A Bi-Level Multi-Objective System for Renewable Energy Self-Consumption: A Resident-Aware Approach to Leveraging Energy Flexibility

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***Abstract*—The efficient exploitation of renewable energy sources is crucial for addressing the global energy crisis and increase in CO_2 emissions. Energy management system aggregators, functioning as nonprofit cooperatives within energy communities, manage renewable energy resources and incentivize residents towards self-consumption through dynamic, cost-attractive pricing schemes, receiving subsidies and long-term contracts as reward. This interaction between aggregator and residents is typically modeled using bi-level optimization frameworks, however, research studies often ignore the role of aggregators as self-consumption catalysts and the conflicting nature of the residents' objectives. Moreover, lack of cooperation between the decision levels results in inflexible decision making when prioritizing between the respective objectives. This paper defines and formulates a bi-level multi-objective optimization problem for optimizing self-consumption in energy communities, while considering the residents' welfare by maximizing satisfaction of their appliance-scheduling preferences and minimizing energy costs. We introduce the Bi-level Multi-Objective Energy Management System II (BiMO-EMS-II), composed of an Adaptive Population Transfer strategy, a Uniform Partially Mapped Crossover and a Decision Making heuristic with Cooperation. Our experimental evaluation has shown that BiMO-EMS-II simultaneously offers near-optimal self-consumption at the aggregator level and a high-quality trade-off between the conflicting objectives at the resident level, subject to different objective prioritization and decision-making assumptions.**

***Index Terms*—bi-level optimization, evolutionary multi-objective optimization, self-consumption, evolutionary transfer optimization, multi-criteria decision making.**

I. Introduction

[1] [2]. [3] [4]

IN an attempt to reduce the CO_2 emissions caused due to grid electricity consumption[5], the European Green Deal advocates for efficient electrical energy usage at all levels of the ecosystem. At the most foundational level, such as homes, apartment blocks and commonly inhabited spaces,

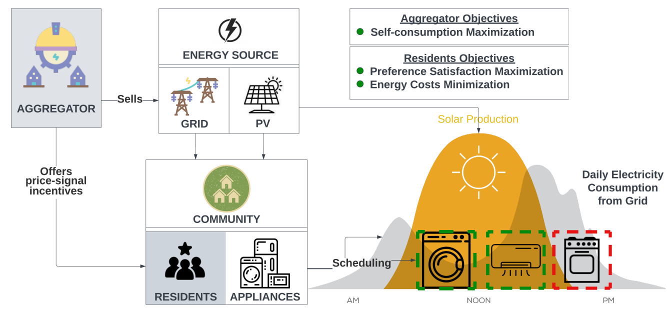

Fig. 1: Aggregator offers energy price-signal incentives, which affect the residents' appliance-scheduling decisions and consequently the overall communal self-consumption.

energy efficiency is primarily achieved by harnessing self-generated *renewable energy* (RE) (e.g., solar energy from photovoltaic PV cells), a practice commonly known as *self-consumption*. Self-consumption entails reduced reliance on the grid, consequently maximizing the utilization of RE at the production site to satisfy energy needs and minimizing the energy demand from CO_2-emitting fossil sources [1].

Energy Management System Aggregators (EMSA) play a crucial role [2] in supporting the cooperation between different levels of the energy management ecosystem towards achieving energy efficiency. They provide Demand-Response (DR) and Ancillary Services to Distribution System Operators (DSO) through Demand-Side Management (DSM) programs [3], in order to address the DSO energy flexibility requests [4], with profit maximization being their goal. These programs assess the consumption patterns of the residents and leverage their energy flexibility, incentivizing their cooperation as key stakeholders through benefits such as reduced energy costs or monetary compensation for altering their preferred appliance-scheduling [3]. Alternatively, EMSAs also act as local non-profit cooperatives to energy communities by managing their RE and incentivizing self-consumption through dynamic pricing schemes, receiving subsidies or long-term contracts by the EU/government as rewards [5]. With more than 2400 RE cooperatives across Europe [5], and given the growing capacity of prosumers (end-users with RE production capabilities) to facilitate self-consumption, DSM programs focused on self-consumption gain significance.

The bi-directional interaction between the aggregator and resident decision levels has been investigated within the framework of non-cooperative Stackelberg games [6], with

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[5] European Commission, 2023. EU Mission: Climate-Neutral and Smart Cities. LINK: https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe/eu-missions-horizon-europe/climate-neutral-and-smart-cities

existing approaches predominantly employing bi-level linear programming strategies [7], [8]. Furthermore, the existence of conflicting objectives at the resident decision level, such as preference satisfaction maximization and energy costs minimization, embolden the utilization of *evolutionary bi-level multi-objective optimization (EBLMO)* approaches [9]. However, existing approaches often ignore the role of aggregators as self-consumption catalysts and the conflicting nature of the residents' objectives. Moreover, the lack of cooperation between the decision levels results in inflexible decision making when prioritizing between the respective objectives. For instance, prioritization of cost-minimization is more attractive for self-invested communities whose cost-averse residents seek to recover their investment, and prioritization of self-consumption maximization is more suitable for cost-indifferent residents and communities aimed at energy self-sufficiency [10]. In addition, although effective, EBLMO approaches, and especially nested optimization approaches, typically suffer from being computationally expensive [9].

An effective way to increase the performance of EBLMO approaches, in terms of both accuracy and execution time, is by employing a Knowledge-Transfer strategy, where knowledge gained from previously-evaluated solution(s) is utilized in different ways [11]–[14] to aid in the evaluation of new solutions. However, existing Knowledge-Transfer strategies [12], [13] insufficiently examine the appropriate amount of knowledge transfer or the appropriate distribution of transferred knowledge in the search space. Additionally, the utilization of these strategies is advised [13] when computational resources are limited, otherwise their effectiveness decreases.

In our previous work [15], we introduced a *bi-level multi-objective problem (BMOP)* for aggregator participation in the day-ahead energy market that aims at optimizing self-consumption in *collective self-consumption communities* [10] (communities that share a RE source), while considering the residents' welfare by maximizing satisfaction of their appliance-scheduling preferences and minimizing energy costs. As illustrated in Fig. 1, we leveraged the connection between the decision levels through the *Bi-level Multi-Objective Energy Management System* (BiMO-EMS) for self-consumption optimization. This framework suffers from three major limitations: (i) energy flexibility is only achievable through load curtailment/reduction, which significantly limits its utilization potential in optimizing self-consumption, (ii) the system is inefficient in terms of execution time, and (iii) the proposed *optimistic* decision-making model, which assumes that EMSAs anticipate the behavior of end-users to their advantage, overlooks the unpredictability of end-users as decision-makers, who may prioritize preference satisfaction or cost savings to the detriment of maximizing self-consumption.

In this paper, we extend our work in [15] by proposing a BMOP that supports load shifting, and introduce a bi-level multi-objective optimization framework, coined BiMO-EMS-II, composed of three (3) new components: (i) a novel Adaptive Population Transfer strategy for optimized exploitation of acquired knowledge, (ii) an adapted Uniform Partially Mapped Crossover operator for maximal exploitation of energy flexibility, and (iii) a novel Decision Making heuristic with Cooperation for supporting decision-making with regards to the prioritization between objectives under different assumptions. Specifically, our contributions are as follows.

1) We propose a BMOP that enables appliance-scheduling subject to load shifting in addition to load curtailment, thus allowing for maximal utilization of energy flexibility and increasing the optimization potential at both decision levels.
2) We propose a Knowledge-Transfer strategy for decomposition-based EBLMO approaches, inspired by SPT [13], coined Adaptive Population Transfer (APT), that utilizes weight vector λ to selectively-transfer solutions and achieve an optimized balance between exploration and the exploitation of acquired knowledge. Contrary to SPT, APT is shown to work best when high computational resources are available, offering competitive solution quality and faster execution time.
3) We deploy an adapted Uniform Partially Mapped Crossover (UPMX) for metaheuristics with order-based permutation chromosomes, inspired by the original PMX [16], that optimizes the required (due to load shifting) mapping between appliance usages and resident scheduling-preferences for maximal exploitation of energy flexibility.
4) We define a generalizable framework for Decision Making with Cooperation (DMC) between the upper-level (UL) and lower-level (LL) entities in BLMOPs which supports the following approaches: i) optimistic, (ii) pessimistic, (iii) a *"resident-aware"* approach subject to the community-level residents' profile, (iv) a fixed-coop approach that assumes a specified level of cooperation by the LL decision-makers, and (v) a dynamic-coop approach that allows dynamically-tuning cooperation based on a concept of trade-off fairness, aspiring for a balanced trade-off between self-consumption maximization and resident convenience. A sensitivity analysis on the gap in performance (with regards to both UL and LL objectives) between all approaches is presented.
5) The proposed *Bi-level Multi-Objective Energy Management System II (BiMO-EMS-II)*, composed of APT, UPMX and DMC, is evaluated on realistic resident-preference datasets derived from appliance-usage patterns and solar energy production datasets. Our experimental evaluation has demonstrated that BiMO-EMS-II achieves near-optimal self-consumption at the aggregator level and a high-quality trade-off between the conflicting objectives at the resident level, while also being capable of offering a variety of attractive solution trade-offs based on diverse objective prioritization and decision-making assumptions.

The remainder of this paper is organized as follows: Section II discusses related work. Section III presents the system model, problem definition and formulation. BiMO-EMS-II is explained in section IV, along with DMC, APT and UPMX. The experimental setting and evaluation are presented in sections V and VI, respectively. Section VII concludes the paper.

II. Related Work

A. Energy Flexibility and Bi-level EMSA Models

Energy flexibility is defined as the amount of load that can be shifted, reduced or curtailed towards achieving energy-management objectives. The exploitation of energy flexibility in energy communities is handled by EMSAs and the deployment of the decided load-operation schedule is often being automatically handled by home and building energy management systems (HEMS/BEMS) [17]. A well-established model for citizen-led energy communities is the "energy cooperatives" model [5], in which the residents voluntarily participate as economic stakeholders and the EMSAs act as local for-profit or nonprofit cooperatives. In the latter scenario, the EMSAs manage the community's RE supply and define billing conditions in order to incentivize self-consumption and promote energy self-sufficiency. From an economic point of view, the EMSAs receive subsidies or long-term contracts by the EU/government as reward, while the residents benefit from reduced energy costs, due to energy self-sufficiency.

Bi-level approaches are attractive in exploiting the relationship between interdependent decision levels, such as those that aggregator and residents operate on [6]: by optimally solving the LL parameterized problem before attending to the UL problem, they result in trade-offs between objectives that are desirable by both entities, given their adversarial/cooperative relationship. Antunes and Alves have developed bi-level models on the interaction between aggregator and residents in the electricity market, experimenting with numerous HEMS modeling aspects including different types of loads and operation cycles, pricing schemes with fixed/varying periods and price ranges [18], battery/storage modeling and resident preference modeling, with later works [19] providing these models for modular use in problems with different settings. Additionally, the authors evaluated the impact that different pricing schemes, rewarding/penalizing strategies and decision-making approaches [20] have on energy costs, self-consumption [10] and energy flexibility mobilization [21].

Bi-level approaches have also been used to model the relationship between aggregator and residents under different energy-market settings: Nizami et al. [22] propose a BEMS acting as a load-scheduling and energy-quantity bidding agent for prosumers wishing to engage in the transactive energy market. Davide et al. [7] propose a bi-level model for an energy community whose residents buy, sell and share energy amongst each other, and evaluate it against an equally-sized community of independent residents, showing that both the UL aggregator and the LL residents profit from the application of this model. All the above authors transformed their bi-level problems into Mixed-Integer Linear Programming problems, and solved them using mathematical programming solvers.

B. Evolutionary Bi-level Multi-Objective Models

Given the complexity that bi-level problems introduce, such as non-linearity, non-convexity, and disconnectedness, a consistent rise in the utilization of metaheuristics has been observed over the last 20 years [23], with evolutionary metaheuristics and algorithms being particularly favorable [9]. Furthermore, the concepts of dominance and diversity between solutions, as introduced in multi-objective optimization, are handled particularly well by multi-objective evolutionary algorithms such as dominance-based NSGA-II and decomposition-based MOEA/D [23]. As a result, efforts towards solving semi-vectorial bi-level optimization problems [24] brought forth the use of evolutionary bi-level multi-objective (EBLMO) algorithms, with one pioneering approach featuring self-adaptiveness, local search and adaptive domination criteria based on the UL decision-maker's preferences [25].

Meta-/surrogate models, which are approximations of the actual model that are relatively quicker to evaluate, have also been employed to increase the computational efficiency of EBLMO approaches. For instance in [26], the set of LL optimal decision variables per UL variable is approximated through quadratic fibers, while in [27] its solution mapping is approximated using quadratic functions. Recently, the use of a surrogate model for the UL has also been suggested [28].

To the best of our knowledge, the adoption of EBLMO approaches for "energy-cooperative" communities is very limited. While there is a plethora of works for conflicting objectives in the smart-home context, concerning air quality, thermal/visual comfort, energy costs and resident satisfaction [29], they disregard the impact of these objectives on higher-level stakeholder entities. On the other hand, bi-level approaches that consider aggregators often disregard the conflicting nature of welfare-oriented objectives, opting instead for mathematical programming solutions [20], or focus on other conflicting objectives [8]. Finally, studies with a focus on self-consumption and self-sufficiency [30] often disregard the impact of aggregators in energy management and price regulation. This work aims to address these gaps.

C. Decision Making in Bi-Level Multi-Objective Models

In the presence of a LL Decision Maker (DM) with multiple LL optimal solutions to choose from, it is common for the UL entity to assume either (i) an optimistic approach, implying a fully cooperative LL DM that allows choosing the optimal solution for the UL objective(s), or (ii) a pessimistic approach, implying an adversarial/non-cooperative LL DM that chooses the solution resulting in the worst objective function value(s) for the UL objective(s). A few works have attempted to address the "optimism" gap between the two approaches in various ways. For instance, Sinha et al. [25] proposed a progressively-interactive EBLMO algorithm where the UL preferences are utilized for adapting the LL domination criteria in order to achieve the most preferred solution. A similar concept was proposed by Ibrahim and Mahmoud [31] through a fuzzy TOPSIS algorithm, in which the UL preferences are established along with acceptable levels of tolerance dictating the feasible region from which the LL DM selects a satisfactory solution. Antunes and Alves [20] introduced the concept of deceiving solutions in the optimistic approach and rewarding solutions in the pessimistic approach, and later introduced the concept of moderate solutions as a trade-off between the two based exclusively on the UL preferences. Corpus and Camacho-Vallejo [32] extended this list with the concept of

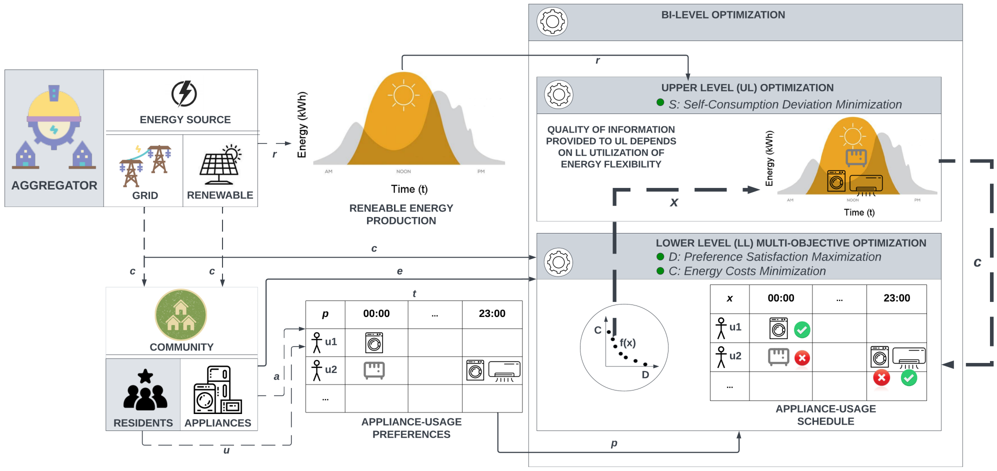


Fig. 2: Aggregator (UL) encourages RE self-consumption by providing energy price-signals. Residents (LL) use price-signals to establish an appliance-usage schedule subject to their preferences. Bi-level MOO results in a pricing scheme and schedule with optimized self-consumption.

neutral and awkward density-based solutions, studying the impact of selecting each out of seven different types of solutions. Finally, assuming an UL DM in addition to the LL DM, Deb et al [33] proposed an approach for the UL DM to select a "minimum expected deviation" solution that results in the smallest-possible maximal deviation from its optimistic values given that the LL DM's preferences are unknown. More on multi-criteria decision-making can be found in [34]. While the incorporation of a-priori UL/LL preference-information can help reduce computational complexity [24], it may also allow for more satisfactory "preference trade-offs" if cooperation between the UL entity and the LL DM is established. This work presents such a novel approach, with either fixed or adaptable cooperation as different trade-offs emerge.

D. Knowledge Transfer

Knowledge Transfer is a performance-enhancing strategy for BLMOPs that utilizes knowledge gained from previously-evaluated solution(s) in different ways to aid in the evaluation of new solutions: In [11], two parallel LL evolutionary processes exchange and utilize solution-feature information for improving their own search. In [14], the authors model a constrained MOP as a multitasking optimization problem and devise a metric identifying the tasks that would benefit the most from a particular solution transfer. Direct neighbor Solution Transfer (DST) [12] utilizes the LL optimal solution of a neighboring UL solution as a starting point for running a local search on the LL problem of the current solution. Moreover, Selective Population Transfer (SPT) [13] seeds the LL initial population of currently-evaluated solutions by transferring the LL Pareto-optimal set of the closest neighboring UL solution, however, the authors have not examined whether a smaller number of transferred solutions, or different distributions of these solutions, perform better. Furthermore, their approach is shown to work best when computational resources are limited, with its performance compared to the baseline declining as more resources become available. Contrary to SPT, APT is shown to work best when high computational resources are available, offering competitive solution quality and faster execution time.

III. System Model

Consider a multi-residential building that, at time $t \in [1\,..\,T]$, consumes electricity from two types of sources: renewable energy r_t from photovoltaic (PV) cells, if available, or grid energy otherwise, with the price c_t per kWh dictated by the aggregator's pricing scheme $c = \langle c_1, \ldots, c_T \rangle$. The building is inhabited by residents $u \in [1\,..\,U]$ that own a number of shiftable/real-time appliances $a \in [1\,..\,A]$, each requiring energy e^u_a for operation. Each resident u has a set of preferences $P^u = \{p^u_{at}\}$, where p^u_{at} depicts preferred usage of appliance a at time t, however, usage x^u_{at} of appliance a at time t results in resident u being charged with a cost equal to $e^u_a * c_t$. A community-level profile v establishes the residents' prioritization between preference satisfaction and costs reduction. Finally, an appliance-usage schedule x is established and the building's energy management system (BEMS) is responsible for deploying schedule x.

The efficiency of schedule x in terms of self-consumption is expressed as the total difference between the energy E_t consumed and the available r_t at t. Moreover, pricing scheme c affects the formation of schedule x (different prices c_t result in different appliance-scheduling decisions by the residents) and x affects the levels self-consumption, as presented in Fig. 2. For system model notations and their definitions, see Table I.

TABLE I
System Model Notations

Notation	Description
t, a, u	time, appliance, resident
x^u_{at}	usage of appliance a by resident u at time t
x	appliance-usage schedule
p^u_{at}	preference for usage of a by u at t
P^u	set of appliance-scheduling preferences of u
m^u_{at}	index of preference satisfied by x^u_{at}
m_x	usage-to-preference mapping of x
c_t	price of energy (in €) at t
c	pricing scheme
r_t	renewable energy (RE) available (in kWh) at t
e^u_a	energy (in kWh) required for operation of a of u
v	community-level residents' profile
S, D, C	objectives: self-consumption, dissatisfaction, costs

A. Problem Definition and Research Goal

The primary research goal of this study is as follows: *How to optimally leverage energy flexibility in order to produce a pricing scheme c and appliance-usage schedule x that offer optimal self-consumption **S**, as well as a high-quality trade-off between the welfare-oriented objectives of resident dissatisfaction[6] **D** and energy costs **C** ?*

Self-consumption objective *S* aims at minimizing the deviation of energy consumption from RE availability, given schedule $x = \langle x^u_{at} | u = 1, \dots, U, a = 1, \dots, A, t = 1, \dots, T \rangle$ expressed as a binary vector, and is defined as follows:

$$\min_x S(x) = \sum_{t=1}^{T} | \; E_t - r_t \; |, \qquad \textit{where} \;\; E_t = \sum_{u=1}^{U} \sum_{a=1}^{A} e^u_a * x^u_{at} \tag{1}$$

Since energy flexibility in the form of load shifting allows appliances to be operated at times other than those preferred, a mapping is required between the time of usage of an appliance and the preference satisfied by said usage. Thus, schedule x is assigned an *appliance usage-to-preference (x-to-p)* mapping $m_x = \langle m^u_{at} | u = 1, \dots, U, a = 1, \dots, A, t = 1, \dots, T \rangle$, expressed as an integer vector subject to:

$$G(x, m_x) : m^u_{at} = \begin{cases} t + i & \text{if } x^u_{at} = 1 \\ 0 & \text{if } x^u_{at} = 0 \end{cases}, \qquad \textit{where} \quad i \in [-t, T - t], \quad \forall u \in [1 \, .. \, U], \forall a \in [1 \, .. \, A], \forall t \in [1 \, .. \, T] \tag{2}$$

Constraint G ensures that no preference may be satisfied by an inactive appliance and that an active appliance may satisfy up to one preference. Shifting step i represents the deviation of the actual time of use of an appliance from the preferred time. As a result, three distinct scenarios regarding preference satisfaction emerge, which can be observed in Fig. 3:
(i) $m^u_{at} = t \leftrightarrow$ preference p^u_{at} is *fully satisfied* by appliance usage x^u_{at} at the requested time t (i = 0, scenario (c)).
(ii) $m^u_{at} = t + i \leftrightarrow$ preference $p^u_{a,t+i}$ is *partially satisfied* by x^u_{at} at time t, instead of the requested $t + i$ (scenario (a)).
(iii) $m^u_{at} = 0 \rightarrow$ *no preference is satisfied* (scenario (b)).
Notice that no constraint exists between m_x and a set of preferences P^u, i.e., a mapping is feasible even when a number of mapped preferences are not part of any resident's set P^u. The residents' dissatisfaction and energy costs can be defined as follows:

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

$$\min_{m_x} D(m_x) = \sum_{u=1}^{U} \frac{\sum_{a=1}^{A} \sum_{t=1}^{T} d^u_{at}}{| \; P^u \; |},$$
$$\textit{where} \;\; d^u_{at} = \begin{cases} 1, & \text{if } p^u_{at} \in P^u \text{ and } \nexists i, m^u_{a,t+i} = t \\ 1 - k^{|i|}, & \text{if } p^u_{at} \in P^u \text{ and } \exists i, m^u_{a,t+i} = t \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

[6] the equivalent of maximizing appliance-scheduling preference satisfaction

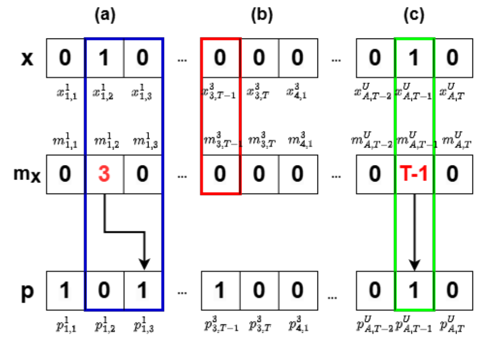


Fig. 3: The relationship between decision vectors x, m_x and resident preferences p for three (3) scenarios: (a), (b), and (c).

Objective D attempts to minimize the total dissatisfaction[6] of residents. The dissatisfaction of a single resident u is defined as the ratio of the sum of u's dissatisfaction d^u_{at} per preference, to the total number $| \; P^u \; |$ of u's preferences. Dissatisfaction d^u_{at} represents either full, partial or non-dissatisfaction of preference p^u_{at}, based on mapping m_x as explained. Penalty factor $k \in (0, 1)$ dictates the amount of dissatisfaction incurred by every unit of difference between the preferred time t and the actual time of usage $t + i$ of appliance a, and is set to $k = 0.5$ for this study. Finally, 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 that of demanding residents.

Costs objective *C* aims at minimizing the maximum cost for any resident, encouraging preference satisfaction in a uniform/fair manner by not penalizing the satisfaction of preferences for residents with lower costs than others:

$$\min_x C(x) = \max_{u \in [1..U]} \sum_{a=1}^{A} \sum_{t=1}^{T} e^u_a * c_t * x^u_{at} \tag{4}$$

B. Bi-level Multi-Objective Optimization Problem Formulation

Pricing scheme c is the UL decision vector used by the UL aggregator to optimize $S(x)$. The LL is responsible for the residents' welfare, aiming at minimizing both $D(m_x)$ and $C(c, x)$, and is expressed as a MOP with schedule x and preference mapping m_x as its decision vectors. Hence, the bi-level MOP can be formulated as follows:

$$\min_{c,x} F(c, x) = \sum_{t=1}^{T} S_t(x) * p_t(c_t),$$
$$\textit{where} \;\; p_t(c_t) = \begin{cases} 1 + (c_t - c_{min}), & \text{if } E_t - r_t < 0 \\ 1 + (c_{max} - c_t), & \text{otherwise} \end{cases}$$
$$\textit{s.t.} \quad x \in \Psi(c) = \operatorname*{argmin}_{x, m_x} \begin{pmatrix} f_1 \\ f_2 \end{pmatrix} \Bigg| \; G(x, m_x),$$
$$\textit{where} \;\; f_1 = D(m_x), \;\; f_2 = C(c, x) \tag{5}$$

where $c_t \in [c_{min}, c_{max}]$, F denotes the UL objective function (consisting of objective S with the additional incorporation of a penalty coefficient $p_t \in [1, 1 + (c_{max} - c_{min})]$), while $f1, f2$ denote the LL conflicting objectives, and Ψ is the LL reaction set, from which a solution is selected based on a decision-making model incorporating the residents' profile v.

Objective function F uses p_t to penalize deviation from self-consumption S of schedule x, with the amount of penalty dictated by c: if the consumed energy E_t is less than the available r_t, a lower price c_t results in lower penalty and, conversely, a higher price c_t when E_t is greater than r_t results in lower penalty. Consequently, the lower prices assigned within the RE production curve incentivize the residents towards appliance usage during high RE production hours, as depicted by Fig. 4.

C. Decision Making

The UL aggregator may assume (i) an optimistic approach, expecting the LL Decision Maker (DM) to select a solution from the optimistic reaction set Ψ^o that optimizes F, or (ii) a pessimistic approach, expecting that the LL DM will select a solution from the pessimistic set Ψ^P resulting in the worst objective function value for F. Furthermore, by assuming knowledge of the LL DM preferences, the community-level residents' profile index $v \in [0, 1]$ may be used to indicate the decision/choice of a solution from Ψ by the LL DM, with extreme-cases $v = 1$ and $v = 0$ representing exclusive prioritization of minimizing dissatisfaction (objective D) and minimizing costs (objective C), respectively. This allows for (iii) a *"resident-aware"* approach in which the LL-desired solution is accepted. Finally, by assuming willingness by the LL DM to be influenced by the UL preferences, we may propose (iv) a fixed cooperation approach in which cooperation index $q \in (0, 1)$ allows for setting the trade-off between the UL and LL desired solutions, or (v) a dynamic cooperation approach in which q is iteratively estimated and tuned based on a concept of trade-off fairness. Consequently, our decision-making model is defined subject to the UL approach, the LL residents' profile v and the cooperation index q.

D. Pricing Schemes

Pricing scheme c follows the fixed-period and variable-pricing model [18], assuming that for each period $t \in [1\,..\,T]$ the price c_t may vary between c_{min} and c_{max}. For generalizability, we opt for a normalized range $c_t \in [0, 1]$ instead of an empirically-established range as in the works of Antunes and Alves [18]. For single-level optimization approaches, which do not support a dynamic pricing scheme, a fixed pricing scheme is assumed and specifically a flat tariff [35], resulting in equal prices c_t with the average $c_t = (c_{max} - c_{min})/2$ of the price range assigned to all t. A flat tariff offers no incentives to the residents to participate in RE self-consumption.

IV. Bi-Level Multi-Objective Energy Management System II (BiMO-EMS-II)

This section starts with an overview of BiMO-EMS-II, followed by a detailed introduction of the main components.

A. Algorithm Overview

BiMO-EMS-II follows a nested evolutionary approach: The upper level (UL) employs the traditional Genetic Algorithm (GA), while the lower level (LL) employs the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [36]. Over multiple iterations, the UL infers the energy demand at the LL and updates the energy price-signals to guide the LL process towards improved levels of self-consumption. An overview of BiMO-EMS-II is provided below and in Algorithm 1, while a detailed description of the evolutionary algorithms used per level can be found in [15]:

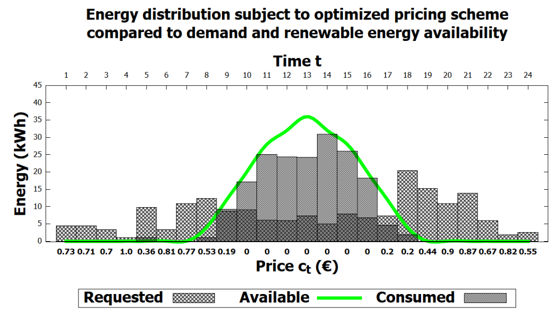


Fig. 4: Energy-consumption distribution of appliance-usage schedule x subject to pricing scheme c, given the energy demand and RE availability.

A population C of pricing schemes c is initialized and each c is sent to the LL for evaluation. During LL evaluation, a population X is initialized, consisting of appliance-usage schedules x, either by using the APT strategy (after the UL initial population has been fully evaluated), or by initializing a uniformly-random population, with the required preference mapping m_x per initialized x generated by the Mapping Heuristic (MH). After the evaluation of all $x \in X$, the MOEA/D with the normalized Tchebycheff approach [36] is executed and, upon convergence, the External Population containing pairs (x, m_x) is returned as the LL reaction set Ψ. From Ψ, the Decision-Making with Cooperation (DMC) heuristic selects a single x_c and the "pricing scheme-schedule" pair (c, x_c) is returned. The evaluation of all solutions in the UL initial population is followed by the execution of the GA. The best solution c^* from the resulting population, along with its coupled x_{c^*} and preference mapping $m_{x_{c^*}}$, are returned.

Algorithm 1 BiMO-EMS-II

Input: r; P; e; v; q;
Output: (c, x_c, m_{x_c})
Init population $C_0 = \{c^1, \ldots, c^N\}$, // Uniformly random
$\forall c \in C_0, F(c, x_c) \leftarrow$ **UL EVALUATE**(c, r, P, e)
GA // Bin. Tourn. Select., SBX Cross., Uni. Mut.
return $(c^*, x_{c^*}, m_{x_{c^*}}) \in C$ // c^* : best solution

function UL EVALUATE(c, r, P, e)
  $\Psi \leftarrow$ **LL EVALUATE**(c, P, e) // LL Reaction set Ψ
  $x_c \leftarrow DMC(v, q, \Psi)$ // Decision-making
  return $F(c, x_c, r)$
end function

function LL EVALUATE(c, P, e)
  Init population $X = \{x^1, \ldots, x^N\}$ in 3 steps:
  1) use APT, or $x^1 = \overrightarrow{0}$, $x^N = \overrightarrow{1}$, unif. rand. $x^2 : x^{N-1}$,
  2) $\forall x \in X$, $(x, m_x) \leftarrow MH(x, P)$,
  3) $f(x, m_x) \leftarrow \binom{f_1}{f_2}$, $f_1 = D(m_x, P)$, $f_2 = C(c, x, e)$
  MOEA/D // Tchebycheff, UPMX Cross., BitFlip Mut.
  return External Population $\{(x, m_x)\}$
end function

Mapping Heuristic: Establishing an appropriate preference mapping m_x is crucial in obtaining a good LL solution: An empty mapping $m_x = \langle 0 \rangle$ assigns LL solution (x, m_x) the worst possible value for objective D. On the other hand, a "strict" mapping in which all mapped preferences are fully satisfied (i.e., all mappings are between $x^u_{at} = 1$ and its respective p^u_{at}), offers a better value for D while still satisfying constraint G (Eq. 2). We employ a two-step Mapping Heuristic (MH) [37], that first creates a "strict" mapping by only allowing mappings that result in fully satisfied preferences, and then all remaining (unmapped) appliance usages are mapped to the closest preference not yet assigned to a mapping.

B. Decision Making with Cooperation (DMC) Heuristic

DMC in Algorithm 2, takes advantage of any knowledge regarding the LL DM preferences, as well as any cooperation between the UL and LL entities, with cooperation defined as "the willingness" of the LL DM to be influenced by the UL preferences. DMC supports the following approaches:

Optimistic/Pessimistic: The traditional UL optimistic and pessimistic approaches assume no knowledge of the LL DM preferences and no cooperation between the UL and LL entities. Hence, the optimistic approach returns any optimistic solution x^* from Ψ^o, and the pessimistic approach returns any pessimistic solution x^P from Ψ^P (lines 3-4).

Resident-aware: Assuming knowledge of the LL DM preferences, yet no cooperation between the UL and LL entities, the resident-aware approach returns the LL-desired solution $\overline{z} \in \Psi$. Solution $\overline{z}$ is defined as the solution whose sub-problem's weight vector λ is closest, in terms of Euclidean distance, to the weight vector w desired by the LL DM, as derived by profile index v (lines 5-8). For non-decomposition algorithms, the solutions in Ψ may be assigned weight vectors through ordering Ψ by objective-value and indexing via a uniform weight vector.

DMC with fixed cooperation: Given that the LL DM is cooperative to some extent, with the extent represented by cooperation index $q \in (0, 1)$, an UL and LL score is associated with all solutions $x \in \Psi$ based on their desirability by the UL and the LL DM, respectively: the UL score is defined as the value of the UL objective function F, while the LL score calculation utilizes the Tchebycheff ASF to measure the distance of x to reference point $\overline{z}$, with v serving as the weight coefficient. Then, a decision-making reaction set Ψ^D is established, containing only those solutions whose scores fall within the acceptable boundaries, i.e., between the LL score of the optimistic x^* and the UL score of the LL-desired $\overline{z}$ (lines 10-13). Finally, each $x \in \Psi^D$ assumes a weighted-sum of its UL and LL scores, weighted based on coop index q and normalized based on boundary-solutions x^* and $\overline{z}$, as follows:

$$\begin{gathered} SCORE(q, w, x, \overline{z}, x^*) = \\ q * UL(x, \overline{z}, x^*) + (1-q) * LL(w, x, \overline{z}, x^*), \\ \textit{where } UL(x, \overline{z}, x^*) = \frac{F(x) - F(x^*)}{F(\overline{z}) - F(x^*)}, \\ LL(w, x, \overline{z}, x^*) = \max_{i \in \{1,2\}} \left[w_i \left(\frac{f_i(x) - f_i(\overline{z})}{f_i(x^*) - f_i(\overline{z})} \right) \right] \end{gathered} \quad (6)$$

The solution x with the best overall score is returned (line 14).

DMC with dynamic cooperation: Assumes that both the UL entity and the LL DM are willing to sacrifice a desired solution if a fairer solution is available, with the "fairness" principle defined as "sacrifice a desired solution at one level in pursuit of a solution at the other level offering more/equal gain compared to the loss due to sacrifice". Consequently, the dynamic-coop approach starts off by pushing coop index q in both directions

Algorithm 2 Decision Making with Cooperation (DMC)

Input: v; q; Ψ;
Output: x_c

1: $\Psi^o \leftarrow \text{argmin}_{x \in \Psi} F(x)$ // Optimistic reaction set
2: $\Psi^P \leftarrow \text{argmax}_{x \in \Psi} F(x)$ // Pessimistic reaction set
3: **Optimistic approach: return** $x^* \in \Psi^o$
4: **Pessimistic approach: return** $x^P \in \Psi^P$
5: **Resident-aware approach:**
6: $w_0 \leftarrow v$; $w_1 \leftarrow (1 - v)$ // LL desired solution's weight
7: $\{z\} \leftarrow \text{argmin}_{x \in \Psi} \mid w - \lambda_x \mid$ // vector λ closest to v
8: **return** $\overline{z} \leftarrow \text{argmin}_{z \in \{z\}} F(z)$ // LL-desired solution
9: **DMC with fixed cooperation approach:**
10: $F^{nad} \leftarrow F(\overline{z})$ // Worse allowed UL-score
11: $f^{nad} \leftarrow \max_i [w_i(f_i(x^*) - f_i(\overline{z}))]$ // Worse al. LL-score
12: $\Psi^D \leftarrow \{\}$ // Decision-making reaction set
13: $\forall x \in \Psi$, **if** $F(x) \leq F^{nad}$ **or** $\max_i [w_i(f_i(x) - f_i(\overline{z}))] \leq f^{nad}$ **then** $\Psi^D \leftarrow \Psi^D \cup x$ // Dismiss not-allowed solut.
14: **return** $x \leftarrow \text{argmin}_{x \in \Psi^D} \text{SCORE}(q, w, x, \overline{z}, x^*)$ // Eq. 6
15: **DMC with dynamic cooperation approach:**
16: $j \leftarrow 0.01$ // Amount of cooperation to add/remove
17: $y_U \leftarrow \text{ADJUST COOP}(j, q, w, x, \overline{z}, x^*)$ // Increase coop
18: $gain_U \leftarrow \text{UL}(x, \overline{z}, x^*) - \text{UL}(y_U, \overline{z}, x^*)$ // UL gain, Eq.6
19: $loss_L \leftarrow \text{LL}(w, y_U, \overline{z}, x^*) - \text{LL}(w, x, \overline{z}, x^*)$ // LL loss
20: $y_L \leftarrow \text{ADJUST COOP}(-j, q, w, x, \overline{z}, x^*)$ // Decre. coop
21: $gain_L \leftarrow \text{LL}(w, x, \overline{z}, x^*) - \text{LL}(w, y_L, \overline{z}, x^*)$ // LL gain
22: $loss_U \leftarrow \text{UL}(y_L, \overline{z}, x^*) - \text{UL}(x, \overline{z}, x^*)$ // UL loss, Eq.6
23: **if** $gain_U > gain_L$ **then** // Decide coop direction
24:     **while** $gain_U >= loss_L$ **do** // Increase coop
25:         $x \leftarrow y_U$
26:         $y_U \leftarrow \text{ADJUST COOP}(j, q, w, y_U, \overline{z}, x^*)$
27:         // Calculate gain/loss as in 18-19
28:     **end while**
29: **else**
30:     **while** $gain_L >= loss_U$ **do** // Decrease coop
31:         $x \leftarrow y_L$
32:         $y_L \leftarrow \text{ADJUST COOP}(-j, q, w, y_L, \overline{z}, x^*)$
33:         // Calculate gain/loss as in 21-22
34:     **end while**
35: **end if**
36: **return** x

37: **function** ADJUST COOP$(j, q, w, x, \overline{z}, x^*)$
38:     **while** $y = x$ **do** // Stop when new best solution
39:         $q \leftarrow q + j$ // Increase/decrease coop
40:         $y \leftarrow \text{argmin}_{y \in \Psi^D} \text{SCORE}(q, w, y, \overline{z}, x^*)$
41:     **end while**
42:     **return** y
43: **end function**

until a solution other than x becomes the best trade-off solution for the UL (y_U) and the LL (y_L), respectively, with respect to the updated scores (lines 17, 20, 37-43). Next, the gain and loss in desirability of y_U and y_L by each entity is calculated (lines 18-19, 21-22): the entity with the highest gain (lines 23, 29) gets to push q in its favorable direction (up for the UL and down for the LL) as long as the "fairness" principle holds (lines 24-28, 30-34). Finally, the best trade-off solution x given the established cooperation is returned (line 36). Coop index q is passed-on from UL parent to offspring solutions, enabling DMC to start at an appropriate cooperation level for each solution before making optimizations.

C. Uniform Partially Mapped Crossover (UPMX)

The proposed Uniform Partially Mapped Crossover (UPMX) is an adaptation of the original, widely-used PMX, hence inheriting the same benefits and advantages. PMX is a two-point crossover operator for order-based permutation chromosomes that "repairs" the offspring into a valid permutation by replacing the resulting duplicate values outside its crossover region with the original overwritten values within its crossover region. In the proposed BMOP, the initial crossover operation on x^1, x^2 might produce infeasible offspring $(x^1, m_{x^1}), (x^2, m_{x^2})$ due to constraint G (Eq. 2). Therefore, a repair heuristic is utilized for updating the preference mappings m_{x^1}, m_{x^2} into feasible solutions. Moreover, an adaptation is required given that a mapping slot may be empty (m^u_{at} = 0: either an inactive appliance or an active appliance that maps to no preference), which is equivalent to assuming that the order-based permutation chromosome contains null genes. The adapted UPMX is described below.

UPMX aims at an optimized 1-1 matching between appliance usages and preferences for maximal exploitation of energy flexibility. It follows the same gene-selection process as the Uniform Crossover variant of PMX [38]: for every position in either chromosome x^1, x^2 with a gene that is set ($x^u_{at} = 1$), there is a 50% probability of reversing those genes in the offspring. Depending on the values of the reversed genes, their preference mappings m^u_{at} may be affected in different ways, with complementary scenarios provided in Fig. 5: **(a)**:

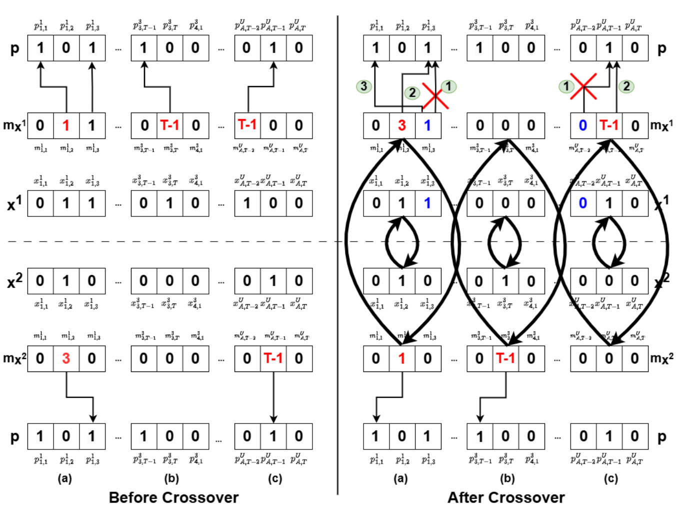


Fig. 5: Two pairs of decision vectors (x^1, m_{x^1}) and (x^2, m_{x^2}) before and after applying UPMX, for 3 scenarios: (a), (b), (c).

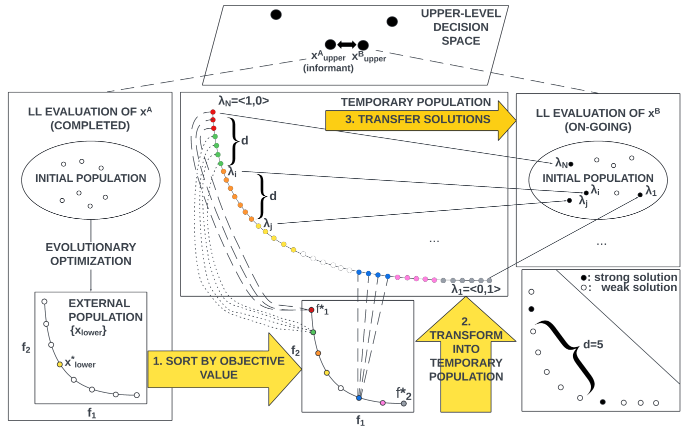


Fig. 6: The Adaptive Population Transfer process from informant solution x^A to currently-evaluated x^B. The MOEA/D weight vector λ can be observed, as well as the APT parameter of transfer selection-distance d.

Both genes are set. The preference mappings for $p^1_{1,1}$ and $p^1_{1,3}$ are exchanged. Since $p^1_{1,3}$ was already covered by $(x_1)^1_{1,3}$, and given that the previously-mapped preference $p^1_{1,1}$ is now available again, $(x_1)^1_{1,3}$ is mapped to $p^1_{1,1}$ instead. **Scenario (b)**: One gene is set. The mapping for preference $p^3_{3,T-1}$ is removed from x^1 and assigned to $(x^2)^3_{3,T}$. **Scenario (c)**: One gene is set. The mapping for preference $p^U_{A,T-1}$ is removed from x^2 and assigned to $(x^1)^U_{A,T-1}$. Since $p^U_{A,T-1}$ was already covered by $(x^1)^U_{A,T-2}$, the mapping is removed and the gene is reset.

D. Adaptive Population Transfer

Our proposed Adaptive Population Transfer (APT) utilizes the decomposition-specific weight vector λ to selectively-transfer solutions and achieve a better balance between exploration and exploitation than SPT [13]. APT is split into 3 phases: (i) informant selection, (ii) knowledge extraction and processing, and (iii) knowledge application. These phases are demonstrated in Fig. 6.

In the informant selection phase (i.e., the selection of the UL solution from which the knowledge will be extracted), the selection criterion is identical to SPT: the closest (in terms of Euclidean distance) neighboring UL solution to the currently-evaluated offspring is selected from the current population, in the absence of an UL Pareto-optimal archive.

In the knowledge extraction and processing phase, a temporary population (TP) of size N is filled with solutions from the LL reaction set Ψ of the informant as follows: Ψ is sorted by objective-value in ascending order, matching the order of weight vector λ (i.e., starting from the worst value for the first objective). The sorted Ψ is then iterated over in pairs of adjacent solutions, starting from the pair with indices (0,1), then (1,2), etc. In each iteration, the first solution in the pair is transferred to TP and assigned to all consecutive subproblems, identifiable by λ, for which a better Achievement Scalarization Function value is achieved compared to the second solution in the pair. Once the last solution in the sorted Ψ is transferred, it is assigned to all remaining subproblems and the process ends. When $|\Psi| < N$, the final TP is an extension of Ψ

containing duplicated solutions for consecutive subproblems. When $|\Psi| \geq N$, TP is a subset of Ψ.

The final knowledge-application phase applies a uniformly-distributed subset B of solutions from TP to the LL initial population (IP) of the currently-evaluated solution, with each solution in B assigned to the subproblem in IP identified by its λ. The transferred solutions within IP are referred to as "strong" solutions, and the remaining randomly-generated solutions in IP are referred to as "weak" solutions. Subset B is created by transferring solutions from the ordered TP that are d solutions away from each other, with d defined as the *transfer selection-distance*.

V. Experimental Setup

This section describes the datasets, the algorithms and algorithmic settings, as well as the performance metrics considered in the experimental evaluation.

A. Datasets

BiMO-EMS-II is evaluated on twelve (12) 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 for a specific season and day. The preferences were extracted from the *REFIT dataset* [39], 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 pre-processing performed in order to extract the preferences included (i) converting kW readings per second into per-minute readings by removing duplicate records, (ii) aggregating per-minute readings into hourly readings through summation, (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 examining the kW readings in the original dataset. The resulting datasets can be found in Table III.

Each dataset also includes RE production data, which is uniformly varied based on the number of households and season. A dataset's hourly peak-production is defined as the output of a $4.5kW$ PV-system per household, using the standard formula for calculating solar panel energy production:

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

subject to (i) solar panels with $P_{peak} = 450W$ and a temperature-coefficient $a = 0.3$, (ii) the Standard Test Conditions and (iii) the average seasonal temperature G[7] and irradiance T [40] in the UK:

Autumn: $G: 9, T: 833$; *Winter:* $G: 5, T: 750$;
Spring: $G: 13, T: 916$; *Summer:* $G: 17, T: 1000$.

Finally, a RE production curve is formed from 06:00 to 18:00 by assigning the peak-production value at 12:00 and adjusting the hourly production values according to the standard RE production curve as often encountered.

TABLE II
PARAMETER VALUES FOR ALGORITHMS

Parameter	GA	MOEA/D	APT
Population size (N)	100	300	-
Crossover probability	0.9	1.0	-
Mutation probability	10^{-2}	10^{-2}	-
Neighborhood size (T)	-	25	-
Transfer selection-distance (d)	-	-	2
Convergence requirement: UL: no new best solution for 10 gen; LL: $conv \geq HV_{gen} - HV_{(gen-5)}$ (relaxed: 10^{-3}, semi-strict: 10^{-4}, strict: 10^{-6})			

TABLE III
THE REALISTIC DATASETS GENERATED BY USING INFORMATION FROM THE REFIT PUBLIC DATASET

Dataset	Date	U	A	T	House holds(ID)	Demand (kWh)	Avail. RE (kWh)
Sml_Aut	23/10/2013	5	25	24	1 2 3 4 5	113.4	114
Sml_Win	11/12/2013	5	25	24	1 3 4 5 6	96.2	92
Sml_Spg	05/04/2014	5	25	24	1 2 3 4 5	156.7	136
Sml_Sum	02/06/2014	5	25	24	1 2 3 4 5	97.5	162
Med_Aut	29/11/2013	10	49	24	1-10 (2*, 9*)	183.6	228
Med_Win	19/01/2014	10	50	24	1 3 4 5 6 7 8 9 10 13	241.0	184
Med_Spg	18/03/2014	10	49	24	1 - 10	186.4	272
Med_Sum	15/06/2014	10	47	24	1 2 3 4 5 17-21	156.0	324
Lrg_Aut	23/10/2014	20	91	24	All 1-21	248.9	456
Lrg_Win	25/01/2015	20	91	24	All 1-21	418.7	368
Lrg_Spg	21/03/2014	20	91	24	All 1-21 (4*, 11*)	340.8	544
Lrg_Sum	28/06/2014	20	91	24	All 1-21	302.1	648

*date unavailable, closest date retrieved

B. Algorithms and Algorithmic Settings

BiMO-EMS-II is implemented on the jMetal 4.5[8] Java-framework for multi-objective optimization (MOO) and evaluated both as a complete system and at the lower level only.

1) Bi-Level MOO: The performance of BiMO-EMS-II is compared against the following approaches:

BiMO-EMS [15]: The original algorithm performs appliance-scheduling only subject to load curtailment, equivalent to only creating "strict mappings" with fully-satisfied preferences. It uses the two-point crossover and no Knowledge Transfer.

OptaPlanner (OP)[9]: an open source AI constraint solver using metaheuristics and state-of-the art techniques for tackling NP-complete/hard optimization problems formulated by the user. The default solver configuration is assumed. OP does not support MOO, hence we opt for a hierarchical evaluation function where S is the primary objective and:

(i) OPD: the secondary objective is dissatisfaction D.

(ii) OPC: the secondary objective is energy costs C.

Given OP's prioritization of objectives compared to BiMO-EMS-II, a direct comparison of their performance is irrational. Instead, we use OP as an evaluation of the achievable levels of self-consumption when S is designated the primary objective.

Resident preferences (PRF): satisfies all sets of preferences P^u for all residents and, consequently, optimizes objective D, which implies the worst possible value for objective C.

[7] statista, 2024. UK: average temperature by month 2024 | Statista. LINK: https://www.statista.com/statistics/322658/monthly-average-daily-temperatures-in-the-united-kingdom-uk/

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

[9] OptaPlanner, 2024. OptaPlanner - The fast, Open Source and easy-to-use solver. LINK: https://www.optaplanner.org

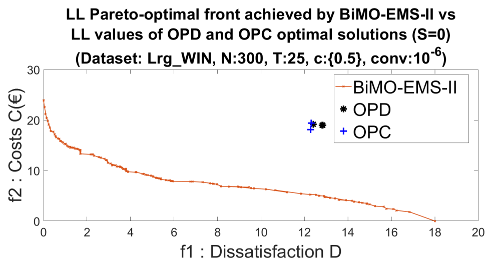


Fig. 7: LL Pareto front by BiMO-EMS-II compared to the LL values of the optimal solutions (S=0) by OptaPlanner on the Lrg_WIN dataset with fixed pricing for all algorithms.

Each approach is executed thirty (30) times. The single-level approaches adopt the fixed pricing scheme described in section III-D. For bi-level approaches, the optimistic approach is assumed, unless stated otherwise. The UL and LL algorithms adopt the parameter values in Table II (parameter calibration experiments are available as supplementary material). The termination criterion is reaching convergence, defined for the UL as "new best solution not found within ten generations" and for the LL as a difference in hypervolume between five generations smaller than $conv$, which is updated from the relaxed 10^{-3} up to the strict 10^{-6} as the difference in fitness F between best and worst solution in the UL population shrinks.

2) Lower-Level MOO: MOEA/D is compared with the state-of-the-art Pareto-dominance based Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [41]. Both algorithms adopt the parameter values in Table II (parameter calibration experiments are available as supplementary material). The convergence requirement is set to strict from the start.

C. Decision Making Experimental Setup

The performance of BiMO-EMS-II is compared subject to all the decision-making approaches supported by DMC, which results in seven variations: optimistic (OPT), pessimistic (PES), resident-aware (RA), and decision-making with cooperation (DMC), both with a dynamic cooperation index q and three variations of uniformly-distributed fixed values for q. Furthermore, each variation is evaluated on five uniformly-distributed community-level residents' profiles v.

D. Knowledge Transfer Experimental Setup

To justify our experimental setup, we begin by pointing out a trait of our bi-level MOP: As illustrated by Singh et al. [13], "LL accuracy and UL accuracy are not always positively correlated", i.e., LL solution 'A' may be worse than LL solution 'B' but result in a better UL solution than 'B' does. Such behavior is evident in our problem, as seen in Fig. 7, where the LL solutions of optimal UL solutions are not on the LL Pareto-optimal front (PF). For such problems, evaluating the performance at the UL is impractical unless the theoretical LL PF is known, in which case a re-evaluation of the UL solutions can be performed [13] by decoupling them from the LL search and having them assume their theoretical LL PF. Since the theoretical LL PF for our problem in unknown, our performance evaluation takes place at the lower level.

We adopt the following approach: The proposed APT with $d = 2$ is compared against SPT [13], as suggested by Singh et al, as well as the baseline strategy NT of applying no Knowledge Transfer. SPT and NT are applied to both MOEA/D and NSGA-II. Given that MOEA/D associates each solution in its population with a unique subproblem, SPT was adapted in two steps: (i) upon addition to the External Population, each LL solution of the informant maintains its subproblem's weight vector λ and is assigned to the same subproblem in the IP of the receiving UL solution, and (ii) duplicate solutions, in terms of equal λ, are removed, with the surviving solution being the one with the highest Achievement Scalarization Function value. We experiment using three variations of MOEA/D (one per Knowledge-Transfer strategy) and two variations of NSGA-II for the two applicable strategies SPT and NT. An experiment consists of all five algorithm variations evaluated on a dataset, resulting in a total of twelve experiments. Each experiment takes the following form:

Two UL IPs are initialized, one assuming MOEA/D as its LL algorithm and one assuming NSGA-II, with the UL decision vectors being randomly generated (using a different seed per dataset) and equal between the UL IPs, i.e., each solution in the first IP has a 1-1 match with a solution in the second IP for which the UL decision vector is equal. Note that the UL and LL objective values between solutions in the IPs are not equal, due to the different underlying LL algorithm. Then, for each of the five algorithm variations, an UL offspring population is created from the respective UL IP using the UL evolutionary operators and then it is evaluated.

E. Crossover Experimental Setup

UPMX is evaluated against alternative crossover operators:

1) **PMX**: Original Partially Mapped two-point Crossover.
2) **UNI**: Uniform Crossover.

The operators are used in both MOEA/D and NSGA-II to evaluate an initialized UL IP on all datasets, with the UL decision vectors being randomly generated using a different seed per dataset. Note that no Knowledge Transfer is applied.

F. Performance Metrics

The performance metrics used for evaluating solutions of multi-objective algorithms in our experiments consist of the *hypervolume indicator* (**HV**), as a percentage, *spread* (**Δ**), and *coverage* (**C-metric**), as proposed by Zitzler and Thiele and used in [15]. For statistical analysis, we used the two-sample ***T*-test** with a null hypothesis rejection $h = +$ indicating significantly different results with 95% confidence, and $h = -$ otherwise. CPU time was used for evaluating the algorithms' execution time.

VI. Experimental Evaluation

This section presents the experimental results regarding (a) the performance of BiMO-EMS-II, (b) the DMC heuristic, (c) our choice of APT as the Knowledge-Transfer (KT) strategy, and (d) our choice of UPMX as the crossover operator. The computing machine used consists of an Intel Xeon Processor E5-2697 v2 @2.70GHz and 24GB of RAM.

TABLE IV

PERFORMANCE COMPARISON BETWEEN BIMO-EMS-II, BIMO-EMS, OPD, OPC AND PRF WITH RESPECT TO S, D AND C. NOTATION S^{**} DENOTES THE UTOPIAN VALUE. RESULTS CORRESPOND TO AVERAGES ACROSS 30 DISTINCT RUNS

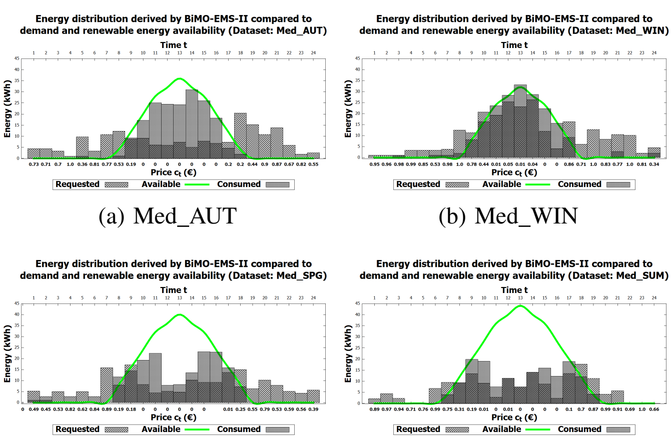
Data set Sml	***BiMO II***	***BiMO EMS***	***OPD***	***OPC***	***PRF***	
	Objective S (in kWh)					S^{**}
AUT	10.3	53.5	2.79	**1.39**	101	0.6
WIN	6.37	48.7	**0.49**	0.79	100	0
SPG	18.3	50.0	0.29	**0**	92	0
SUM	**64.5**	99.0	**64.5**	**64.5**	132	64.5
	Objective D					D^{*}
AUT	**1.87**	2.22	2.97	3.48	0	0
WIN	**2.58**	2.94	3.75	3.80	0	0
SPG	0.91	**0.90**	3.29	3.46	0	0
SUM	**1.06**	1.40	2.31	3.07	0	0
	Objective C (in €)					
	Pricing scheme					
	Dynamic		***Fixed***			C^{*}
AUT	2.15	**1.60**	19.4	19.4	19.4	0
WIN	0.82	**0.17**	11.5	12.5	12.5	0
SPG	8.45	**7.51**	26.65	22.4	28.7	0
SUM	**1.14**	2.21	16.0	16.0	16.0	0

Data set Med	***BiMO II***	***BiMO EMS***	***OPD***	***OPC***	***PRF***	
	Objective S (in kWh)					S^{**}
AUT	50.5	157	**44.4**	**44.4**	267	44.4
WIN	15.3	48.5	**0**	**0**	141	0
SPG	110	179	**107**	**107**	265	85.6
SUM	**168**	213	**168**	**168**	255	168
	Objective D					D^{*}
AUT	**5.97**	6.32	8.04	7.77	0	0
WIN	3.98	**3.93**	7.18	7.13	0	0
SPG	**3.84**	4.07	4.92	5.83	0	0
SUM	**1.78**	2.33	4.73	6.50	0	0
	Objective C (in €)					
	Pricing scheme					
	Dynamic		***Fixed***			C^{*}
AUT	1.05	**0.43**	20.3	20.3	20.3	0
WIN	3.08	**1.96**	15.9	14.7	26.0	0
SPG	**1.49**	1.56	15.5	15.5	20.4	0
SUM	**1.98**	2.08	19.0	19.0	19.0	0

Data set Lrg	***BiMO II***	***BiMO EMS***	***OPD***	***OPC***	***PRF***	
	Objective S (in kWh)					S^{**}
AUT	**207**	326	**207**	**207**	431	207
WIN	46.9	164	0	**0**	352	0
SPG	240	374	**225**	**225**	534	203
SUM	368	432	**348**	**348**	503	345
	Objective D					D^{*}
AUT	**7.93**	7.99	10.1	12.6	0	0
WIN	**7.35**	7.68	12.4	12.2	0	0
SPG	**7.88**	8.44	10.5	10.5	0	0
SUM	4.59	**4.48**	7.3	12.0	0	0
	Objective C (in €)					
	Pricing scheme					
	Dynamic		***Fixed***			C^{*}
AUT	**0.99**	1.55	24.2	24.2	24.2	0
WIN	3.64	**1.93**	19.1	18.1	23.9	0
SPG	1.73	**0.76**	20.3	20.3	20.4	0
SUM	2.14	**1.77**	23.2	23.2	23.2	0

A. System Evaluation

Table IV compares the performance of BiMO-EMS-II against all algorithms of section V-B, on each objective of the BMOP, for each dataset. Notation S^{**} represents the utopian value with regards to S (derived by deducting the demand from the available RE per dataset as seen in Table III), "utopian" because a perfect distribution of the demand to exactly match the RE distribution might not exist. We provide an overview of the results and then proceed to discuss the potential daily savings of BiMO-EMS-II in terms of energy and costs.



(a) Med_AUT (b) Med_WIN

(c) Med_SPG (d) Med_SUM

Fig. 8: Energy distribution derived by BiMO-EMS-II compared to demand and RE availability, on the Medium datasets.

1) Overall and per-objective performance: BiMO-EMS-II achieves the optimal solution with regards to S *in 3 datasets*. For the rest of the datasets, the distance from the optimal S varies: up to 19 kWh for the Small datasets, (ii) up to 25 kWh for the Medium datasets and (iii) up to 47 kWh for the Large datasets. OPD and OPC, who are used to estimate the highest-achievable levels of self-consumption, consistently achieve optimal or near-optimal solutions with the exception of the Medium and Large Spring datasets. The original BiMO-EMS, on the other hand, is consistently inferior to BiMO-EMS-II, and since both algorithms employ the same UL process, this difference in performance is attributed to the *enhanced capability of BiMO-EMS-II to exploit energy flexibility and hence more-efficiently explore the LL space, producing an abundance of LL solutions which in turn enable better UL exploration as well*. PRF is used to indicate how poor self-consumption levels can be if energy flexibility is disregarded: for the Small datasets, S is 68-100 kWh worse, for the Medium datasets it is 87-223 kWh worse and for the Large datasets it is 158-352 kWh worse than if optimized. Regarding objective D, BiMO-EMS-II consistently outperforms all other approaches, indicating its *capability of minimally-sacrificing the residents' satisfaction in achieving high levels of self-consumption*. Regarding objective C, the original BiMO-EMS is competitive to BiMO-EMS-II, indicating that *both versions of the algorithm produce cost-attractive pricing schemes*. Moreover, BiMO-EMS-II exhibits greater difficulty in achieving a good S when the optimal value is zero, i.e., it performs better when the demand cannot fully exhaust the available renewable energy. Overall, *BiMO-EMS-II achieves optimal or high levels of self-consumption, subject to a high-quality trade-off between the resident-oriented objectives of maximizing preference satisfaction and minimizing costs*.

2) Utilization of energy flexibility: Fig. 8 illustrates the performance of BiMO-EMS-II on the Medium datasets, subject to varying seasonality. In conjunction with Table IV, we can identify four distinct scenarios: **(a)** Demand within the RE production curve is limited, and a big proportion of the plentiful demand outside the curve is transferred inside, leading to near-optimal levels of self-consumption. **(b)** The demand within the RE production curve almost matches the curve but, contrary to OP, a distribution perfectly-fitting the curve cannot be established. **(c)** Demand within the RE production curve is limited and, despite the transfer of demand from outside to fill the curve, both OP and BiMO-EMS-II struggle to achieve the utopian level of self-consumption. Nonetheless, both approaches achieve similarly-high levels of

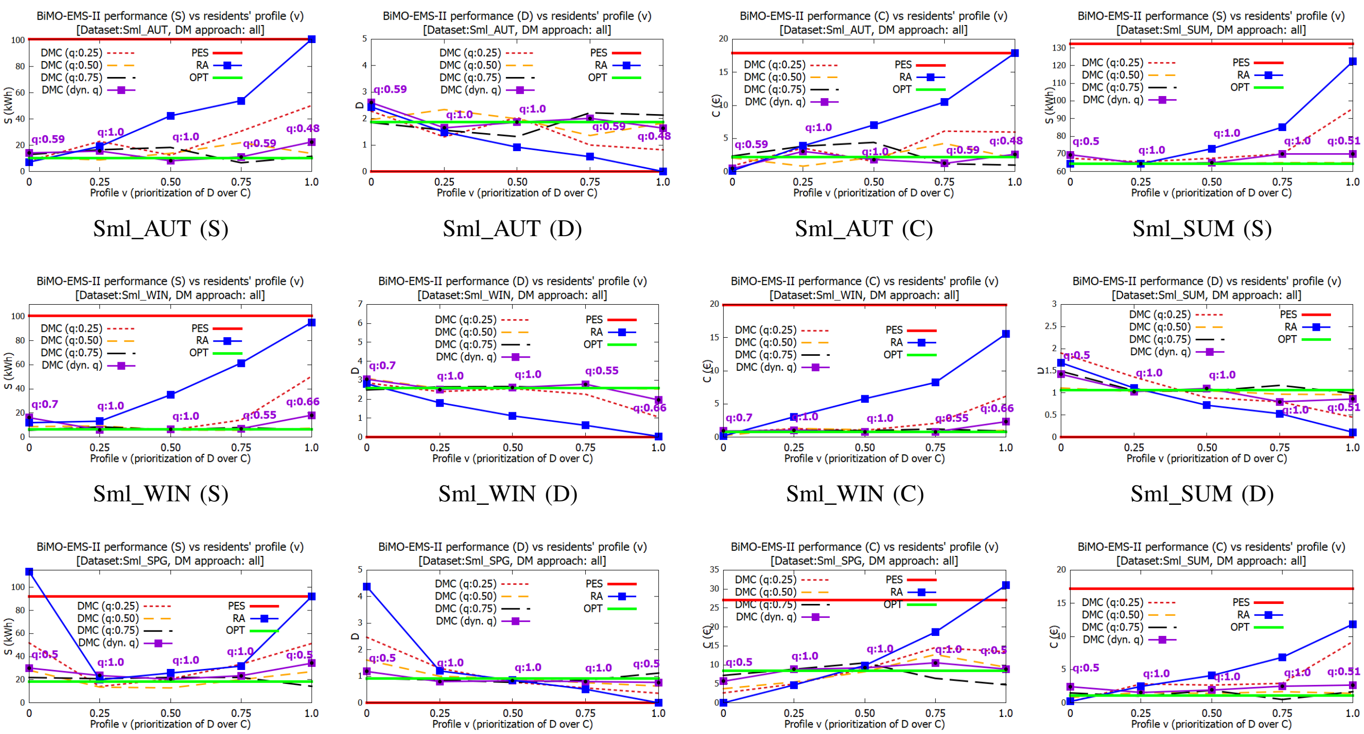
TABLE V

DAILY ENERGY SAVINGS (IN KWH), RESIDENT DISSATISFACTION AND COST SAVINGS (IN €) OF BIMO-EMS-II COMPARED TO DISREGARDING ENERGY FLEXIBILITY (PRF APPROACH) USING THE SAME DYNAMIC PRICING SCHEME. RESULTS CORRESPOND TO AVERAGES ACROSS 30 DISTINCT RUNS

Difference in obj. val. from PRF	Datasets: Small							
	AUT	%	WIN	%	SPG	%	SUM	%
S (kWh)	-90.7	-89	-94.2	-93	-75.3	-81	-67.8	-51
D	1.87	37	2.58	51	0.73	14	1.06	21
C (€)	-10.1	-82	-17.2	-95	-13.3	-61	-8.71	-88

Difference in obj. val. from PRF	Datasets: Medium							
	AUT	%	WIN	%	SPG	%	SUM	%
S (kWh)	-217	-81	-126	-89	-155	-58	-87.4	-34
D	5.97	59	3.98	39	3.84	38	1.78	17
C (€)	-26.5	-96	-16	-83	-17.8	-92	-6	-75

Difference in obj. val. from PRF	Datasets: Large							
	AUT	%	WIN	%	SPG	%	SUM	%
S (kWh)	-224	-52	-306	-86	-294	-55	-135	-26
D	7.93	39	7.35	36	7.88	39	4.59	22
C (€)	-24.0	-96	-26.9	-88	-19.6	-91	-11.2	-83



Sml_AUT (S) Sml_AUT (D) Sml_AUT (C) Sml_SUM (S)

Sml_WIN (S) Sml_WIN (D) Sml_WIN (C) Sml_SUM (D)

Sml_SPG (S) Sml_SPG (D) Sml_SPG (C) Sml_SUM (C)

Fig. 9: BiMO-EMS-II performance comparison between the decision-making approaches with respect to S, D and C on the Small datasets, as the residents' profile v shifts in prioritization from C to D. Results correspond to averages across 30 runs.

self-consumption. **(d)** Demand within the RE production curve is limited and, due to limited demand outside the curve as well, a lot of RE remains unutilized. Nonetheless, the optimal level of self-consumption is achieved.

The above observations further-support the claim that *BiMO-EMS-II effectively utilizes energy flexibility towards achieving high levels of self-consumption*. Finally, the form of the pricing schemes is as expected/described in section III-B: low costs when RE is available (given the energy-consumption distribution) and high costs when RE is unavailable.

3) Energy and Cost Savings: This section provides insights regarding the potential daily savings of BiMO-EMS-II in terms of energy and costs. Table V shows a comparison in performance per objective in units and as a percentage, between BiMO-EMS-II and the alternative of applying its optimized dynamic pricing scheme without utilizing energy flexibility, i.e., using the PRF approach. Overall, the results are promising: The highest levels of self-consumption are achieved in winter, regardless of the community size, with energy savings ranging between 86-93%, or, equivalently, 94-306 kWh. These savings result from the sacrifice of 36-51% of the residents' preference satisfaction, however, their costs are also reduced by 83-95% as compensation, i.e., the most heavily-charged resident will pay 16-26 € less (note that the cost savings would be different for a realistic price range compared to the normalized $c_t \in [0, 1]$, yet still analogous). Furthermore, in half of the experiments, more than 80% in energy savings or, equivalently, more than 75 kWh, is achieved. This performance comes at a sacrifice in satisfaction ranging between 14-59%, with the compensation in costs ranging between 82-96%.

Despite the promising results, the optimistic decision-making approach is unrealistic for real-life applications of BiMO-EMS-II. Next, we present the results obtained by different decision-making approaches.

B. Decision Making Experiments

Fig. 9 presents a performance comparison of BiMO-EMS-II subject to different decision-making approaches with respect to S, D and C on the Small datasets, as the community-level residents' profile v shifts in prioritization from costs minimization (objective C) to preference dissatisfaction minimization (objective D). We draw the following conclusions:

TABLE VI

LL PERFORMANCE OF NT, APT AND SPT APPLIED ON MOEA/D AND NSGA-II, FOR ALL DATASETS, $conv = 10^{-6}$. THE RESULTS ARE AVERAGES OF 100 RUNS, AS DESCRIBED IN SECTION V-D. T-TEST COMPARISONS: BETWEEN ADJACENT COLUMNS TO THE LEFT/RIGHT SIDE. C-METRIC COMPARISONS: BETWEEN ADJACENT COLUMNS

Metric	Dataset	Algorithm							
		MOEA/D					***NSGA-II***		
Statistical Analysis		T				T	T		
	Sml		***NT***	***APT***	***SPT***			***NT***	***SPT***
HV (%)	AUT	+	89.70	89.74	**90.13**	-	+	87.89	**88.03**
	WIN	+	88.23	88.30	**88.32**	-	+	85.85	**86.04**
	SPG	-	90.66	90.68	**90.91**	-	+	89.04	**89.30**
	SUM	+	89.60	89.64	**89.73**	-	+	87.84	**88.08**
Δ	AUT	-	.8963	**.8926**	.9088	+	+	**.8931**	.9181
	WIN	-	.8194	.8168	**.8134**	-	+	**.8074**	.8244
	SPG	-	.9165	**.9135**	.9174	-	+	**.8632**	.8792
	SUM	-	.8776	.8752	**.8741**	-	-	**.8678**	.8680
$Time$ (s)	AUT	+	5.208	**4.268**	4.706	+	+	1.418	**1.354**
	WIN	+	5.111	**4.172**	4.427	-	+	1.444	**1.372**
	SPG	+	7.337	**5.689**	6.158	-	+	1.610	**1.521**
	SUM	+	4.95	**3.876**	4.031	-	+	1.440	**1.373**
C $metric$ (%)	AUT	+	36.49	**45.09**			+	25.08	**55.87**
				38.54	**48.53**	-			
	WIN	+	36.81	**46.43**			+	25.53	**51.46**
				41.20	**45.28**	-			
	SPG	-	40.22	**43.13**			+	21.01	**65.77**
				41.68	**45.17**	-			
	SUM	+	36.38	**46.24**			+	23.48	**56.72**
				42.34	**43.04**	-			
	Med		***NT***	***APT***	***SPT***			***NT***	***SPT***
HV (%)	AUT	+	91.29	91.41	**91.52**	-	-	88.71	**88.76**
	WIN	+	91.05	91.13	**91.14**	-	+	88.63	**88.94**
	SPG	+	90.30	**90.36**	90.26	-	+	87.60	**87.77**
	SUM	+	91.66	**91.72**	91.54	-	+	89.09	**89.26**
Δ	AUT	+	.9304	**.9235**	.9437	+	+	**.9026**	.9468
	WIN	-	.9311	**.9293**	.9297	-	+	**.8494**	.8658
	SPG	-	.8657	.8638	**.8636**	-	-	.9573	**.9561**
	SUM	-	.9183	**.9133**	.9160	-	+	**.9051**	.9220
$Time$ (s)	AUT	+	13.12	**10.98**	12.15	+	+	22.75	**20.69**
	WIN	+	16.90	**12.98**	14.52	+	+	25.27	**23.70**
	SPG	+	13.14	**10.76**	11.67	+	+	22.01	**20.79**
	SUM	+	11.92	**9.369**	10.15	-	+	21.70	**19.54**
C $metric$ (%)	AUT	+	37.71	**45.46**			+	25.31	**52.99**
				40.76	**48.98**	-			
	WIN	+	35.32	**50.44**			+	19.45	**70.08**
				42.36	**47.14**	-			
	SPG	+	35.61	**47.24**			+	21.24	**45.49**
				46.07	42.64	-			
	SUM	+	36.70	**48.00**			+	25.04	**55.76**
				46.43	43.00	-			
	Lrg		***NT***	***APT***	***SPT***			***NT***	***SPT***
HV (%)	AUT	+	93.63	**93.76**	93.74	-	-	91.49	**91.50**
	WIN	+	88.08	**88.41**	88.01	-	+	85.00	**85.41**
	SPG	+	89.71	**89.89**	89.56	-	+	86.32	**86.67**
	SUM	+	92.76	92.89	**92.97**	-	+	90.41	**90.67**
Δ	AUT	+	.9741	**.9650**	.9715	-	+	**.9273**	.9646
	WIN	+	.8856	.8774	**.8736**	-	+	**.7981**	.8154
	SPG	+	.9123	**.8996**	.9083	-	+	**84.13**	88.06
	SUM	+	.9718	**.9610**	.9811	+	+	**.8983**	.9298
$Time$ (s)	AUT	+	26.89	**22.77**	23.45	-	+	38.40	**32.96**
	WIN	+	36.28	**31.00**	31.64	-	+	43.67	**36.18**
	SPG	+	36.38	**30.68**	31.97	-	+	40.80	**37.36**
	SUM	+	34.87	**28.86**	29.18	-	+	45.00	**39.37**
C $metric$ (%)	AUT	+	35.21	**50.03**			+	22.73	**58.86**
				44.73	**45.16**	-			
	WIN	+	31.13	**58.02**			+	22.25	**66.96**
				48.30	43.62	-			
	SPG	+	33.77	**52.63**			+	19.89	**66.96**
				50.11	41.18	-			
	SUM	+	32.31	**54.87**			+	19.09	**69.11**
				44.89	**45.85**	-			

TABLE VII

LL PERFORMANCE OF PMX, UPMX AND UNI APPLIED ON MOEA/D AND NSGA-II, FOR ALL DATASETS, $conv = 10^{-6}$. THE RESULTS ARE AVERAGES OF 100 RUNS, AS DESCRIBED IN SECTION V-E. T-TEST COMPARISONS: BETWEEN ADJACENT COLUMNS TO THE LEFT/RIGHT SIDE. C-METRIC COMPARISONS: BETWEEN ADJACENT COLUMNS

Metric	Data set	Algorithm									
		MOEA/D					***NSGA-II***				
Statist. An.		T				T	T				T
	Sml		***PMX***	***UPMX***	***UNI***			***PMX***	***UPMX***	***UNI***	
HV (%)	AUT	+	89.85	**89.90**	89.87	-	+	87.60	**88.13**	87.78	+
	WIN	+	87.27	**87.31**	87.23	+	+	84.01	**84.82**	84.30	+
	SPG	+	90.35	**90.47**	90.42	+	+	88.35	88.98	**88.98**	-
	SUM	+	89.84	**89.88**	89.77	+	+	87.69	**88.11**	87.69	+
Δ	AUT	+	.9033	.9096	**.8921**	+	+	**.8884**	.9008	.9333	+
	WIN	+	.8274	.8092	**.7905**	+	-	.8141	**.8044**	.8151	-
	SPG	-	.9295	.9297	**.9159**	+	-	.8650	**.8635**	.8843	+
	SUM	-	.8892	.8856	**.8670**	+	-	**.8669**	.8705	.8959	+
T (s)	AUT	+	6.463	**4.808**	13.55	+	+	**1.372**	1.444	3.611	+
	WIN	+	6.185	**5.226**	13.25	+	+	**1.344**	1.374	3.529	+
	SPG	+	8.370	**6.552**	15.41	+	+	**1.388**	1.519	3.648	+
	SUM	+	5.652	**4.300**	12.42	+	-	**1.413**	1.422	3.734	+
C $met.$ (%)	AUT			**62.67**	21.99	+			**48.93**	30.24	+
		-	38.74	**44.39**			+	25.10	**57.17**		
	WIN			**57.05**	27.11	+			**55.05**	22.45	+
		-	**44.93**	38.20			+	29.78	**48.86**		
	SPG			**66.08**	20.51	+			32.75	**51.74**	+
		+	34.89	**49.35**			+	26.12	**61.35**		
	SUM			**57.57**	24.55	+			**44.90**	28.94	+
		+	**48.90**	32.45			-	36.69	**44.14**		
	Med		***PMX***	***UPMX***	***UNI***			***PMX***	***UPMX***	***UNI***	
HV (%)	AUT	+	90.83	**90.93**	90.84	+	+	87.54	**88.44**	88.07	+
	WIN	+	90.50	90.72	**90.75**	-	+	87.40	**88.46**	88.37	+
	SPG	+	89.54	**89.59**	89.54	+	+	86.02	**87.03**	86.81	+
	SUM	-	91.27	**91.29**	91.20	+	+	88.10	**88.79**	88.35	+
Δ	AUT	-	.9269	.9284	**.9106**	+	-	**.8829**	.8899	.9221	+
	WIN	-	.9279	.9310	**.9145**	+	+	.8582	**.8439**	.8632	+
	SPG	+	.8628	.8560	**.8422**	+	+	**.8706**	.9632	.9865	+
	SUM	-	.9132	.9174	**.8959**	+	+	**.8857**	.9049	.9350	+
T (s)	AUT	+	17.24	**12.18**	34.04	+	+	**2.143**	2.285	6.833	+
	WIN	+	19.15	**14.76**	43.28	+	+	**2.452**	2.634	7.246	+
	SPG	+	16.46	**12.42**	35.38	+	+	**2.054**	2.225	6.808	+
	SUM	+	15.48	**10.57**	29.59	+	+	**2.279**	2.322	6.385	+
C $met.$ (%)	AUT			**55.38**	27.50	+			**42.46**	32.49	+
		-	**41.92**	36.22			+	21.77	**57.67**		
	WIN			**45.69**	38.86	-			33.82	**51.92**	+
		+	35.18	**52.24**			+	22.81	**64.08**		
	SPG			**44.54**	35.81	-			32.80	**33.37**	-
		+	**51.46**	33.04			+	19.45	**58.70**		
	SUM			**53.72**	28.47	+			**43.69**	32.73	-
		-	**47.30**	36.35			+	24.38	**55.61**		
	Lrg		***PMX***	***UPMX***	***UNI***			***PMX***	***UPMX***	***UNI***	
HV (%)	AUT	-	93.25	**93.25**	93.14	+	+	90.17	**91.16**	90.91	+
	WIN	+	87.57	**88.04**	87.94	+	+	83.48	**84.85**	84.81	-
	SPG	-	89.22	**89.25**	89.15	+	+	85.26	**86.14**	86.06	+
	SUM	-	**92.01**	91.98	91.87	+	+	88.74	**89.71**	89.66	+
Δ	AUT	-	.9666	.9679	**.9584**	+	-	**.9081**	.9111	.9640	+
	WIN	-	.8753	.8782	**.8663**	+	+	**.7636**	.7960	.8170	+
	SPG	-	.9042	.9066	**.8886**	+	+	.8686	**.8518**	.8732	+
	SUM	-	.9620	.9589	**.9470**	+	-	**.8758**	.8866	.9051	+
T (s)	AUT	+	32.27	**23.85**	74.09	+	+	3.682	**3.659**	12.45	+
	WIN	+	40.80	**28.86**	92.98	+	+	**4.192**	4.616	13.21	+
	SPG	+	37.52	**29.72**	88.00	+	+	**4.110**	4.284	12.55	+
	SUM	+	36.72	**25.09**	81.29	+	+	**3.874**	4.194	12.33	+
C $met.$ (%)	AUT			**52.23**	32.17	+			28.06	**49.63**	+
		-	**45.29**	41.31			+	24.31	**56.88**		
	WIN			**50.58**	37.40	-			36.79	**51.26**	+
		-	38.36	**52.24**			+	12.84	**79.58**		
	SPG			**49.46**	37.15	-			36.69	**48.21**	+
		-	41.88	**46.96**			+	21.38	**66.72**		
	SUM			**57.25**	27.41	+			29.94	**58.28**	+
		-	**46.04**	40.26			+	22.86	**68.40**		

(i) *DMC (dyn. q) maintains a consistent performance as the residents' profile v varies*, with a variation in performance of up to: 15 kWh for S, 1.09 dissatisfaction-units for D and 4.88 € for C. Moreover, the performance of DMC (dyn. q) approximates that of OPT, with a worst-case difference of 16 kWh, 0.73 dissatisfaction-units and 2.11 €. **(ii)** For the RA approach, on all datasets but Spring, as cost reduction C is increasingly prioritized, performance with regards to S and C is increasingly improved, while it monotonically deteriorates for D. Conclusively, *when the residents are given full authority as LL DMs, the best solutions in terms of self-consumption S lie at the extreme of pursuing cost reduction*, while for the Spring dataset a 25% interest in preference satisfaction is optimal (Fig. (i) Sml_SPG (S)). **(iii)** For DMC (dyn. q), for the Spring and Summer datasets, a LL profile of $v \in [0.25, 0.75]$ allows for full cooperation between the UL and LL entities, while for other values of v the LL DM resists full cooperation. Conclusively, *for the Spring and Summer datasets, satisfying UL preferences results in a greater deviation from the LL preferences if the extreme profiles are assumed*. **(iv)** On all datasets and when preference satisfaction D is fully prioritized ($v = 1$), as the approach becomes more optimistic or cooperative, the performance with regards to S and C is significantly improved, while it deteriorates for D. As a result, establishing cooperation is especially important in these scenarios for the UL entity. This is further supported by the resulting value of cooperation index q for DMC (dyn. q), which is consistently greater than 0.47, whereas approaches with less cooperation or optimism deviate significantly in performance with regards to S. Conclusively, *a cooperation level close to or above 50% offers a good balance between UL and LL preference satisfaction in these scenarios*, below which the deviation from the UL preferences is more intense. *Overall, the results deem DMC (dyn. q) a viable alternative to both the extreme UL approaches, given its approximation of the optimistic approach in performance, provided that LL preference information is known and cooperation between the UL and LL entities is allowed.*

C. Knowledge Transfer Experiments

The results in Table VI show that APT applied on MOEA/D is consistently faster than SPT by 1-2 seconds, while performing competitively on the Medium and Large datasets for all other metrics listed in section V-F. On the Small datasets, the larger difference in speed can be attributed to the premature convergence of APT compared to SPT. NT is significantly outperformed by APT on all datasets and for all metrics, with the exception of Δ, which shows the positive impact of Knowledge Transfer. Furthermore, APT significantly outperforms all NSGA-II variations in terms of HV and the C-metric. Regarding MOEA/D, APT is significantly faster than SPT on the Medium datasets and, on the Large datasets, APT's PF is never dominated by more than 1% by SPT. Finally, the control experiments for APT in the supplementary material indicate that selecting alternative values for d can yield better results in terms of HV and the C-metric, at the expense of computational effort.

D. Crossover Experiments

Table VII compares the performance of the MOEA/D and NSGA-II variants. Overall, UPMX applied on MOEA/D significantly outperforms all MOEA/D alternatives by up to a significant 0.1%, in terms of HV, with the difference increasing by several units against NSGA-II alternatives. Regarding the C-metric, UPMX and PMX perform competitively. Conclusively, *UPMX indicates a better capability of approximating the true PF*. In terms of Δ, NSGA-II outperforms MOEA/D with all operators but UNI, which is also the best operator for achieving a good Δ when using MOEA/D. Moreover, NSGA-II is extremely faster than MOEA/D, which is attributed to its premature convergence, as supplementary-material Fig. 1 indicates. Finally, UPMX applied on NSGA-II consistently achieves a significantly-better HV compared to NSGA-II alternatives by up to 0.1%. In terms of the C-metric, however, it loses its dominance to UNI on larger datasets.

VII. Conclusion

This study presented BiMO-EMS-II, an evolutionary bi-level multi-objective approach for aggregator participation in the day-ahead energy market, that focuses on optimizing self-consumption through maximal utilization of energy flexibility within an energy community, while accounting for the welfare of the residents in terms of appliance-scheduling preference satisfaction and energy costs reduction. BiMO-EMS-II, fitted with an Adaptive Population Transfer strategy, an adapted Uniform Partially Mapped Crossover operator and a Decision Making heuristic with Cooperation, is shown to achieve remarkable energy and cost savings at the expense of reasonable resident satisfaction, offering quality solution trade-offs based on varying decision-making approaches and residents' profiles.

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