosia, Cyprus

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Keywords: multi-objective · evolutionary · energy efficiency

1 Introduction

Cities worldwide account for more than 65% of energy consumption and 70% of CO_2 emissions, a significant part of which is caused by indirect emissions due to grid electricity consumption[1] To combat the imminent environmental threats including global warming, sea-level rise, etc., the European Green Deal aims at reducing EU emissions by at least 55% by 2030, and establishing Europe as the first climate neutral continent by 2050. Efficient electrical energy usage is vital in attaining said targets, requiring action at the foundational level of the ecosystem, i.e., homes and living spaces.

[1] European Commission, 2023. EU Mission: Climate-Neutral and Smart Cities. LINK: https://shorturl.ac/7az54.

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Energy efficiency in communal living spaces is predominantly achieved through the utilization of green energy from renewable sources and, consequently, a reduction in grid-energy demand which results in a high CO_2 footprint. Furthermore, suggested governance practices encourage the involvement of residents as key stakeholders with co-benefits, such as energy demand-satisfaction and reduced energy costs (See footnote 1). However, objectives related to satisfying energy demands and reducing billing charges are conflicting in nature since the energy cost of operating any appliance results in a direct increase in billing charges. Energy management challenges involving conflicting objectives are often tackled through the formulation of Multi-Objective Optimization (MOO) problems and the use of Evolutionary Multi-Objective Optimization (EMO) approaches [12,13]. The problem's complexity is amplified by the rise of communal living arrangements, which entail multiple residents sharing a single source of renewable energy.

This work utilizes EMO to produce optimal trade-offs between the resident-oriented objectives, with the most energy-efficient trade-off selected through Decision Making. The main contributions of this paper are summarised below:

- We define and formulate a *MOO problem* that aims at maximizing the satisfaction of the residents' appliance-scheduling preferences and minimizing their billing charges. Energy flexibility, i.e., the capacity for energy load to be shifted or reduced, is incorporated in the problem through a mapping function that links energy usage to preference satisfaction.
- We propose *Green-MOEA/D*, a Multi-Objective Evolutionary Algorithm based on Decomposition, combined with a *Mapping Improvement Heuristic* for energy flexibility management, that aims at producing a set of appliance-usage schedules with optimal trade-offs between the residents' objectives.
- We propose a *Decision Making Heuristic* for selecting the best schedule from the set produced by Green-MOEA/D, for CO_2 emission minimization.
- The experimental evaluation uses realistic resident preference datasets derived from the consumption patterns of 10 UK households, as found in the REFIT public dataset, as well as solar energy production datasets. We evaluate Green-MOEA/D against alternative state-of-the-art approaches, which are shown to be clearly outperformed.

The remainder of this paper is organised as follows: Sect. 2 discusses background and related work. Section 3 presents the system model, problem definition and formulation, and the Decision Making Heuristic. Green-MOEA/D and the Mapping Improvement Heuristic are explained in Sect. 4. The experimental setting and evaluation are presented in Sects. 5 and 6, respectively. Section 7 concludes the paper.

2 Background and Related Work

This section discusses the fundamentals of EMO, and its applications in the context of energy management for smart homes.

2.1 Evolutionary Multi-objective Optimization

A Multi-Objective Optimization Problem (MOP) is formulated as follows:

$$\begin{aligned} \min_{x \in X} f(x) &= \big(f_1(), .., f_q(x)\big), \quad q = 1, .., Q \\ s.t. \quad g_j(x) &\leq 0, \quad j = 1, .., J \\ h_m(x) &= 0, \quad m = 1, .., M \end{aligned} \tag{1}$$

where q represents the number of conflicting objectives to be optimized, $g_j : X \rightarrow \mathbb{R}$ denote the inequality constraints, and $h_m : X \rightarrow \mathbb{R}$ denote the equality constraints. EMO is the branch of optimization that focuses on tackling MOPs by using evolutionary algorithms. Evolutionary Algorithms (EA) are population-based optimization methods inspired from the process of natural evolution, which makes them general, complex, and non-linear. Multi-objective Evolutionary Algorithms (MOEA) are a special category of EAs for dealing with MOPs. Because of the multiple conflicting objectives and the inherent trade-off between objective values, MOEAs produce a set of optimal solutions rather than a single solution. Comparison between solutions is established based on the concept of dominance [14]: given two feasible solutions x^1 and x^2, we say that x^1 dominates x^2 (denoted as $x^1 \succ x^2$) if, $\forall i \in 1, .., Q, f_i(x^1) \leq f_i(x^2)$ and $\exists i \in 1, .., Q, f_i(x^1) < f_i(x^2)$. If a feasible solution $x \in X$ is not dominated by any other solution in X, then x is defined as a Pareto-optimal solution. MOEAs aim to obtain the set of all Pareto-optimal solutions, referred to as the Pareto set, with the set of its corresponding objective-function values called the Pareto front. Finally, the process of selecting a single or a subset of Pareto-optimal solutions is known as Decision Making, which often involves objective prioritization or minimum-performance thresholds [10].

2.2 EMO Applications on Energy Management in Smart Homes

Regarding energy management in smart homes, there exists an abundance of possible objectives to consider [2,5,8], such as power supply reliability, profit/lifetime maximization, grid-dependency elimination, air quality [7], thermal/visual comfort [6,13,15] and resident preference-satisfaction with respect to appliance-scheduling [11–13]. Many of these objectives are conflicting, and thus tackled using EMO approaches. For instance, the resident-oriented objectives of thermal/visual comfort and appliance-scheduling preference satisfaction may negatively impact the objectives of grid-dependency elimination, emissions reduction, and billing charges reduction. In [13], the authors propose a hierarchical control architecture to estimate optimal set points for user comfort and energy saving in buildings, utilizing the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. S.N. Makhadmeh et al. [12] attempt to solve the Power Scheduling Problem in Smart Homes by introducing a formulation for the smart home battery that stores power at unsuitable periods and uses it at suitable ones, and solve the problem using the *PSO-based Grey Wolf Optimizer*. Constantinou et al. [1] propose a framework for balancing the trade-off between user comfort and energy consumption, utilizing energy flexibility through load reduction. To the best of our knowledge, no research study has tackled the conflicting nature of resident preference satisfaction and billing charges by allowing energy load to be both shifted and reduced, while limiting CO_2 emissions.

3 System Model and Problem Formulation

This section introduces our system model, defines and formulates the proposed MOP, and introduces the basic terminology used throughout this paper.

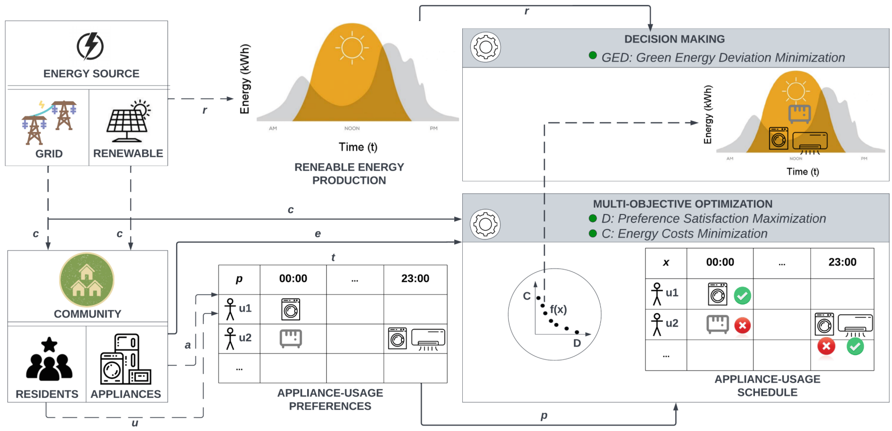

Fig. 1. Multi-Objective Optimization produces a set of appliance-usage schedules offering optimal trade-offs between satisfying appliance-scheduling preferences and reducing billing charges, with Decision Making opting for the most energy-efficient schedule.

3.1 System Model and Research Goal

Consider a multi-residential building that, at time $t = 1, .., T$, may consume electricity from two types of sources: renewable (green) energy r_t from photovoltaic (PV) cells, if available, or grid energy otherwise, with the price c_t per kWh dictated by pricing scheme $c = \langle c_1, .., c_T \rangle$. The building is inhabited by residents $u = 1, .., U$ that own a number of shiftable/real-time appliances $a = 1, .., A$, each requiring energy e_a^u for operation. Furthermore, a resident u sets their appliance-usage preferences p_{at}^u, indicating preferred usage of appliance a at time t. Usage x_{at}^u of appliance a at time t results in resident u being charged with a cost equal to $e_a^u * c_t$. Figure 1 is a representation of the system model.

Research goal: *How can a green appliance-schedule x be produced, such that it simultaneously minimizes both resident dissatisfaction*[2] **D** *and energy costs* **C**, *while limiting deviation from the utilization of green energy* **GED***?*

[2] the equivalent of maximizing appliance-scheduling preference satisfaction.

3.2 Problem Definition

Assume an appliance-usage schedule $x = \langle x^1, x^2, ..., x^J \rangle$, $J = U * A * T$, as well as an appliance-usage preference list $p = \langle p^1, p^2, ..., p^J \rangle$, both expressed as binary vectors and defined as follows:

$$\begin{aligned} x^j &= x^u_{at} \in \{0, 1\}, \\ p^j &= p^u_{at} \in \{0, 1\}, \\ \textit{where} \ \ j &= (u-1) * (A * T) + (a-1) * T + t. \end{aligned} \tag{2}$$

Index j serves to link x^u_{at}, p^u_{at} to a unique position in vectors x, p, respectively. Furthermore, given the shifting/real-time nature of the appliances, estimating the extent to which each resident is satisfied requires a mapping between schedule x and preferences p. We represent this *appliance usage-to-preference (x-to-p) mapping* through vector $m = \langle m^1, m^2, ..., m^J \rangle$, where:

$$m^j = \begin{cases} j + i & \text{if } x^j = 1 \\ 0 & \text{if } x^j = \ 0 \end{cases} \tag{3}$$

Shifting step $i \in [-t, T - t]$ represents the deviation of the actual time of use of an appliance from the preferred time. As a result, the three distinct scenarios regarding preference satisfaction are:
(i) $m^j = j$ iff preference $p^j = p^u_{at}$ is *fully satisfied* by appliance usage x^j at the requested time t (i = 0).
(ii) $m^j = j + i$ iff preference $p^{j+i} = p^u_{a,t+i}$ is *partially satisfied* by appliance usage x^j at time t, instead of the requested $t + i$.
(iii) $m^j = 0$: *No preference is satisfied.*

Dissatisfaction Objective *D*: The residents' dissatisfaction is expressed as:

$$\min_x D(x) = \sum_{u=1}^{U} \frac{\sum_{a=1}^{A} \sum_{t=1}^{T} d^u_{at}}{\mid p^u \mid},$$
$$\textit{where} \ \ d^u_{at} = d^j = \begin{cases} 1, & \text{if } p^j = 1 \text{ and } \nexists i, m^{j-i} = j) \\ 1 - 0.5^{|i|}, & \text{if } p^j = 1 \text{ and } \exists i, m^{j-i} = j) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Objective D attempts to minimize the total dissatisfaction (See footnote 3) of residents. The dissatisfaction of a single resident is defined as the ratio of the sum of all dissatisfaction-per-preference d^u_{at}, to the total number of resident's u preferences p^u. Dissatisfaction d^j represents either full, partial or non-dissatisfaction of preference p^j, based on the existence of a mapping m^{j-i} for it, as explained. Additionally, formulating the objective as a fraction of the total preferences ensures higher priority for residents with fewer preferences, as the impact of dismissing their requests is higher than in the case of more demanding residents.

Costs Objective *C:* The residents' energy costs are defined as:

$$\min_x C(x) = \max_{u \in \{1,..,U\}} \sum_{a=1}^{A} \sum_{t=1}^{T} e_a^u * c_t * x_{at}^u \quad (5)$$

Objective C aims at keeping the maximum total cost for any resident as low as possible. The proposed objective encourages the satisfaction of resident preferences in a uniform and fair manner, since no penalty is involved in satisfying the preference of a resident who is not charged as heavily as others.

Green Energy Deviation Objective *GED:* A green/energy-efficient schedule maximizes the utilization of green energy from renewable sources for the satisfaction of demand and minimizes the use of grid energy, and consequently the CO_2 emissions. Hence, we define the energy efficiency of schedule x in terms of its deviation from the use of green energy, expressed as the total difference between the energy E_t consumed and the available r_t, for all t:

$$\begin{aligned} \min_x GED(x) &= \sum_{t=1}^{T} \mid E_t - r_t \mid, \\ where \;\; E_t &= \sum_{u=1}^{U} \sum_{a=1}^{A} e_a^u * x_{at}^u \end{aligned} \quad (6)$$

3.3 Multi-objective Optimization Problem Formulation with Decision Making

Given the conflicting nature between objectives D and C, the problem can be expressed as an MOP, with objective GED set as a performance-based Decision Making Heuristic for selecting a final solution from the resulting Pareto-front:

$$\begin{aligned} & \min_x GED(x) \\ s.t. \quad & x \in \operatorname*{argmin}_{x \in X} f(x) = \big(D(x,p), C(c,x,e)\big) \end{aligned} \quad (7)$$

4 Green-MOEA/D

This section presents Green-MOEA/D and the Mapping Improvement Heuristic.

4.1 Algorithm Description

MOEA/D [17], an algorithm that works especially well on multi-objective 0-1 knapsack-type problems and allows the incorporation of problem-specific knowledge [9], serves as the basis of the proposed Green-MOEA/D, as summarized in

Algorithm 1: A population S consisting of appliance-usage schedules s is initialized; both the empty schedule and the schedule that has all appliances active are added to the population (line 1), to avoid the possibility of unreachable optimal solutions. The proposed problem-specific Mapping Improvement Heuristic (MIP) is then applied to each solution s (line 2), followed by an evaluation of s (line 3). Additionally, the MOEA/D-specific parameters of uniform weight vector λ, neighbourhood vector $B(i)$ per solution s^i, and ideal vector z are initialized (line 4), with the latter given the optimal value of zero (0) per objective function. A single iteration of Green-MOEA/D (lines 6–20) includes: For every solution s^i in the population, two of its neighbouring solutions are randomly selected as parents and used to create new offspring solutions o^1, o^2 through (i) Uniform Crossover: $\forall j \in [1, J]$, swaps x^j between parent solutions s^1 and s^2 with a 50% probability, (ii) Bit-Swap Mutation: $\forall j \in [1, J]$, swaps x^j with a random $x^l, l \in [j+1, J]$ given the mutation probability, and (iii) re-applying the MIP. After their evaluation, the Pareto-dominant (or otherwise, random) solution among them is selected as offspring o. Then, neighbours s^b of solution s^i (included) are examined (lines 14–18) for possible replacement by o: if the Tchebycheff approach [17] with normalization produces a better evaluation for

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Algorithm 1. Green-MOEA/D

Input: p, e, c
Output: Pareto-front {s}

1: Init population $IP = \{s^1, s^2, s^3.., s^N\}$, $s^1 = \overrightarrow{0}$, $s^2 = \overrightarrow{1}$, uniformly random $s^3 : s^N$
2: $\forall s \in S, MIH(s)$ // Apply Mapping Improvement Heuristic
3: $\forall s \in S, f(s) \leftarrow \binom{f_1}{f_2}$, $f_1(s) = D(s,p), f_2(s) = C(c,s,e)$ // **Evaluation**
4: Init MOEA/D params $\lambda = \langle \lambda^1, .., \lambda^N \rangle; \forall i \in 1, .., N,\ B(i) = \langle b^1, .., b^I \rangle; z = \langle z^1, z^2 \rangle \leftarrow \langle 0, 0 \rangle; EP = \{\}$
5: **while** $(\gamma = 0; \gamma \leq gen_{max})$ **and** not converged **do**
6: **for** $i = 1$ to N **do**
7: Select random $b^1, b^2 \in B(i)$ // **Selection**
8: $q^1 \leftarrow s^{b^1}, q^2 \leftarrow s^{b^2}$
9: $o^1_{cross}, o^2_{cross} \leftarrow uniformCrossover(q^1, q^2)$ // **Crossover**
10: $o^1_{mut} \leftarrow bitSwapMutation(o^1_{cross})$ // same for o^2_{cross}, **Mutation**
11: $o^1 \leftarrow MIH(o^1_{mut})$ // same for o^2_{mut}, **Improvement**
12: $f(o^1) \leftarrow \binom{f_1}{f_2}$ // same for o^2, **Evaluation**
13: $o \leftarrow dominantOrRandom(o^1, o^2)$ // Select best offspring
14: **for** $b \in B(i)$ **do** // Update s^i and its neighbourhood
15: **if** $o \succ s^b$ **or** $g^{te}(o|\lambda^b, z) < g^{te}(s^b|\lambda^b, z)$ **then**
16: $s^b \leftarrow o, f(s^b) \leftarrow f(o)$ // g^{te}: Tchebycheff function
17: **end if**
18: **end for**
19: Update EP // Update EP using Pareto-front $\{s\} \in IP$
20: **end for**
21: **end while**
22: **return** EP

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o, then s^b is replaced. Alternatively, s^b is replaced if o dominates s^b, as suggested by Xiang et al. [16]. Finally, external population EP is updated with the dominant solutions of population IP and all dominated solutions are removed. The process is terminated and EP is returned if the maximum number of iterations or convergence is reached.

4.2 Mapping Improvement Heuristic Description

Our Mapping Improvement Heuristic (MIH) produces a usage-to-preference (x-to-p) mapping m, as presented in Sect. 3.2, linking each appliance usage to a preference and enabling the evaluation of objective D. It consists of two steps:

1. $\forall j \in [1, J]$, if $x^j = x^u_{at} = 1$ and $p^j = 1$, then set $m^j \leftarrow j$, else set $m^j \leftarrow 0$.
2. $\forall j \in [1, J]$, if $x^j = x^u_{at} = 1$ and $m^j = 0$, find the shifting step $i \in [-t, T - t]$ that minimizes $t + i$, given that $p^{j+i} = p^u_{a,t+i} = 1$ and $\nexists l$ s.t. $m^l = j + i$, then set $m^j \leftarrow j + i$. If no such i exists, set $x^j = x^u_{at} = 0$ (turn appliance OFF).

The first step creates a mapping for all appliance usages x^j that fully satisfy a preference p^j, i.e., shifting step i is equal to zero (0). The second step handles the rest of usages x^j, assigning the closest possible preference to each usage in order to minimize dissatisfaction, or turns the appliance OFF when no unsatisfied preference can be found. In this way, the second step allows for energy flexibility by shifting energy load, contrary to simply reducing it, and improves schedule x by disabling appliances that do not improve overall preference satisfaction.

5 Experimental Settings

This section describes the datasets used in the experiments, algorithms and algorithmic settings adopted, and performance metrics considered.

5.1 Datasets

Green-MOEA/D is evaluated on six (6) realistic datasets encapsulating the residents' preferences p, with each dataset representing the appliance-usage preferences expressed for a variant set of households by their respective residents during a specific season and date. The preferences were extracted from the *REFIT dataset*, a public 500MB dataset which contains real kW readings of the power output for the most energy-intensive shiftable/real-time appliances in 20 households in the UK, between September 2013 and July 2015. The preprocessing performed in order to extract the preferences included (i) converting kW readings per second into per-minute readings by removing duplicate records, (ii) converting per-minute readings into hourly readings by summing them up, (iii) defining preference (or not) of an appliance, per hour, through threshold values, and (iv) mapping each household to a resident and assigning the 24-hour preference-batch for a specific date for that household to the corresponding resident. Furthermore, the energy consumption per appliance was derived by

Table 1. The realistic datasets generated by using information from the REFIT public dataset.

Dataset	Season	Date	U	A	T	Households(ID)
Sml_Aut	Autumn	23/10/2013	5	25	24	1 2 3 4 5
Sml_Win	Winter	11/12/2013	5	25	24	1 3 4 5 6
Sml_Sum	Summer	02/06/2014	5	25	24	1 2 3 4 5
Lrg_Aut	Autumn	29/11/2013	10	49	24	1 2* 3 4 5 6 7 8 9* 10
Lrg_Win	Winter	19/01/2014	10	50	24	1 3 4 5 6 7 8 9 10 13
Lrg_Sum	Summer	15/06/2014	10	47	24	1 2 3 4 5 17 18 19 20 21

*date unavailable, closest date retrieved

examining the kW readings in the original dataset. The datasets that resulted from the above pre-processing can be found in Table 1.

Each dataset also includes renewable energy production data, which is uniformly varied based on the number of households and season. The hourly values were derived by estimating the energy output of a 4.5 kW PV-system per household, using the standard formula for calculating solar panel energy production:

$$P_{PV} = P_{peak} * (G/G_{standard}) - a * (T - T_{standard}) \quad (8)$$

The formula was applied subject to (i) a $P_{max} = 450\,\text{W}$ solar panel with a temperature-coefficient $a = 0.3$, (ii) the Standard Test Conditions and (iii) the average seasonal temperature G and irradiance T in the UK [4]:

Autumn: $T : 11, G : 875$; *Winter:* $T : 5, G : 750$; *Summer:* $T : 18, G : 1000$.

Finally, all datasets assume a pricing scheme c subject to a renewable energy tariff[3] resulting in prices inversely proportional to r_t, thus encouraging consumption during peak-production hours. For example, the maximum price (when $r_t = 0$) is $c_t = 1.0$, the minimum price (when r_t is the highest) is $c_t = 0.2$, and intermediate prices are $c_t = 0.4, c_t = 0.6$ and $c_t = 0.8$.

5.2 Algorithms and Algorithmic Settings

The experimental studies described in this section aim at evaluating the effectiveness of ***Green-MOEA/D***, as well as the choice of its evolutionary operators. Green-MOEA/D, as described in Sect. 4, is implemented on the jMetal 4.5[4] Java-framework for MOO and is compared with the state-of-the-art Pareto-dominance based Non-Dominated Sorting Genetic Algorithm II (***NSGA-II***) [3]. Each algorithm is executed 20 times subject to the following operators and parameter values, resulting in an equal number of function evaluations, for fairness:

[3] endesa, 2023. Solar Simply, the best tariff for self-consumption with surpluses. LINK: https://shorturl.ac/7az57.

[4] jMetal, 2015. jMetal Web site. LINK: https://jmetal.sourceforge.net.

- $N : 300, gen_{max} : 500, B : 100$ (for Green-MOEA/D only)
  Crossover probability: 1.0, Mutation probability: 0.01

The termination criterion is the maximum number of generations, unless convergence (defined as a difference in hyper-volume smaller than 1e−7 between 3 generations) is reached. Additionally, the Uniform Crossover (***UC***) operator adopted by Green-MOEA/D is compared against:
*(i) Two-point Crossover (**TPC**)*: swaps a random sub-vector $\langle x^l, .., x^k \rangle$ between parent solutions s^1 and s^2, where $l, k \in [1, J]$ and $l \leq k$.
*(ii) Single-Point Crossover (**SPC**)*: swaps a random sub-vector $\langle x^l, .., x^J \rangle$ between parent solutions s^1 and s^2, where $l \in [1, J]$.
The BitSwap Mutation (**BSM**) operator of Green-MOEA/D is compared against:
*(i) BitFlip Mutation (**BFM**)*: $\forall j \in [1.J]$, reverses bit x^j with a probability equal to the mutation probability.
*(ii) No Mutation (**NM**)*: Perform no mutation.

5.3 MOO Performance Metrics

This section discusses the performance metrics used for comparing the MOO solutions derived from our experiments.
(i) Hypervolume indicator (HV): evaluates the quality of the approximation to the true Pareto-optimal front by calculating the "size of dominated space" S by the Pareto front in question. It requires no prior knowledge of the true Pareto-optimal front, in which case the whole solution domain D can be approximated:

$$HV = S/D \tag{9}$$

(ii) Coverage (C)-metric: commonly used for comparing two sets of non-dominated solutions A and B and proposed by Zitzler and Thiele, $C(A, B)$ calculates the ratio of non-dominated solutions in B dominated by non-dominated solutions in A, divided by the total number of non-dominated solutions in B.

$$C(A, B) = \frac{|\{x \in B \| \exists y \in A : y \succ x|\}}{|B|} \tag{10}$$

$C(A, B) = 1$ means that all solutions in B are dominated by A.
(iii) Spread (Δ): The Δ-metric, proposed by Deb et al. [3], measures the extent of spread achieved among the obtained solutions, as follows:

$$\Delta = \frac{d_{f1} + d_{f2} + \sum_{i=1}^{N} |d_i - d|}{d_{f1} + d_{f2} + (N - 1)d} \tag{11}$$

where d_{f1}, d_{f2} is the distance between the extreme and the optimal solution, per objective. A low Δ implies a uniform spread, allowing a variety of choices.
(iv) Non-Dominated Solutions (NDS): Usually considered in discrete optimization problems, a high number of Non-Dominated Solutions (NDS), as explained in Sect. 2.1, represents an adequate number of choices.

CPU Time: In all experiments, the CPU time is also used for evaluating the execution time of the algorithms.

6 Experimental Studies

The computing machine used for the experiments consists of an Intel Core i7-8750H CPU @2.20 GHz and 16 GB of RAM. For conciseness, we hereby refer to Green-MOEA/D as G-MOEA/D.

6.1 Green-MOEA/D Vs NSGA-II

Table 2 presents the results of our performance comparison between G-MOEA/D and NSGA-II, across all datasets. G-MOEA/D consistently outperforms NSGA-II with regards to HV, Δ and time, while NSGA-II dominates with regards to NDS. Regarding HV, G-MOEA/D is slightly better than NSGA-II, with the difference ranging from 0.2% up to 1.1%. NSGA-II seems more scalable than G-MOEA/D with regards to Δ, as the difference in performance from the smaller to the larger datasets is decreased from 7% to 3%, although G-MOEA/D still remains superior. NSGA-II also greatly outperforms G-MOEA/D with regards to NDS, producing about 1.5 times as many non-dominated solutions. Nonetheless, G-MOEA/D is a lot faster, with the difference from the smaller to the larger datasets increasing from 25% up to 72%. Finally, the coverage comparisons demonstrate the dominance of G-MOEA/D, with roughly only 1/10th of its solutions being dominated while dominating more than half of the NSGA-II solutions. Figure 2 provides a visualization for a subset of the results.

Table 2. Performance comparison between Green-MOEA/D (M) and NSGA-II (N) on all datasets. Results correspond to averages across 20 distinct runs.

Dataset	Metrics									
	HV		Δ		*NDS*		*Time*		*Coverage*	
	N	*M*	*N*	*M*	*N*	*M*	*N*	*M*	*C(N,M)*	*C(M,N)*
Sml_Aut	0.73197	**0.73482**	1.011	**0.939**	**148**	95	1781	**1432**	0.13	**0.54**
Sml_Win	0.66988	**0.67541**	1.022	**0.954**	**143**	76	1390	**1102**	0.07	**0.61**
Sml_Sum	0.71746	**0.71942**	1.018	**0.944**	**149**	88	1473	**1145**	0.11	**0.62**
Lrg_Aut	0.79470	**0.80400**	0.982	**0.969**	**110**	88	3866	**2668**	0.13	**0.58**
Lrg_Win	0.78166	**0.78950**	0.954	**0.947**	**117**	104	5003	**3601**	0.16	**0.64**
Lrg_Sum	0.74708	**0.75088**	0.993	**0.955**	**116**	72	3443	**1995**	0.22	**0.39**

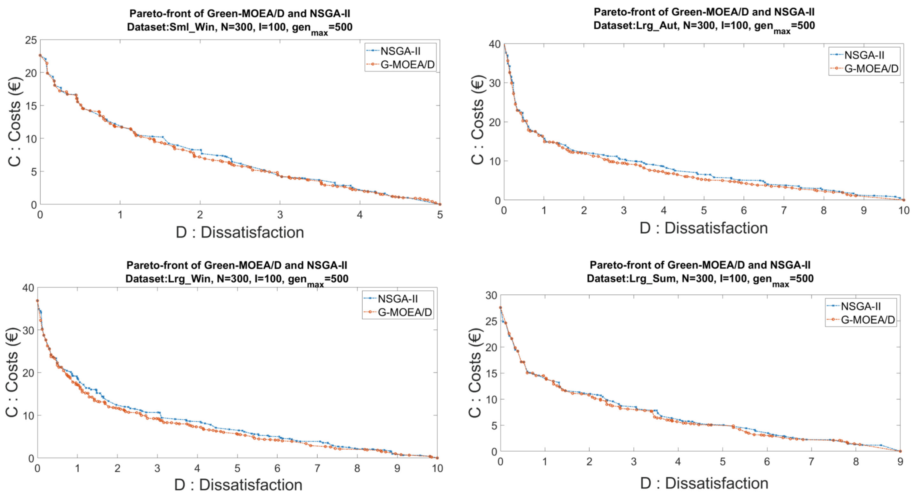


Fig. 2. Pareto-fronts of Green-MOEA/D and NSGA-II on four (4) datasets $N = 300, I = 100, gen_{max} = 500$

6.2 Evaluation of Mapping Improvement Heuristic

We evaluate our ***MIH***, as described in Sect. 4.2, against the alternative ***MH*** of only invoking its first step, i.e., we compare the effectiveness of being able to shift load or reduce load by altering the schedule, against the alternative of considering exclusively the fully satisfied preferences.

The results in Table 3 show that, on dataset "Lrg_Sum", MIH has a significant 0.8% performance increase regarding HV and a 35% increase regarding Δ. Although, as a heuristic, MIH is more time consuming, it helps speed algorithm convergence up, resulting in a faster execution time by half a second. Finally, MIH consistently dominates more than 68% of the solutions of MH on all datasets.

Table 3. Green-MOEA/D performance comparison between MIH and the alternative MH. Results correspond to averages across 20 distinct runs.

Dataset:	**Algorithm**	
Lrg_Sum	*MIH*	*MH*
Metric		
HV	**0.75088**	0.74443
Δ	**0.955**	1.286
NDS	72	72
$Time$	**1995**	2413

	Coverage	
Dataset	*C(MIH,MH)*	*C(MH,MIH)*
Sml_Aut	**0.73**	0.06
Sml_Win	**0.71**	0.07
Sml_Sum	**0.78**	0.03
Lrg_Aut	**0.68**	0.21
Lrg_Win	**0.68**	0.22
Lrg_Sum	**0.70**	0.15

Table 4. Green-MOEA/D performance comparison between crossover operators UC, TPC and SPC on dataset "Lrg_Sum". Results correspond to averages across 20 runs.

Mut.:	**Crossover**		
BSM	*UC*	*TPC*	*SPC*
Metric			
HV	**0.750**	0.745	0.735
Δ	0.955	**0.948**	0.951
NDS	72	**76**	75
Time	**1995**	3024	2645

	Coverage					
	U:UC, T:TPC, S:SPC					
Mut.	*C(T,U)*	*C(U,T)*	*C(S,U)*	*C(U,S)*	*C(S,T)*	*C(T,S)*
NM	0	**0.88**	0	**0.87**	0.10	**0.70**
BFM	0.25	**0.56**	0.19	**0.65**	0.34	**0.48**
BSM	0.20	**0.58**	0.11	**0.73**	0.29	**0.52**

6.3 Control Experiments

Table 4 presents a two-fold comparison of the performance of G-MOEA/D on dataset "Lrg_Sum" by varying crossover operators: On one hand, the crossover operators are tested while accompanied by the selected BSM mutation operator, and on the other, coverage comparisons are performed subject to different mutation operators. This ensures that a dominant crossover operator is not dominant only subject to an accompanying mutation operator. The results show that UC achieves the best Pareto-front by 0.6% better and 1.5 times faster than the second-best TPC, albeit having worse Δ and NDS by 0.73% and 4 NDS, respectively. The coverage comparisons suggest the dominance of UC scales across all mutation operators, with no more than 25% of its solutions being dominated and dominating more than half of the other operators' solutions.

Table 5 presents a two-fold comparison of the performance of G-MOEA/D on dataset "Lrg_Sum" by varying mutation operators: On one hand, the mutation operators are tested while accompanied by the selected UC crossover operator, and on the other, coverage comparisons are performed subject to different crossover operators. This ensures that a dominant mutation operator is not dominant only subject to an accompanying crossover operator. The results show that BSM achieves the best Pareto-front by 0.2% and 0.4% better than NM regarding HV and Δ, respectively, and with 4 more NDS, albeit being twice as slow. The coverage comparisons suggest the dominance of BSM scales across all crossover

Table 5. Green-MOEA/D performance comparison between mutation operators NM, BFM and BSM on dataset "Lrg_Sum". Results correspond to averages across 20 runs.

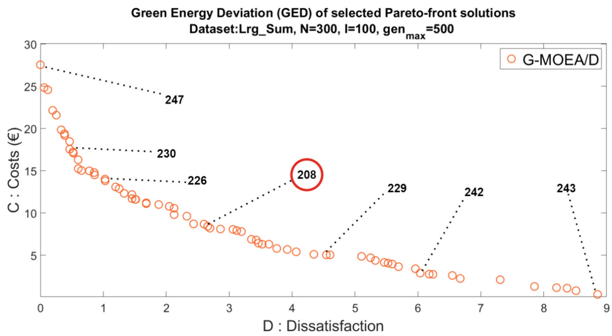
Cross:	**Mutation**		
UC	*NM*	*BFM*	*BSM*
Metric			
HV	0.748	0.727	**0.750**
Δ	0.959	**0.944**	0.955
NDS	68	**77**	72
Time	**831**	2900	1995

	Coverage					
	N:NM, F:BFM, S:BSM					
Cro.	*C(F,N)*	*C(N,F)*	*C(S,N)*	*C(N,S)*	*C(S,F)*	*C(F,S)*
UC	0.29	**0.38**	**0.45**	0.26	**0.43**	0.28
TPC	**0.58**	0.23	**0.82**	0.05	**0.48**	0.28
SPC	**0.69**	0.10	**0.85**	0.01	**0.48**	0.29

operators, with no more than 30% of its solutions being dominated and dominating more than 40% of the other operators' solutions.

6.4 Discussion on the Decision Making Heuristic

We evaluate our Decision Making Heuristic (***DMH***) by merging all three objectives: GED, D, C, into a single, normalized percentage-value using weighted sum scalarization with a coefficient of 1/3 per objective. Figure 3 provides (i) a visualization of the Pareto-front achieved by G-MOEA/D on dataset "Lrg_Sum", along with the GED of selected solutions, and (ii) the performance of selected solutions per objective and their weighted sum. It is shown that DMH achieves a significantly better weighted-sum value than both extreme solutions of the Pareto front and the random solutions, creating the best trade-off between the optimization objectives.



Solution	Objective			Weighted Sum
	GED	D	C	
Extreme C	243	9.0	**0.0**	63.18
Extreme D	247	**0.0**	27.54	66.6
DMH	**208**	2.65	8.42	**19.98**
Random 1	226	5.10	4.86	40.10
Random 2	229	1.25	12.88	38.12

Fig. 3. *Left*: GED of Green-MOEA/D Pareto-front solutions on dataset "Lrg_Sum". *Right*: Evaluation of some solutions for each objective and their weighted sum (%).

7 Conclusion

This paper presents Green-MOEA/D, a Multi-Objective Evolutionary Algorithm based on Decomposition that aims at producing appliance-usage schedules with optimal trade-offs between maximizing the satisfaction of the residents' appliance-scheduling preferences and minimizing their billing charges. The problem is defined and formulated as a Multi-Objective Optimization Problem with Decision Making, incorporating energy flexibility through load shifting and reduction. A Mapping Improvement Heuristic is introduced as part of Green-MOEA/D for energy flexibility management. Furthermore, a Decision Making Heuristic is proposed for selecting the most energy-efficient schedule from the set produced by Green-MOEA/D, in terms of limiting deviation from the use of green energy and, consequently, limiting CO_2 emissions. The experimental studies, which include evaluations of the Mapping Improvement Heuristic, the evolutionary operators adopted and the Decision Making Heuristic, show that Green-MOEA/D clearly outperforms alternative state-of-the-art approaches.

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Chapter 32

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