Energy Management in Energy Communities with Participation in MIBEL

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Abstract

The European energy landscape has evolved to include the concept of energy communities in most countries. In order to fully benefit the entire value chain, from consumers to producers, particularly including renewables, integration with electricity markets should be considered and further explored. This paper presents the results of methods and simulations conducted within the scope of the TRADERES project, which aims to develop "New Markets Design & Models for 100% Renewable Power Systems". The focus will be on the operational context of energy communities in Portugal, including integration with MIBEL (Iberian Electricity Market). The implemented methodology will involve the following steps: - Energy management of an energy community, considering available renewable-based generation, storage, and flexibility; - Negotiation of energy between energy communities; - Negotiation of energy from communities in MIBEL; - Updating energy management in each community according to market results. The numerical case study will consider actual bidding scenarios in MIBEL, with real bids and prices. Various scenarios will be discussed at the community level within a specific market context.

1 Introduction

Energy communities play a crucial role in fostering a sustainable market design tailored for the long term within electricity systems heavily reliant on variable renewable energy sources. By facilitating the integration of renewables, such as solar and wind, energy communities help optimize generation, storage, and consumption within local contexts [1]. This decentralized approach enhances the resilience and security of the electricity grid while promoting consumer participation and engagement in the energy transition. Moreover, energy communities mitigate price risks associated with renewables by diversifying energy sources, optimizing consumption patterns, and potentially implementing local energy trading mechanisms [2]. Their involvement ensures affordability and predictability of energy expenditures for community members, contributing to the overall stability of the electricity market. In the TradeRES project, energy communities serve as valuable testbeds for evaluating market designs, providing insights into the effectiveness of incentives, investment mechanisms, and regulatory frameworks in achieving key objectives such as security of supply, cost-effectiveness, and investment cost recovery. Thus, energy communities emerge as indispensable actors in realizing a sustainable, resilient, and consumer-centric energy future [3].
Load shifting and load reduction are vital components of energy communities, offering significant benefits to both utilities and consumers [4]. Firstly, load shifting involves redistributing electricity consumption from peak to off-peak periods. By encouraging consumers to utilize electricity during times when demand is lower, load shifting helps to balance the load on the electrical grid. This reduces the strain on infrastructure during peak hours, mitigates the risk of blackouts or brownouts, and minimizes the need for additional power generation capacity, which can be expensive and environmentally impactful [5]. Secondly, load reduction focuses on actively reducing overall electricity consumption during peak periods through demand response measures. This can include temporarily reducing energy-intensive activities in industrial settings or adjusting the operation of appliances and HVAC systems in commercial and residential buildings. By curbing demand during peak times, load reduction contributes to grid stability, reliability, and resilience [5]. It also supports energy conservation efforts, reduces greenhouse gas emissions associated with electricity generation, and promotes environmental sustainability. In essence, both load shifting and load reduction strategies play crucial roles in optimizing the performance and efficiency of energy communities. They empower consumers to actively manage their energy usage, contribute to grid stability, and support the integration of renewable energy sources. Finally, by reducing peak demand and optimizing resource utilization, load shifting, and load reduction help to create more resilient, sustainable, and cost-effective energy systems for communities worldwide.
A Demand Response Service Provider (DRSP) acts as an intermediary between utility companies and customers participating in demand response programs. These providers play a central role in pooling together groups of customers who are willing to adjust their energy usage during periods of peak demand. By aggregating the load profiles of small and medium consumers, DRSPs can effectively coordinate and manage participation in demand response events. DRSPs utilize advanced technologies and communication systems to facilitate real-time monitoring and control of electricity consumption among participating customers. They work closely with utilities to forecast demand patterns, identify peak

periods, and optimize strategies for load reduction or shifting. Additionally, DRSPs handle the logistics of demand response programs, including customer enrollment, event notification, and incentive management. By offering aggregation services and expertise in demand response, these providers enable smaller consumers to participate in programs that they might not have been able to access independently. This not only benefits individual customers by providing financial incentives or other rewards but also contributes to grid stability, reliability, and overall energy efficiency. In essence, DRSPs play a crucial role in bridging the gap between utilities and consumers, facilitating effective demand response participation, and ultimately supporting a more resilient and sustainable energy ecosystem.

The flexibility of energy communities has been studied in different references. The proposed model [6] introduces a stochastic energy/reserve mixed integer linear program tailored for multi-energy communities, addressing the challenge of maximizing flexibility potential. By considering various services subject to uncertain calls, including storage and power factor manipulation, it ensures occupant comfort while integrating electric heat pumps and optimizing revenue from multiple markets/services. The study [7] introduces clustering techniques for designing demand response programs targeting commercial and residential prosumers in an Italian distributed energy community. By minimizing reverse power flow and shifting system-wide peak demand, the clustering algorithm, particularly k-means with dynamic time warping distance and 14 clusters, achieves the highest performance, facilitating the development of personalized demand response policies for energy communities. The study [8] presents a control-oriented methodology for assessing energy flexibility potential in residential building portfolios within energy aggregators, aiding in optimizing load management for demand response programs and achieving significant reductions in energy consumption and peak demand. The proposed model [9] identifies factors affecting the contracted energy flexibility potential of homes in demand response programs, demonstrating sustained demand reductions through a model-predictive control strategy while considering factors like preheating, coordination, penalties, and notice periods, crucial for meeting challenges in transitioning to a low-carbon energy system. [10] proposes a data-driven approach to quantify the potential of individual flexible load users for participation in demand response, introducing a metric for predictability and demonstrating significant energy reduction potential through selective participation of flexible loads in real-world scenarios. The proposed model [11] demonstrates the interplay between energy efficiency measures and demand flexibility enabled by home energy management systems (HEMS), showcasing significant reductions in HVAC energy use and utility bills through energy efficiency upgrades, and increased load flexibility with the addition of HEMS and home battery systems in an all-electric residential community model. [12] presents a two-stage real-time multi-energy demand response framework for high-renewable building microgrids, optimizing economic scheduling and flexibility allocation to reduce operating costs by up to 36.9% and improve operational flexibility.

In this paper, a linear model is introduced to effectively manage load shifting and load reduction within an energy community. The proposed load reduction model empowers the system operator to dynamically adjust consumption levels, ensuring a balance between generation and consumption on the electrical grid. This capability is essential for maintaining grid stability and reliability, particularly during peak demand periods. Furthermore, the paper outlines specific characteristics for load shifting, including operation periods and working hours. By defining these parameters, the optimal scheduling of flexible loads becomes achievable. The model aims to minimize costs associated with electricity consumption by strategically shifting loads to off-peak periods or reducing overall demand during peak hours. This cost minimization approach enhances efficiency within the energy community while also contributing to broader goals of sustainability and resource optimization. Overall, the proposed linear model offers a systematic framework for managing load shifting and load reduction, providing valuable insights for system operators and stakeholders in optimizing energy usage, reducing operational expenses, and enhancing the overall performance of the energy community.

The rest of the paper is organized as follows: the proposed model is presented in section 2, followed by simulation results and discussion in section 3. Finally, the conclusion and remarks are presented in section 4.

2. Methodology

In this section, we introduce a cost minimization model aimed at optimizing the scheduling of load shifting and load reduction within the energy community. The model accounts for various factors including the permissible operation period, consumption levels, the maximum reducible load, cost of load reduction, and required operation periods of flexible devices as defined by consumers. By minimizing costs, the model determines the optimal starting times for each device as well as the load reduction of each community member, ensuring efficient utilization of resources and effective management of energy consumption.

3.1 Load Shifting

Each flexible appliance j (set of flexible appliances is denoted by N), belonging to the consumer k (set of consumer is denoted as M), is characterized by its allowable operation period (permissible start and end times), and the working hour denoted as $S_{j,k}$, $E_{j,k}$, and $O_{j,k}$, respectively. The load shifting cost is calculated by (1), as follows:

$$\mathrm{LSC} = \sum_{k=1}^{M} \sum_{j=1}^{N_k} \sum_{t=X_{j,k}}^{X_{j,k}+Oj,k} \rho_t . LR_{t,j,k} \tag{1}$$

where, ρ_t is the energy price of operation period t.

3.2 Load Reduction

The required load reduction (RLR) is specified by the operator, and the participation level of consumers (LR_k) is determined through cost minimization. The cost of load reduction is directly influenced by both the quantity of reduced load and the inconvenience cost of consumers (IC_k). Accordingly, the cost of load reduction is formulated by equation (2), as follows:

$$LRC = \sum_{k=1}^{M} \sum_{t=1}^{T} LR_{t,k}.IC_{t,k} \quad (2)$$

3.3 Objective function and constraint

As mentioned before, the cost minimization the objective function of the proposed model, as follows:

$$O.F. = \min LSC + LRC \quad (3)$$

Such that:

$$0 \leq LR_{t,k} \leq \mathrm{LR}_{t,k}^{max} \quad (4)$$

$$RLR_t = \sum_{k=1}^{M} LR_{t,k} \quad (5)$$

$$S_{j,k} \leq X_{j,k} \leq E_{j,k} - O_{j,k} \quad (6)$$

$$D_{t,k} + \sum_{j=1}^{N_k} LR_{t,j,k} \leq D_{t,k}^{max} \quad (7)$$

The capacity of load reduction and the requested load reduction by the system operator are represented by (4) and (5), respectively. Moreover, constraints (6) and (7) show the starting time limitation and demand capacity of each consumer.

3 Results

To evaluate the performance of the proposed model, it was tested on a system comprising 20 consumers with shiftable loads and 100 consumers with reducible loads. The data for flexible loads and equipment of each consumer are presented in Tables 1 and 2, respectively.

Table 1 Data of flexible loads.

	Working time	Power (kW)	Starting time (S)	Ending time (E)
Washing machine	3	3.5	59	79
Clothes dryer	4	3.2	59	88
Dishwasher	8	2.8	71	93
Microwave	1	0.9	72	76
Electric kettle	1	1.8	27	30
Electric stove	1	5.2	25	31
Blender	1	0.8	68	74
Hair dryer	2	1.5	25	31
Steam iron	2	1.4	77	93
Vacuum cleaner	2	1.35	55	82
Coffee maker	1	1.1	25	30
Phone charger	8	0.01	71	95

It should be noted that in this study, each hour is divided into 4 periods, resulting in a total daily operation period of 96. To evaluate the flexibility of consumers, the load reduction program is assessed across two time slots:

- Time slot 1: March 15, 2023, Period 20
- Time slot 2: March 27, 2023, Period 21

Table 3 presents the consumption of consumers in different time slots, inconvenience cost, and the maximum participation level in the load reduction program for 100 consumers.

Table 2 Equipment for flexible consumers.

Consumer	Washing machine	Clothes dryer	Dish washer	Microwave	Electric kettle	Electric stove	Blender	Hair dryer	Steam iron	Vacuum cleanere	Coffee maker	Phone charger
1	1	0	1	1	1	1	0	1	0	0	1	1
2	1	1	0	1	1	1	1	1	1	0	1	1
3	0	0	1	1	1	0	0	1	0	1	1	1
4	1	0	1	1	0	1	0	1	1	0	1	1
5	1	1	0	1	1	1	0	1	0	0	1	1
6	1	0	1	1	1	0	0	1	0	1	1	1
7	1	0	0	1	0	0	0	1	1	0	1	1
8	1	1	1	1	1	1	0	1	1	1	1	1
9	0	0	0	1	1	0	1	1	0	0	1	1
10	1	0	1	1	1	0	0	1	0	1	1	1
11	1	1	0	1	0	1	0	1	1	0	1	1
12	1	0	1	1	1	1	0	1	0	0	1	1
13	1	0	0	1	1	0	0	1	0	0	1	1
14	1	1	1	1	1	0	0	1	0	1	1	1
15	0	0	1	1	1	0	1	1	1	0	1	1
16	1	0	1	1	0	1	0	1	0	0	1	1
17	1	0	1	1	1	0	0	1	0	0	1	1
18	1	0	0	1	1	1	0	1	0	1	1	1
19	1	1	1	1	1	0	0	1	1	1	1	1
20	0	0	0	1	1	1	0	1	0	0	1	1

Table 3: Data of reducible loads.

Consumer	1	2	3	4	5	6	7	8	9	10
L_Slot1	5.266	0.252337	0.143539	0.2903	1.890665	1.431736	4.842359	0.158586	4.397216	1.484715
L_Slot2	5.89	0.306735	0.215522	0.55071	0.926636	0.87828	2.686047	0.249575	3.094731	0.919189
Inc. Cost	0.03447	0.033795	0.016335	0.010665	0.001575	0.023895	0.010665	0.036	0.03141	0.03348
Max LR	18.72	19.81	12.33	19.52	14.17	18.73	12.43	18.25	18.51	10.41
Consumer	11	12	13	14	15	16	17	18	19	20
L_Slot1	5.337121	0.440115	0.457889	0.246358	1.415806	1.513373	0.317015	1.308736	0.371012	1.727309
L_Slot2	3.283778	0.702785	0.901397	0.299718	0.624371	0.839551	0.752308	0.796531	0.696042	0.740969
Inc. Cost	0.003915	0.001935	0.03159	0.03312	0.041535	0.022815	0.0144	0.044505	0.038925	0.00396
Max LR	16.17	18.85	12.1	13.87	17.77	18.2	13.96	15.23	19.77	16.51
Consumer	21	22	23	24	25	26	27	28	29	30
L_Slot1	0.661095	1.546671	1.839065	0.620593	1.323087	1.409691	0.298924	3.100328	2.686266	3.103749
L_Slot2	1.29375	0.91864	0.836161	0.844308	0.753809	0.796786	0.476745	1.34894	1.560843	1.20629
Inc. Cost	0.01134	0.02124	0.002655	0.040725	0.012915	0.043695	0.03402	0.019575	0.02484	0.03069
Max LR	11.95	17.79	15.39	15.77	10.6	14.51	14.14	10.34	16.96	11.37
Consumer	31	32	33	34	35	36	37	38	39	40
L_Slot1	0.159193	4.333808	1.84263	1.361004	0.412966	0.54814	1.775542	0.482412	0.420044	1.915437
L_Slot2	0.310004	1.978383	1.018887	0.961072	0.878071	0.816844	1.329294	0.691331	0.970172	0.903856
Inc. Cost	0.04356	0.01665	0.01926	0.021465	0.0414	0.008145	0.02331	0.009765	0.036	0.003015
Max LR	14.33	15.89	11.25	11.71	17.71	11.42	13.57	13.39	10.41	17.29
Consumer	41	42	43	44	45	46	47	48	49	50
L_Slot1	0.733209	1.447633	1.460167	0.167071	0.581232	0.668325	1.38344	1.604285	0.765001	0.706687
L_Slot2	0.346391	0.524419	0.771547	0.285661	0.345203	0.367051	0.712424	0.967283	0.360698	0.328512
Inc. Cost	0.03519	0.009045	0.030825	0.024345	0.00747	0.006345	0.038025	0.03393	0.034425	0.01791
Max LR	11.18	19.79	17.48	17.05	19.02	10.53	16.25	12.02	10.5	12.37
Consumer	51	52	53	54	55	56	57	58	59	60
L_Slot1	2.818403	1.511272	0.97929	2.09776	2.767694	1.137516	3.181133	0.119366	3.774387	1.017047
L_Slot2	4.075044	0.337045	0.188572	0.491359	3.898033	0.684626	2.530997	0.256077	3.140686	0.656242
Inc. Cost	0.01899	0.026865	0.03879	0.02259	0.011115	0.0441	0.02538	0.01593	0.00162	0.043155
Max LR	11.9	12.92	13.31	15.21	12.54	18.29	10.6	16.23	11.83	16.97
Consumer	61	62	63	64	65	66	67	68	69	70
L_Slot1	3.608028	3.318437	0.35139	1.632349	2.798384	1.357906	0.267643	2.303284	0.240279	0.898095
L_Slot2	2.929005	0.497219	0.749503	0.31111	2.847878	0.734367	0.507179	4.165691	0.583056	0.739441
Inc. Cost	0.009405	0.015615	0.003645	0.034245	0.0072	0.02403	0.018765	0.029835	0.030195	0.01755
Max LR	13.15	11.89	12.25	13.34	14.02	16.11	13.57	19.23	19.05	17.6
Consumer	71	72	73	74	75	76	77	78	79	80
L_Slot1	0.461323	0.902603	3.384934	0.39612	1.902045	2.47113	0.203445	2.063823	2.085045	3.421867
L_Slot2	0.905452	0.97892	4.281038	0.961002	2.784562	3.564453	0.497656	1.28536	1.848625	5.014733
Inc. Cost	0.04122	0.03672	0.01917	0.031995	0.02691	0.00873	0.016965	0.028035	0.025335	0.039645
Max LR	16.79	11.26	18.5	12.15	11.5	13.36	10.79	17.97	16.59	16.26
Consumer	81	82	83	84	85	86	87	88	89	90
L_Slot1	0.129996	2.891657	3.697436	2.3615	0.244758	0.375195	4.178856	0.336468	0.395318	1.03527
L_Slot2	0.333725	1.697533	3.526427	2.797683	0.491905	0.897214	5.056568	0.789321	0.834021	0.89497
Inc. Cost	0.04023	0.022275	0.026865	0.015435	0.01116	0.04311	0.03033	0.019305	0.01098	0.0063
Max LR	11.47	10.13	13.07	10.99	18.73	14.58	18.94	15.29	12.69	15.06
Consumer	91	92	93	94	95	96	97	98	99	100
L_Slot1	1.251191	0.982474	1.027839	0.113358	0.878897	0.991394	1.151233	1.137008	1.245559	1.273519
L_Slot2	2.20259	0.856896	0.761434	0.200849	1.316118	1.601967	0.76383	0.871609	1.733479	1.594001
Inc. Cost	0.039555	0.043335	0.0153	0.02394	0.01521	0.022005	0.018585	0.02808	0.01845	0.043515
Max LR	17.58	15.26	19.9	10.65	17.7	16.17	11.62	14.08	13.11	13.42

The participation levels of consumers in the load reduction program for the first and second time slots are depicted in Figures 1 and 2, respectively. As anticipated, the participation levels of consumers increase with the escalation of the requested load reduction by the operator.

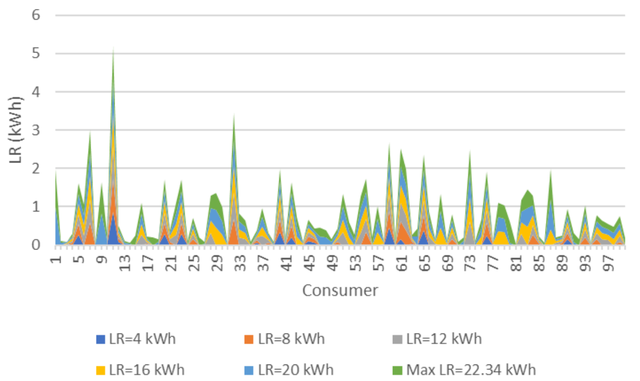

Fig. 1 Participation level of consumers in LR program based on the fixed LR level in time slot 1.

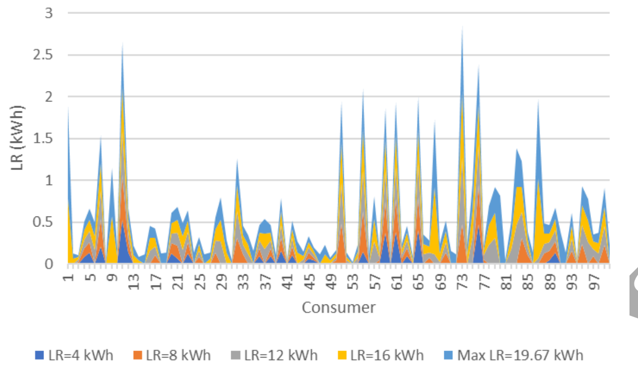

Fig. 2. Participation level of consumers in LR program based on the fixed LR level in time slot 2.

The operator prefers to utilize consumers with lower inconvenience costs to fulfill the required load reduction, aiming to minimize operational cost.

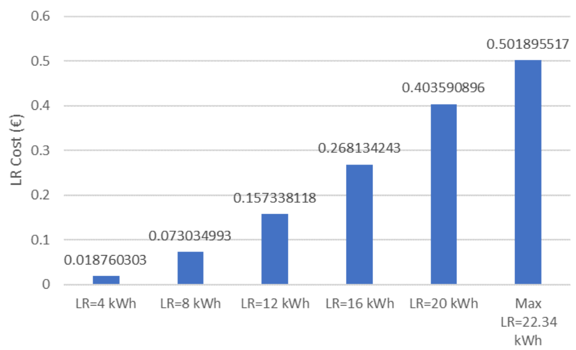

Fig. 3 Cost of load reduction for different requested LR levels in time slot 1.

The total costs of providing different load reduction levels for the first and second time slots are shown in Figures 3 and 4, respectively. Based on the data presented in Table 3, the maximum achievable load reductions in time slots 1 and 2 are 22.34 and 19.67 kWh, resulting in load reduction costs of 0.502 and 0.463 euros, respectively.

It should be noted that the energy prices for periods (1 to 28), (29 to 38, 49 to 74, 85 to 96), and (39 to 48, 75 to 84) are 0.1034, 0.1679, and 0.2314 euros per kWh, respectively. The optimal scheduling of flexible resources for various consumers is depicted in Fig. 5. Load shifting can decrease peak demand and reduce energy costs for flexible consumers by incentivizing them to use electricity during off-peak hours, consequently balancing the grid and optimizing resource allocation. The energy supply cost of flexible consumers is shown in Fig. 6. It should be noted that load shifting decreases the supply cost from 67.76 to 61.85 euros.

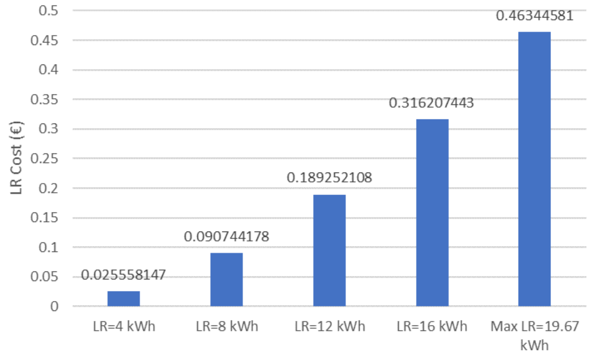

Fig 4 Cost of load reduction for different requested LR levels in time slot 2.

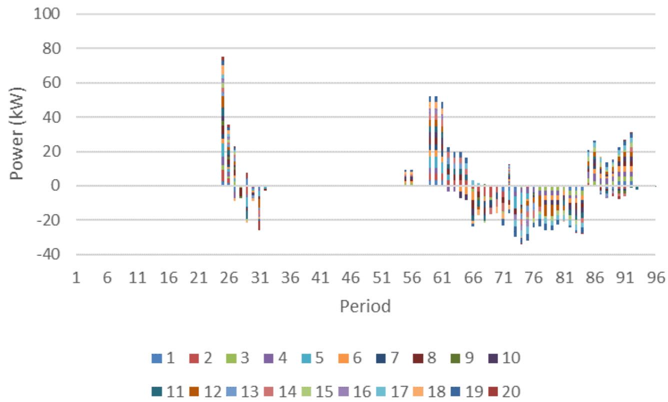

Fig. 5 Optimal scheduling of flexible loads.

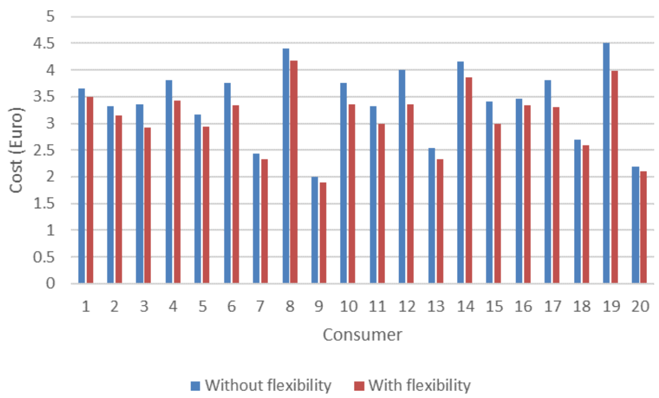

Fig. 6 Impacts of participation in the flexibility service on the energy supply cost of consumers.

4 Conclusion

In this paper, a model is proposed for managing flexible loads in energy communities based on cost minimization. The proposed model enables the system operator to reduce demand peaks by shifting flexible consumption to low-load periods. Moreover, in real-time, the operator could maintain the energy community balance by deploying reducible loads. The presented model is tested on a community containing 100 reducible loads and 20 flexible loads. According to the simulation results, the operator prefers to utilize consumers with lower inconvenience costs to fulfil the required load reduction, aiming to minimize operational costs. Furthermore, using consumption flexibility decreases the supply cost from 67.76 to 61.85 euros.

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