

Application of Multi-Objective Optimization for Short-Term Operation Planning of an Energy Community

Sanja Kelemen, Nemanja Mišljenović, Goran Knežević

Josip Juraj Strossmayer University of Osijek

Faculty of Electrical Engineering, Computer Science and Information Technology Osijek

Kneza Trpimira 2B, 31000 Osijek, Croatia

{sanja.kelemen, nemanja.misljenovic, goran.knezevic}@ferit.hr

Stjepan Babić

Croatian Transmission System Operator Plc., Transmission Area Osijek

Relay protection and control department

Vukovarska cesta 217, 31000 Osijek, Croatia

stjepan.babic@hops.hr

Abstract. *The transition to clean energy increases the importance of Energy Communities (ECs) in achieving sustainability objectives. Effective operational strategies are crucial for ECs to realize their full potential, striking a balance between economic viability and environmental responsibility. This paper presents a multi-objective optimization framework to determine an EC's optimal day-ahead operational strategy, minimizing both electricity costs and CO₂ emissions. The framework consists of an optimization model, developed as mixed-integer linear programming (MILP) in the General Algebraic Modeling System (GAMS) environment, and an algorithm in MATLAB, producing Pareto-optimal solutions. At a weighting factor of 0.05, the optimal solution reduces electricity costs by 7.99 € and CO₂ emissions by 1.03 kg.*

Keywords. CO₂ Emissions, Electricity Costs, Energy Communities, Multi-Objective Optimization

1 Introduction

Energy Communities (ECs) aim to promote local renewable energy generation and consumption, reduce greenhouse gas emissions, enhance energy security, lower energy costs, foster community engagement and social inclusion, support local economic development, and encourage energy efficiency.

ECs may be described as a way of organizing collective energy activities to provide benefits for all community members. There are two types of ECs: "Citizen Energy Communities", which are covered by the Directive on the Internal Electricity Market (EU) 2019/944, and "Renewable Energy Communities", which are included in the Directive on Renewable Energy (EU) 2018/2001. Although ECs participate in economic ac-

tivities, their primary objective is to ensure ecological and social benefits for the community (Caramizaru and Uihlein, 2020).

Given the complexity of planning and operating ECs, where technical, economic, and environmental objectives often conflict, multi-objective optimization (MOO) methods have become essential tools for supporting decision-making and ensuring balanced development. In contrast to single-objective optimization, which targets the improvement of a single performance criterion, MOO simultaneously addresses multiple objectives. Rather than producing a single optimal outcome, MOO algorithms generate a set of trade-off solutions known as the Pareto-optimal set or Pareto front. Each solution within this set is non-dominated, implying that no other solution is superior across all considered objectives.

Although the Pareto front enables a comprehensive evaluation of alternative system configurations, the selection of a final solution necessitates the application of additional decision-making criteria or constraints, aligned with the specific priorities of the system or stakeholders. MOO methods are generally classified into decomposition-based approaches and direct solution approaches. In decomposition-based methods, the original multi-objective problem is transformed into a single-objective problem. Common techniques in this category include the Weighted Sum, Weighted Metric Sum, and the ϵ -constraint method. The main disadvantage of decomposition approaches is that the Pareto front set will be established after multiple iterations. In contrast, direct approaches aim to identify the Pareto-optimal set in a single optimization run by simultaneously evaluating all objective functions. Some of the MOO methods based on direct approaches are: Non-Dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Particle Swarm

Optimization (MOPSO), Strength Pareto Evolutionary Algorithm II (SPEA II), Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D), and Pareto Envelope-based Selection Algorithm II (PESA-II) (Salehi et al., 2022).

2 Related work

Authors in the literature have adopted different approaches to solving multi-objective optimization problems. In (Shaker et al., 2021), the authors proposed a new multi-objective algorithm, Multi-Objective Hunger Game Search Optimizer (MOHGS), to determine the optimal charging or discharging decisions for the energy storage units within the micro-grid system. Four objective functions are proposed: minimizing the operating cost, minimizing the emissions, minimizing the loss of power supply probability, and maximizing the renewable factor (RF). Additionally, the authors modified the first objective function by adding the battery degradation cost. The objective is achieved through the Pareto function. Compared to the multi-objective versions of the latest techniques, including Marine Predators Algorithm (MOMPA), Slime Mould Algorithm (MOSMA), Multi-Verse Optimizer (MOMVO), Golden-Eagle Optimizer (MOGEO), Grasshopper Optimization Algorithm (MOGOA), Antlion Optimizer (MOALO), and Grey Wolf Optimizer (MOGWO), the authors presented the results demonstrating the superiority of the proposed MOHGS-based approach in providing the optimal charging/discharging cycles.

The authors in (Kong et al., 2023) presented a bi-level optimization model for enhancing the independence of distributed generation systems by integrating a shared energy storage system (ESS) and an internal energy market within an EC. At the upper level, a multi-objective optimization approach is adopted. The first objective function is to minimize the total cost associated with the ESS, including investment, replacement, and operating costs, while the second objective function is to maximize the self-sufficiency rate, i.e., the proportion of demand that the community meets. The objective function of the lower-level model is to maximize the community's social welfare, that is, to minimize the operating cost of the community. To solve two optimization problems, the authors applied a nested algorithm: the upper-level multi-objective problem is solved using the NSGA-II to obtain a Pareto front of optimal trade-off solutions, while the lower-level single-objective problem is solved using the Gurobi solver. Furthermore, to obtain an optimal solution from the Pareto solution set, the Utopian point method is applied. Although due to the trade-off relationship between objective functions, no Utopian point could be achieved. In (Wang et al., 2023), the authors proposed a multi-objective optimization problem applied to a combined power system, including

photovoltaics, diesel generators, and fuel cells. The optimization aimed to minimize two objective functions: the loss of power supply probability (LPSP) and the total net present cost (TNPC). To solve the multi-objective problem, the authors improved the Sea Lion Optimization Algorithm (SLOA), which simulates the social behavior of sea lions during hunting. Furthermore, to improve SLOA to be used for MOO purposes, the authors utilized the Particle Swarm algorithm, the optimizer which looks for solutions to multi-objective problems by applying the Pareto dominance principle (using an external archive or secondary population to accumulate non-dominated answers and influence the direction of the search for the next descendant). The multi-objective optimization was conducted using the Multi-Objective Sea Lion Optimization Algorithm (MOSLO) and applying the Pareto ranking technique.

In (Mariuzzo et al., 2023), the authors presented an optimal sizing and management MILP-based methodology for ECs, which incorporates the flexibility of appliances in the form of demand side management (DSM) and demand response (DR). The AUGMENCON2 algorithm, as an improved version of the augmented ϵ -constraint method, is applied. The proposed objective functions are: minimizing total annualized costs, minimizing CO_2 emissions, maximizing social comfort, and minimizing energy exchange with the grid. The solution is obtained by applying the Pareto front. The authors in (Liu et al., 2023) proposed a distributed mixed-integer conic programming (MICP)-based energy management framework for actively interfaced participants, such as distributed energy resources (DERs), flexible loads, and microgrids, embedded within a modern distribution system. The energy management framework is formulated as an MOO problem, including the network operational objectives such as bus voltage deviations, feeder losses, and power factor of the distribution substation, while minimizing the utility grid's total operational cost. These objectives are aggregated into a single objective function using corresponding weighting coefficients, which were determined by the Analytic Hierarchy Process (AHP). To solve the optimization problem, the authors applied the Alternating Direction Method of Multipliers (ADMM).

The authors in (Anuradha et al., 2024) proposed a multi-objective stochastic optimization framework to size and place a community energy storage system (CESS) under three different energy pricing schemes (EPSs) for the CESS provider. The objective functions are to minimize the CESS provider's investment and operating costs, as well as the prosumers' operating costs. The uncertainties in PV generation and real/reactive energy consumption are considered. To solve this multi-objective problem, the authors used the ϵ -constraint method, which generates a Pareto front of non-dominated solutions. Furthermore, the authors in (De Leon et al., 2024) presented a multi-objective lin-

ear programming (MOLP) model to optimize the technical and business design of the novel local energy community DC microgrid scheme. The two objective functions are proposed: minimizing the total lifetime costs of the participating households and of the sponsoring local government unit (LGU). The Pareto optimal front is obtained through the ϵ -constrained algorithm to identify optimal solutions.

In (Di Somma et al., 2022), the authors proposed stochastic MOO model, based on mixed integer linear programming (MILP), of a real case study, which is treated as an integrated local energy community (ILEC) with two electrically interconnected multi-energy hubs involving technologies such as PV, solar thermal, combined heat and power systems, electric and geothermal heat pumps, absorption chillers, electric and thermal storage. The optimization model has two objective functions: the minimization of the net daily energy costs and carbon emissions. The optimization problem is solved by applying the Weighted Sum Method, while the optimal solution is established through a Pareto-optimal set of solutions. To account for the uncertainties associated with renewable energy sources (RES), the roulette wheel method (RWM) is applied to generate an initial set of solar irradiance scenarios. the fast forward selection algorithm is applied to retain the most representative scenarios, thereby reducing the computational burden in the subsequent optimization stage.

The literature review reveals that greater emphasis is placed on economic objectives than on environmental ones. To fill this research gap, this paper proposes an MOO framework to determine an EC's optimal day-ahead operational strategy, which simultaneously minimizes electricity costs and CO_2 emissions by applying the Weighted Sum Method. The optimal solution is identified through sets of Pareto-optimal solutions.

This paper is organized as follows. In Chapter 2, the proposed optimization model is presented. In Chapter 3, the input data and the applied optimization technique are described. In Chapter 4, the results are presented, and in Chapter 5, the conclusion is given.

3 The proposed multi-objective optimization framework

3.1 The proposed optimization model

This paper proposed a multi-objective optimization model, which consists of two objective functions: the minimization of electricity costs and the minimization of CO_2 emissions. The optimization problem is solved by applying the Weighted Sum Method, which aggregates two objective functions into one single objective function. The objective is achieved through the Pareto front, which balances electricity costs and CO_2 emissions.

The objective function is defined according to eq. 1.

$$opt = \omega \cdot E_{cost} + (1 - \omega) \cdot CO_{2,total} \quad (1)$$

where: opt represents the function to be minimized; ω represents a weighting factor indicating the importance of each of the two objective functions; E_{cost} represents total electricity costs; $CO_{2,total}$ represents the total amount of CO_2 emissions.

The upper limit of ω is 1, meaning that setting $\omega = 1$ produces a solution that minimizes total expected electricity costs. The lower limit of ω is 0, meaning that setting $\omega = 0$ produces a solution that minimizes the expected $CO_{2,total}$ emissions. Adjusting ω within the range of 0 to 1, the Pareto front can be identified, including possible trade-off solutions between economic and environmental objectives. This method is simple to implement and has been shown to identify all Pareto-optimal solutions in convex problems with only two objective functions (Di Somma et al., 2022).

The total electricity costs of all prosumers in EC are defined according to eq. 2.

$$E_{cost} = c \cdot \sum_{p=1}^P \sum_{t=1}^T \left(\frac{P_{k(p,t)}}{6} \cdot C_{kt(p,t)} - \frac{P_{p(p,t)}}{6} \cdot C_{pt(p,t)} + \frac{P_{lk(p,t)}}{6} \cdot C_{c(p,t)} - \frac{P_{lp(p,t)}}{6} \cdot C_{c(p,t)} \right) \quad (2)$$

where: c represents a scaling factor; $P_{k(p,t)}$ and $P_{p(p,t)}$ represent amounts of power imported and exported to the grid by prosumer p at a time step t , respectively; $P_{lk(p,t)}$ and $P_{lp(p,t)}$ represent amounts of power imported and exported to the local electricity market (LEM) by prosumer p at time step t , respectively; $C_{kt(p,t)}$ and $C_{pt(p,t)}$ represent the price of electricity imported and exported from/to the grid, respectively; $C_{c(p,t)}$ represents the price of electricity imported/exported to the LEM.

The total amount of CO_2 emissions caused by the import of electricity from the grid is defined according to eq. 3.

$$CO_{2,total} = \sum_p CO_2 \cdot E_{imp,uk(p)} \quad (3)$$

where: CO_2 represents the carbon intensity of imported electricity from the grid; $E_{imp,uk(p)}$ represents total electricity imported from the grid by prosumer p .

The state of charge (SOC) of the electric vehicle (EV) battery is defined according to equations 4 and 5. Eq. 4 applies to the first time step ($t = 1$), while eq. 5 is used for each subsequent time step.

$$SOC_{a(p,ev,t)} = SOC_{a(p,ev,start)} + \eta_c \cdot \frac{P_{cha(p,ev,t)}}{6} - \frac{1}{\eta_d} \cdot \frac{P_{dcha(p,ev,t)}}{6} \quad (4)$$

$$SOC_{a(p, ev, t)} = SOC_{a(p, ev, t-1)} + \eta_c \cdot \frac{P_{cha(p, ev, t)}}{6} - \frac{1}{\eta_d} \cdot \frac{P_{dcha(p, ev, t)}}{6} \quad (5)$$

where: $SOC_{a(p, ev, t)}$ represents the SOC of the EV battery at time step t ; $SOC_{a(p, ev, start)}$ represents the SOC of the EV battery at the beginning of the observed scheduling horizon; η_c and η_d represent the charging and discharging efficiencies of EV battery; $P_{cha(p, ev, t)}$ and $P_{dcha(p, ev, t)}$ represent amounts of power required to charge and discharge the EV battery at time step t , respectively.

Constraints related to the import/export of electricity from/to the grid and LEM are defined according to equations from 6 to 9:

$$0 \leq P_{k(p, t)} \leq P_{kmax(p, t)} \cdot P_{kbin(p, t)} \quad (6)$$

$$0 \leq P_{p(p, t)} \leq P_{pmax(p, t)} \cdot P_{pbin(p, t)} \quad (7)$$

$$0 \leq P_{lk(p, t)} \leq P_{lkmax(p, t)} \cdot P_{lkbin(p, t)} \quad (8)$$

$$0 \leq P_{lp(p, t)} \leq P_{lpmax(p, t)} \cdot P_{lpbin(p, t)} \quad (9)$$

where: $P_{kmax(p, t)}$ and $P_{pmax(p, t)}$ represent the maximum amounts of power that prosumer p can import and export to the grid at time t , respectively; $P_{lkmax(p, t)}$ and $P_{lpmax(p, t)}$ represent the maximum amounts of power that prosumer p can import and export to the LEM at time step t , respectively; $P_{kbin(p, t)}$, $P_{pbin(p, t)}$, $P_{lkbin(p, t)}$ and $P_{lpbin(p, t)}$ represent binary decision variables determining the import or export of electricity from the prosumer p at time step t .

Equations 10 and 11 define constraints related to charging and discharging an EV battery, respectively.

$$0 \leq P_{cha(p, ev, t)} \leq P_{cha, max} \quad (10)$$

$$0 \leq P_{dcha(p, ev, t)} \leq P_{cha, max} \quad (11)$$

where: $P_{cha, max}$ represents the maximum amount of charging, i.e., discharging power of the EV battery.

The constraint related to the SOC of the EV battery is defined as:

$$SOC_{min} \leq SOC_{a(p, ev, t)} \leq SOC_{max} \quad (12)$$

where: SOC_{min} and SOC_{max} represent the minimum and maximum SOC of the EV.

The following constraint ensures the balance between electricity import and export to the LEM:

$$\sum_{p=1}^P P_{lk(p, t)} = \sum_{p=1}^P P_{lp(p, t)} \quad (13)$$

The constraint on the simultaneous import and export of electricity to/from the grid and LEM is defined by equations 14 and 15.

$$P_{kbin(p, t)} + P_{pbin(p, t)} \leq 1 \quad (14)$$

$$P_{lkbin(p, t)} + P_{lpbin(p, t)} \leq 1 \quad (15)$$

3.1.1 The proposed algorithm

To ensure that both objective functions are treated equally in the optimization model, a weighting factor (ω) and a constant (c), which presents a scaling factor, are applied. The scaling factor c is introduced into the model to enable the comparison of different units of measurement - electricity costs, expressed in [€], and CO_2 emissions, expressed in [kg]. By varying ω from 0 to 1 in steps of 0.05, the objective is to achieve a balance between minimizing electricity costs and minimizing CO_2 emissions. At $\omega = 1$, the primary focus is on reducing total electricity costs, while at $\omega = 0$, the optimization focuses on reducing CO_2 emissions. To automate the process of multi-objective optimization, an algorithm was developed in MATLAB. The algorithm begins by defining the upper and lower limits of ω . Furthermore, MATLAB passes the necessary input data to the optimization model developed in GAMS, where the optimization problem is solved for each value of ω in the range from 0 to 1. After each iteration, the results are returned to MATLAB and stored, and it is checked whether the upper limit of ω has been reached. If the upper limit has not been reached, the process is repeated. The objective of this algorithm is to find the optimal value of ω . After the upper limit of ω is reached, the optimization results are processed and graphically displayed. Based on the results, the optimal solution is selected, meaning the value of ω that provides the best balance between minimizing electricity costs and minimizing CO_2 emissions. The process of the above algorithm is shown in Fig. 1.

4 Case study

The EC analyzed in the simulation consists of six prosumers. Prosumer P2 represents a business, while prosumers P1, P3, P4, P5 and P6 represent households. The electricity consumption and generation profiles were measured at the real prosumer households, while the business measurements were conducted at a faculty building in Osijek, Croatia.

Fig. 2 shows the electricity consumption profile of each prosumer in the community over the observed day-ahead. As a business, P2 has significantly higher electricity consumption compared to households, which is expected given the greater electricity demands of a business. Household consumption (P1, P3, P4, P5, P6) exhibits a lower and more evenly distributed load.

Fig. 3 shows electricity generation from photovoltaic (PV) power plants within the EC. All prosumers contribute to electricity generation, with P2, as a business, achieving the highest generation output. Household generation is also significant, but aligns with their lower electricity demands. Furthermore, all participants reach peak generation during similar time intervals.

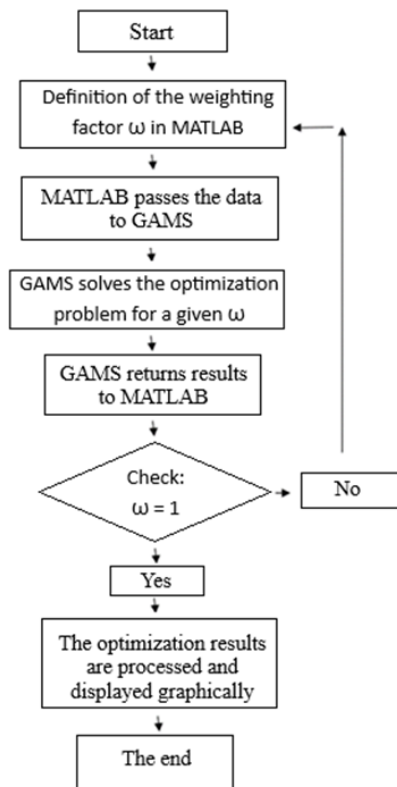


Figure 1. Graphical representation of the algorithm for automating the multi-objective optimization process in MATLAB

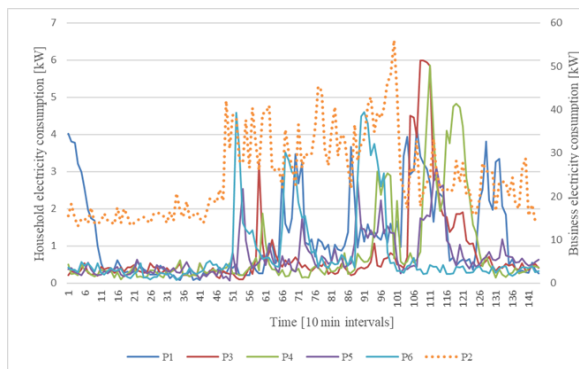


Figure 2. Electricity consumption of prosumers

In this and the following cases, time step t represents an interval of 10 minutes. The power for every time step t is divided by 6, since an hour contains 60 minutes. This approach allows the model to accurately monitor electricity consumption and generation in 10-minute intervals, while simultaneously displaying aggregated values on an hourly basis, which contributes to better analysis and management of electricity flows within the system.

Electricity prices are determined according to the "White Tariff Model", which includes two rates: a lower and a higher tariff. The pricing data was obtained from the official HEP website ("HEP - Tarifne

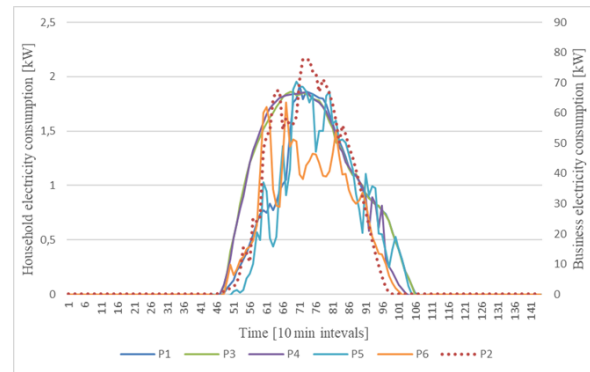


Figure 3. Electricity generation of prosumers

stavke (cijene)", 2024). For households, the prices are 0.083 €/kWh for the lower tariff and 0.159 €/kWh for the higher tariff. For businesses, prices are 0.12 €/kWh and 0.201 €/kWh, respectively. The price of electricity exported to the grid by households and businesses is determined according to the market model "Customer with Own Production." According to this model, households receive 0.05 €/kWh, while businesses receive 0.0374 €/kWh for the exported electricity. The electricity price on the LEM is 0.025 €/kWh, representing the average distribution grid usage fee for households. Other input parameters are given in Table 1, based on real data.

Table 1. Input parameters of the optimization model

Input parameter	Amount
P_{kmax}, P_{lkmax}	13.8/120 kW
P_{pmax}, P_{lpmax}	5/120 kW
η_c, η_d	0.985
P_{chamax}	7.4 kW
CO_2	0.246 kg/kWh
Electricity consumption of EV	0.175 kWh/km

The driving time of the EV and the distance it covers within that time are also considered. On average, EV owners travel between 40 and 90 km per day. In the simulation, each prosumer with an EV is assumed to travel within these limits. The travel time varies for each prosumer, ranging from 30 to 90 minutes (Mišljenović et al., 2024).

5 Results

The impact of ω on electricity costs and CO_2 emissions is shown in Figs. 4 and 5. The costs presented in the figures and tables represent actual electricity costs multiplied by the scaling factor c of 2.1, which was determined before the optimization process, ensuring equal order of magnitude of the two objective functions. According to Fig. 4, electricity costs are highest at $\omega = 0$, amounting to 130.67 €. When the scaling fac-

tor c is considered, the actual electricity cost is 62.22 €. This occurs because, at $\omega = 0$, the objective is to minimize CO_2 emissions. Fig. 5 shows an opposite trend compared to Fig. 4. At $\omega = 0$, CO_2 emissions are at their lowest value of 104.55 kg. However, as ω increases, CO_2 emissions also increase. The emissions stabilize at $\omega \geq 0.4$, reaching a value of 105.96 kg, with a maximum recorded value of 106.04 kg.

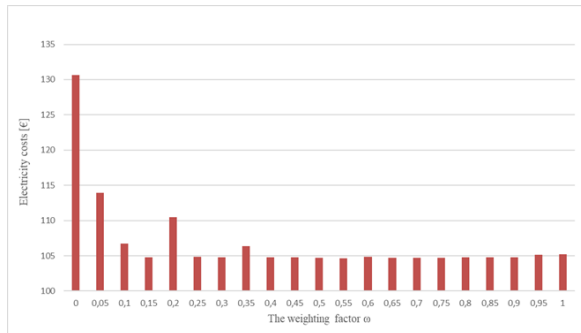


Figure 4. Total electricity costs considering ω

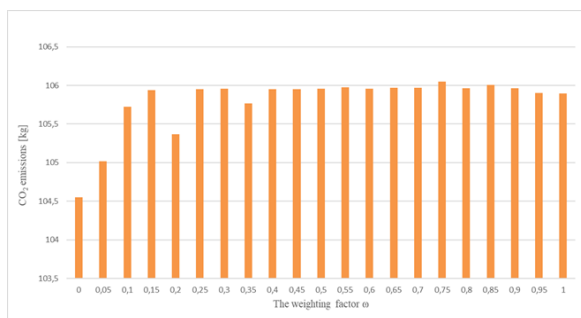


Figure 5. CO_2 emissions considering ω

Fig. 6 shows a comparative representation of scaled electricity costs and CO_2 emissions concerning different values of ω . As ω increases, total electricity costs decrease and stabilize at higher values of ω , while CO_2 emissions increase. This trade-off between economic and environmental objectives is crucial for system decision-making.



Figure 6. Combined representation of electricity costs and total CO_2 emissions

Fig. 7 shows the Pareto front, which shows that electricity costs and CO_2 emissions cannot be minimized

simultaneously. The Pareto front helps identify the most efficient, i.e., optimal solution, where neither total electricity costs nor total CO_2 emissions are significantly aggravated. In this simulation, the Pareto front provides insight into how much the EC must compromise on electricity costs to reduce CO_2 emissions, and vice versa.

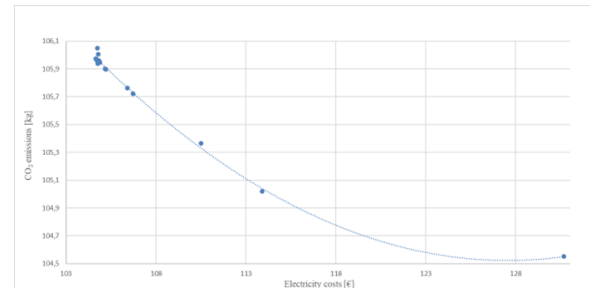


Figure 7. Pareto front

The results presented in the figures correspond to the optimized solution obtained for $\omega = 0.05$.

Fig. 8 shows the amounts of imported and exported electricity throughout the day. These values represent electricity exchange with the grid, as well as LEM. Prosumer P2 imports significantly more electricity than other prosumers, which is expected, as businesses generally have higher electricity consumption than households, making P2 the key electricity importer within the EC. On the other hand, prosumers P1, P3, P4, P5, and P6 (households) require considerably less imported electricity than P2. Additionally, these households contribute to electricity exports within the LEM, reducing the EC's reliance on the grid.

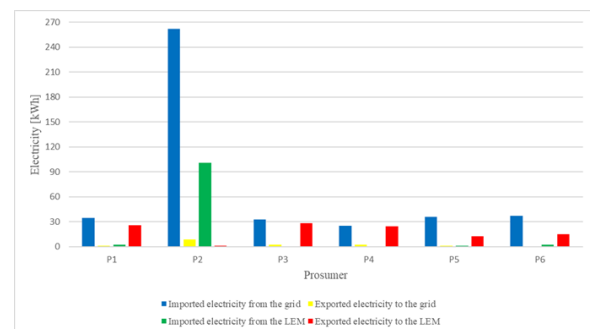


Figure 8. Exchange of electricity of prosumer with the grid and LEM

Fig. 9 shows the SOC of EV batteries throughout the day. The battery state varies depending on the time of day, indicating whether the batteries are charging or discharging. Three intervals can be identified in which the SOC changes. In the first interval, there is an increase in the SOC of the EV batteries when they are connected to home chargers in households. This suggests that households charge their EVs during the night and morning hours when electricity prices are lower.

In the second time interval of the day, the EV batteries are charged at the company during working hours. The EV batteries are charged with the surplus electricity, which is justified by the price of exporting electricity to the grid. EVs require a significant amount of electricity to charge, especially if the company has multiple EVs being charged simultaneously. In the final third of the day, there is a decrease in the SOC, suggesting that EVs in households are being used or the batteries are discharging to cover consumption. The change in SOC during the first and third intervals indicates that households are using electricity from their batteries to meet their daily electricity needs. Instead of charging EV batteries in the evening when electricity prices are higher, prosumers discharge batteries. In contrast, at night and in the morning, when electricity prices are lower, prosumers charge EV batteries. This shows how electricity is used and stored within the EC and provides insight into the efficiency of EV battery management throughout the day. Optimal management allows a balance between consumption, storage, and electricity generation, reducing the need for electricity import from the grid and thereby increasing the electricity independence of the EC.

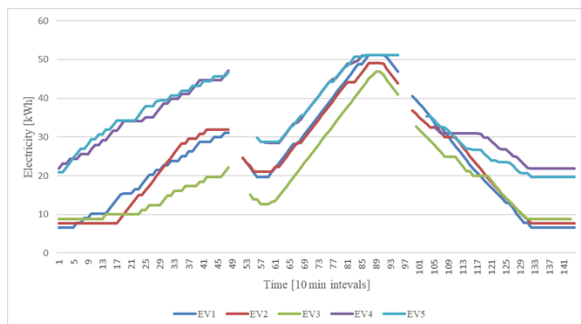


Figure 9. SOC of EV batteries

Correlations between ω and total electricity costs, as well as total CO_2 emissions, are shown in Table 2. The optimal solution is achieved with a weight factor ω of 0.05. At this value of ω , the total scaled electricity costs amount to 113.89 €, or actual electricity costs of 54.23 €, with the scaling factor c of 2.1, while the total CO_2 emissions are 105.01 kg. Through multi-objective optimization of the EC's operations, total electricity costs were reduced by 7.99 €, compared to the initial electricity cost of 62.22 €, and CO_2 emissions were reduced by 1.03 kg, compared to the highest amount of 106.04 kg.

The main objective is to reduce CO_2 emissions while keeping electricity costs within acceptable limits. Although electricity costs are significantly lower at higher values of ω , it is important to consider the objectives of EC. Since ECs in Croatia are non-profit organizations, their primary focus is to reduce CO_2 emissions, i.e., reduce any negative environmental impacts. Therefore, more importance is given to reducing CO_2 emissions than to minimizing electricity costs.

Table 2. Electricity costs and total CO_2 emissions in correlation with ω

ω	Electricity costs [€]	Scaled electricity costs [€]	Total CO_2 emissions [kg]
0.00	62.22	130.67	104.55
0.05	54.23	113.89	105.01
0.10	50.82	106.72	105.72
0.15	49.89	104.76	105.93
0.20	52.61	110.49	105.36
0.25	49.93	104.86	105.94
0.30	49.89	104.78	105.95
0.35	50.66	106.39	105.76
0.40	49.91	104.82	105.94
0.45	49.88	104.76	105.95
0.50	49.86	104.70	105.95
0.55	49.83	104.64	105.97
0.60	49.92	104.83	105.95
0.65	49.86	104.70	105.96
0.70	49.85	104.69	105.96
0.75	49.87	104.73	106.04
0.80	49.88	104.76	105.96
0.85	49.89	104.77	106.00
0.90	49.88	104.76	105.96
0.95	50.08	105.16	105.90
1.00	50.10	105.21	105.89

6 Conclusion

This paper proposes a multi-objective optimization framework to determine an EC's optimal day-ahead operational strategy, simultaneously minimizing electricity costs and CO_2 emissions. The proposed framework consists of an optimization model, developed as an MILP in GAMS, and an algorithm, developed in MATLAB. The optimal solution is determined through sets of Pareto-optimal solutions.

The results show how effective optimization of EC's operations can impact greenhouse gas emissions and the overall costs of electricity generation, consumption, and distribution. Through multi-objective optimization, a balance between ecological and economic objectives is achieved with a weight factor ω of 0.05, where the EC's electricity costs were reduced from 62.22 € to 54.23 €, representing a decrease of 7.99 €, while CO_2 emissions were reduced from 106.04 kg to 105.01 kg, representing a decrease of 1.03 kg. This solution emphasizes that a higher priority was placed on reducing CO_2 emissions, while electricity costs are within acceptable limits for the community members. Although there is potential for further cost reduction, this would result in higher CO_2 emissions, which is not in line with the objectives of ECs, which, as non-profit organizations, aim to reduce their negative environmental impact.

Future research may explore the application of multi-objective optimization to ECs providing flexibility services, simultaneously minimizing electricity costs and CO_2 emissions, while considering stochastic behavior.

7 Acknowledgments

This work was supported by the Croatian Science Foundation under the project “Prosumer-rich distribution power network” (project number: UIP-2020-02-5796). The work of doctoral student Sanja Kelemen has been supported by the “Young Researchers’ Career Development Project - training of Doctoral Students” (DOK-NPOO-2023-10-4888) of the Croatian Science Foundation.

References

- Anuradha, K. B., Iria, J., & Mediawathe, C. P. (2024). Multi-objective planning of community energy storage systems under uncertainty. *Electric Power Systems Research*, 230(December 2023), 110286. <https://doi.org/10.1016/j.epsr.2024.110286>
- Caramizaru, A., & Uihlein, A. (2020). *Energy communities: an overview of energy and social innovation Social aspects of the energy transition*. <https://doi.org/10.2760/180576>
- De Leon, J. A., Tan, R. R., & Billones, R. K. (2024). Multi-Objective Linear Programming for Optimizing a Local Energy Community DC Microgrid System and Business Model. *IEEE Access*, 12(September), 171513–171526. <https://doi.org/10.1109/ACCESS.2024.3493774>
- Di Somma, M., Buonanno, A., Caliano, M., Graditi, G., Piazza, G., Bracco, S., & Delfino, F. (2022). Stochastic Operation Optimization of the Smart Savona Campus as an Integrated Local Energy Community Considering Energy Costs and Carbon Emissions. *Energies*, 15(22), 1–27. <https://doi.org/10.3390/en15228418>
- Hep - tarifne stavke (cijene). (2024). <https://www.hep.hr/elektra/kucanstvo/tarifne-stavke-cijene/1547> (Accessed: 2024.)
- Kong, X., Mu, H., Wang, H., & Li, N. (2023). Independence enhancement of distributed generation systems by integrating shared energy storage system and energy community with internal market. *International Journal of Electrical Power and Energy Systems*, 153(July), 109361. <https://doi.org/10.1016/j.ijepes.2023.109361>
- Liu, G., Ollis, T. B., Ferrari, M. F., Sundararajan, A., & Chen, Y. (2023). Distributed Energy Management for Networked Microgrids Embedded Modern Distribution System Using ADMM Algorithm. *IEEE Access*, 11, 102589–102604. <https://doi.org/10.1109/ACCESS.2023.3316513>
- Mariuzzo, I., Fioriti, D., Guerrazzi, E., Thomopoulos, D., & Raugi, M. (2023). Multi-objective planning method for renewable energy communities with economic, environmental and social goals. *International Journal of Electrical Power and Energy Systems*, 153(March), 109331. <https://doi.org/10.1016/j.ijepes.2023.109331>
- Mišljenović, N., Knežević, G., Žnidarec, M., & Topić, D. (2024). Optimal State of Charge Control of EV Batteries within Energy Community Considering Cost Minimization and Environmental Impact. *International Conference on the European Energy Market, EEM*, 1–6. <https://doi.org/10.1109/EEM60825.2024.10608901>
- Salehi, N., Martinez-Garcia, H., Velasco-Quesada, G., & Guerrero, J. M. (2022). A Comprehensive Review of Control Strategies and Optimization Methods for Individual and Community Microgrids. *IEEE Access*, 10, 15935–15955. <https://doi.org/10.1109/ACCESS.2022.3142810>
- Shaker, Y. O., Yousri, D., Osama, A., Al Gindy, A., Tag Eldin, E., & Allam, D. (2021). Optimal Charging/Discharging Decision of Energy Storage Community in Grid-Connected Microgrid Using Multi-Objective Hunger Game Search Optimizer. *IEEE Access*, 9, 120774–120794. <https://doi.org/10.1109/ACCESS.2021.3101839>
- Wang, H., Mansor, N. N. B., Mokhlis, H. B., & Mashhadi, A. (2023). Optimal size selection of combined diesel generator/fuel cell/photovoltaic system components using a multi-objective strategy and sea lion optimization algorithm. *IET Renewable Power Generation*, (September 2022), 1–16. <https://doi.org/10.1049/rpg2.12795>