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Review

Optimal Scheduling of Controllable Resources in Energy Communities: An Overview of the Optimization Approaches

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Abstract: In recent years, there has been a growing interest in the study of energy communities. This new definition refers to a community sharing energy resources of different types to meet its needs and reduce the associated costs. Optimization is one of the most widely used techniques for scheduling the operation of an energy community. In this study, we extensively reviewed the mathematical models used depending on the objectives and constraints considered. The models were also classified according to whether they address uncertainty and the inclusion of flexibility constraints. The main contribution of this study is the analysis of the most recent research on the mathematical formulation of optimization models for optimal scheduling of resources in energy communities. The results show that the most commonly used objectives are profit maximization and cost minimization. Additionally, in almost all cases, photovoltaic generation is one of the main energy sources. Electricity prices, renewable generation, and energy demand are sources of uncertainty that have been modeled using stochastic and robust optimization. Flexibility services using demand response are often modeled using interruptible loads and shiftable loads. There is still considerable room for further research on the distribution of benefits among the participants of the energy community and the provision of flexibility services to the electricity grid.

Keywords: energy communities; optimization techniques; optimal scheduling

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1. Introduction

The energy community (EC) is a topic of recent application and is popular in different regions of the world, making it an open field of research. The Clean Energy for All Europeans package has introduced two new concepts related to the field of ECs: the citizen energy community (CEC) and the renewable energy community (REC). Both are similar in terms of objectives: to provide a community with environmental, economic, and social benefits. The main difference between them is that a CEC is a concept restricted to the use of electricity, including that generated with renewable energy, and its geographical extension is not precisely defined. However, RECs are limited in extent to relatively small regions.

ECs promote local energy exchange among their participants. They help the system transition to the generation of renewable energy, reducing reliance on fossil fuels and minimizing grid-supplied electricity use. An important social consequence is that they help alleviate energy poverty [1]. ECs also bring benefits to the distribution system operator (DSO) due to the service flexibility they can offer, such as reducing peak demand through the participation in demand response programs (DRPs) [2].

To optimize the resources of an EC, a mathematical problem is formulated and solved through one or several optimization techniques. The objective of this problem can be the minimization of a cost or the maximization of a benefit while complying with a set of constraints. This article presents an overview of the optimization approaches that are used to program the resources of ECs. The optimization model may vary depending on the resources and configuration of the community, the regulatory framework, or the objectives of stakeholders [3,4]. Some researchers have proposed methodologies to optimize a local energy community (LEC) by taking the size of BESS and PV systems as decision variables [5]. Many ECs integrate thermal storage systems and thermal production. In addition, there is still much work to perform in terms of the regulation of thermal production in LECs; some studies addressed the operation of the thermal energy community [6]. There are important challenges and aspects to take into account when modeling an EC: especially relevant is human behavior. The stochastic nature of this factor must be included in the model of an EC [7]. Two of the indicators often mentioned in this type of studies are the self-sufficiency rate (SSR) and self-consumptions rate (SCR). The former refers to the ratio of load demand that is not powered by the grid; the latter refers to the ratio of the local generation that is used to supply the local load demand.

The remainder of the paper is organized as follows: Section 2 presents a general formulation to optimize the resources of an LEC. Section 3 describes the methodology we used to analyze the literature. Section 4 presents a generalization of the objective function of LECs, the most common constraint models found in the literature, and the different optimization techniques used to solve these models. Section 5 summarizes how uncertainty has been introduced in ECs, and Section 6 details the flexibility and ancillary services that have been evaluated in different studies. Finally, Section 7 outlines the main conclusions of this study, the main contributions of which are the presentation of an updated review of (a) the optimization techniques used for scheduling energy community resources, (b) the most common constraints that are considered in the models, and (c) the flexibility and ancillary services offered to the DSO and the transmission system operator (TSO).

2. General Approach

In this section, a general approach is presented that takes into account the different formulations found in the literature. Minimizing total operating cost is the objective function (1), and maximizing profits is another common goal of LECs. In this case, the price of the energy sold and purchased to the grid p_t^{exp}, p_t^{imp} is considered.

The consumption and injection of BESS pc_t^{ba}, pd_t^{ba} and the generation of dispatchable units gt_t^{te} and PV generation, gp_t^{pv}, interruptible load pi_t^{id}, and noninterruptible load pn_t^{ni} are considered the resources to be optimized.

- The objective function is the minimization of the operating cost:

$$OC = \sum_{t\in T}\sum_{te\in TE} co^{te}\cdot gt_t^{te} + \sum_{t\in T}(mp_t^{imp}\cdot p_t^{imp}) - \sum_{t\in T}(me_t^{exp}\cdot p_t^{exp}) + \sum_{t\in T}\sum_{id\in ID}(cr^{id}\cdot Pi_t^{id}). \quad (1)$$

The most common constraints found in the literature are the following:

- Energy balance constraint: In (2), the total energy generated must be equal to the total energy demand plus the power exported to the grid, taking into account the load shedding in the EC.

$$\sum_{pv\in PV} gp_t^{pv} + \sum_{ba\in BA}(pd_t^{ba} - pc_t^{ba}) + \sum_{te\in TE} gt_t^{te} + mp_t^{imp} - me_t^{exp} = \sum_{ni\in NI} pn_t^{ni} + \sum_{id\in ID}(pe^{id} - pi_t^{id}), \quad \forall\, t. \quad (2)$$

- BESS constraints: Constraint (3) presents the evolution of the state of charge of the BESS in each period considering the discharge and charge power of the battery and their respective efficiencies. Constraint (4) ensures that the state of charge of the BESS does not exceed the minimum and maximum limits of the battery parameters. Constraints (5) and (6) model the power limits of the battery charge and discharge, respectively. The battery does not simultaneously charge and discharge, so the binary variable edb_t^{ba} is introduced. The constraint (7) forces the final state of charge of the battery to be equal to the initial state of charge of the battery for better cyclic evolution of the battery. With this equation, the total energy consumed by the battery in the study horizon is equal to the total energy injected into the grid, considering the charge and discharge efficiencies.

$$soc^{ba,t} = soc_{t=1}^{ini,ba} + soc_{t-1}^{ba} + \eta c \cdot pc_t^{ba} \Delta t - \frac{pd_t^{ba}}{\eta d} \Delta t, \quad \forall\, ba, \forall\, t, \tag{3}$$

$$soc_{ba}^{min} \leq soc_t^{ba} \leq soc_{ba}^{max}, \quad \forall\, ba, \forall\, t, \tag{4}$$

$$pd_{ba}^{min} \cdot edb_t^{ba} \leq pd_t^{ba} \leq pd_{ba}^{max} \cdot edb_t^{ba}, \quad \forall\, ba, \forall\, t, \tag{5}$$

$$pc_{ba}^{min} \cdot (1 - edb_t^{ba}) \leq pc_t^{ba} \leq pc_{ba}^{max} \cdot (1 - edb_t^{ba}), \quad \forall\, ba, \forall\, t, \tag{6}$$

$$soc_{ba}^{ini} = soc_{t24}^{ba}, \quad \forall\, ba. \tag{7}$$

- Dispatchable generation: Constraint (8) presents the minimum and maximum limits corresponding to the generators that can be dispatched according to their on or off state defined by the binary variable u_t^{te}.

$$p_{te}^{min} \cdot u_t^{te} \leq gt_t^{te} \leq p_{te}^{max} \cdot u_t^{te}, \quad \forall\, te, \forall\, t. \tag{8}$$

- PV generator: Constraint (9) presents the PV generation availability used in the model.

$$0 \leq gp_t^{pv} \leq pa_t^{pv}, \quad \forall\, pv, \forall\, t. \tag{9}$$

- Energy purchased or sold: Constraints (10) and (11) model the limits of buying and selling energy in each period, respectively. In this case, simultaneously buying and selling energy is not allowed.

$$0 \leq mp_t^{imp} \leq mp^{max} \cdot (1 - bs^t), \quad \forall\, t. \tag{10}$$

$$0 \leq mp_t^{exp} \leq me^{max} \cdot (bs^t), \quad \forall\, t. \tag{11}$$

- Interruptible load: Constraint (12) limits the value of the load-shedding variable to the value set by pe^{id}

$$pi_t^{id} \leq pe^{id}, \quad \forall\, t. \tag{12}$$

3. Methodology

The review of the investigations presented in this paper highlights the different optimization techniques used to program the resources of ECs. This review focused on research papers published between 2012 and 2022. The other selection criterion was that the optimization technique corresponded to classical methods to analyze the approaches in detail. Web of Science was used to search for most of the research articles, as in [8]. Energy communities, optimization, and scheduling were some of the keywords used in the investigation. This review focused on the optimal daily scheduling of the resources of an EC. The study of equipment size or analysis of long-term profitability was not within the scope of this study.

We considered the scheduling studies of RECs and CECs. As this is a relatively recent research topic, among the articles found that belonged to the scope defined in this article, the oldest was from 2017, and the newest were from 2022.

This study emphasizes the operation of LECs and the optimization of their resources; several optimization techniques have been proposed to achieve the objective set by the communities, and the techniques found in this review are presented in Section 4. Most primary sources of generation in the EC are renewable; therefore, variability is their natural characteristic. To optimize the use of these resources, it is necessary to introduce uncertainty into the formulation of the optimization model. Section 5 explains how randomness has been analyzed, mainly for energy consumption and renewable generation. ECs can also offer flexibility services to the system, to the DSO, or to the TSO, as presented in Section 6.

4. Optimization Models

The objective functions of ECs depend on many factors: the resources of the community and their capacities, regulations, and the principal objectives of the participants. The minimization of operating cost and gas emissions, maximization of profits, social welfare, SCR, and SSR are some of the objectives in many studies. To this end, various optimization techniques have been applied to solve the problem, including the constraints.

4.1. Operation Constraints in Energy Communities

Limitations in the capacity of equipment belonging to the EC; operating restrictions related to reserves, conventional generator devices, electrical, and thermal storage systems; availability of renewable resources such as wind and solar; and network constraints are some of the constraints found in the literature, as shown in Table 1.

Regarding network constraints, the maximum power of interchange between the EC and the grid at the point of common coupling (PCC) was considered [9], and a maximum power limitation in the transformer that connects the community to the grid was presented [10]. The low-voltage constraints of an LEC connected to the distribution network was described in [11].

Table 1. Common constraints.

Ref.	Operation Constraints	Grid Constraints	Gas Emissions	Renewable Energy	Storage
[12,13]	-	-	-	-	Yes
[10,14–18]	Yes	-	-	-	Yes
[19]	-	-	Yes	-	Yes
[20–22]	Yes	-	-	-	Yes
[23]	Yes	-	Yes	Yes	Yes
[24]	Yes	Yes	-	-	Yes
[25–27]	Yes	-	-	-	-
[28–31]	Yes	-	-	-	Yes
[32]	Yes	-	Yes	Yes	Yes
[33]	Yes	-	-	Yes	-
[9]	Yes	Yes	-	Yes	Yes
[11]	Yes	Yes	-	-	Yes
[34]	Yes	-	-	-	-

4.2. Optimization Techniques

The studies in the literature that addressed the problem of resource scheduling have used different optimization approaches. Most of them used mixed-integer linear programming (MILP). In this section, a summary description of each optimization technique presented in the literature used for the daily scheduling of LEC resources is outlined.

Table 2 presents a summary of the different optimization techniques found in the literature used to program the resources of the EC.

Table 2. Optimization techniques used to program EC resources.

Optimization Technique	Reference
Linear Programming	[13,27,28,34]
Mixed-integer linear programming (MILP)	[9–12,14,16,18–25,29,32,33,35–38]
Nonlinear programming (NLP)	[15]

4.2.1. Linear Programming (LP)

In this programming, the variables and constraints are linear. In addition, the variables are continuous. The computational cost of a linear programming problem depends on the number of constraints and the number of variables. This type of programming problem does not have local minimum multiples. LP is often the least difficult to solve; another of its characteristics is simplicity. The decision variable should be non-negative and includes a single objective [39,40].

Ref. [13] evaluated the maximization of the social welfare of an LEC with peer-to-peer trading, where the price of willingness to pay was calculated for each user and referred to a price that each participant of the LEC was willing to pay apart from the electricity price of the grid to contribute to the reduction in the marginal emissions from the grid It also expresses the inclination of a user to buy local PV energy. The case study was an LEC with households and medium/small companies. The resource community consisted of prosumers with PV generation, consumers, and BESS. The parameters were from the city of Vienna, Austria. The total study horizon was one year. Linear programming was used in the optimization model. Ref. [27] focused on determining the trustworthiness rate (TR) of consumers who provide DR in an LEC. These indicators were calculated taking into consideration the historical rate (HR) of the behavior of the consumer at a moment to answer a request in real time for the reduction in energy; the DR, the last-day rate (LDR), and the cut rate (CR) are part of the terms for the calculation of the TR. The importance of the TR is that, according to this value, a consumer is selected to participate in the DR to reduce the energy according to the requirement; this is the novelty of this study. The horizon of the study was one day. Ref. [28] assessed the optimization of an REC comprising buildings and electric vehicles (EVs), and the management between the building and the EV as flexible resources, taking into account the Portuguese legislation. The model was implemented in PYTHON, using GUROBI optimizer [41,42]. Ref. [34] addressed the optimization of a large EC with the objective of minimizing operating costs. A day-ahead and real-time optimization was carried out. The day-ahead model determined the flexibility service to offer to the TSO. A parallelizable LP was developed. This model regards the exchange of energy within the EC and between the EC and the grid.

4.2.2. Mixed-Integer Linear Programming (MILP)

In MILP, the objective function and constraints are linear, and the decision variables are continuous, integers, and scalar. The most commonly used solution method for solving integer programming (IP) and MILP problems is the branch-and-bound method. The integer variables allow modeling nonlinear behavior approximations, so that it is not necessary to make use of a nonlinear model that is more complex to solve. Additionally, integer variables make an optimization problem nonconvex and therefore far more difficult to solve [39**?**].

MILP optimization techniques have been widely used for the management of EC resources. Authors [12] maximized the revenue of an REC, optimizing the scheduling of a BESS using an MILP formulation. Day-ahead forecasting with a time window of 24 h and a real-time prediction with an intrahour level with a 1 min time step were conducted. In real time, the set point of the BESS is updated through a decision tree algorithm. The principal problem here is scheduling the BESS of an REC. The objective is to maximize REC revenue. This revenue is obtained from the difference between the levelized cost of storage (LCOS) of the BESS and the income of selling the PV net surplus to the grid, and the incentives related to the energy exchanges with the REC. Ref. [35] assessed the minimization of the operating cost of an LEC that incorporated interruptible and noninterruptible loads, a PV plant, and a BESS. Stochastic and robust optimization were used to program the resources, taking into account the uncertainty in demand load, electricity prices, and PV generation. The K-means method was used to obtain the profiles of uncertainty-sensitive resources. Optimal scheduling was performed for a day ahead for an hour of time step. The objective function of the LEC included the cost of the energy purchased from the grid, the cost of the interruptible loads, and the revenue from the sales of energy. The model was formulated as a mixed-Integer programming (MIP) problem in GAMS, using CPLEX as the solver [44,45].

Authors [14] proposed minimizing the operating cost of an LEC that involves P2P transactions, and the prosumers have PV generation and a BESS. Four scenarios were analyzed and compared, and the best option was the one that included the P2P transaction and the batteries together. The time window was 15 min, for 96 periods in one day of operation. The objective was to minimize the operating cost and energy bill of the prosumers. The objective function was to minimize the operating cost of the LEC. The cost of the energy purchased from the grid and the revenue for the energy sold to the grid were included. The model was implemented in MATLAB using TOMLAB as the optimization platform and the CPLEX solver [45,46].

Researchers [16] studied the optimization of the resources of an LEC that involved buildings with their own building energy management system (BEMS) and community energy storage (CES). Buildings have flexible loads, such as the HVAC. In this study, the flexibility services with a flexible load and the CES were also addressed. Three distinctly different building archetypes were considered: residential houses, offices, and healthcare facilities. The optimization was carried out in two stages using model predictive control (MPC)-based hierarchy. The objective function of the first stage was to minimize the operating cost of each building; in this stage, the BEMS was the one in charge of the optimization. In the second stage, the objective function was to maximize the SSR and SCR of the LEC. The CES was used for this aim. The simulations were performed for one week, with a time step of 15 min, and a prediction horizon of 96 time steps (24 h). This problem was formulated as MILP. The model was implemented in MATLAB using the YALMIP toolbox and the CPLEX solver with an optimal gap of 10^{-4} [45,47,48].

In [36], the authors addressed the optimization of a polygeneration system of buildings that could act as an EC and/or microgrids in Zaragoza, Spain. The daily profile of different energy demands was considered: electrical loads, cooling and heating, and different sources of generation were used. The objective function was to minimize the total annual cost, calculated as the sum of the investment and the operational cost. The formulation took the form of an MILP problem, and the horizon was 24 h with a time step of one hour. The model was implemented in Lingo Optimizer software [49].

Ref. [19] evaluated the impact of indirect flexibility that depended on human behavior modeled a the battery of EVs and direct flexibility devices such as stationary energy batteries on the energy performance of buildings and ECs. The optimization had a horizon of 24 h and a time step of 1 h. The case study was the Predis-MHI platform, which is a living laboratory for teaching and investigation activities in the Presqu'île district of Grenoble in France. In this study, two objective functions (maximize self-consumption and minimize CO2 emissions) were evaluated using six different scenarios. Authors [20] maximized the benefits of the operation of an EC built on a university campus in Romania. This university campus comprised administrative buildings, accommodation facilities, and lecture rooms powered by renewable energy (PV and wind turbines), and diesel generators. It had a BESS and was connected to the main grid. The optimization horizon was one year. Power quality measurements were considered. The objective of the analysis of this EC was to minimize the net present costs and maximize the benefit of the EC using a stochastic optimization model. The formulation of the problem was MILP. Ref. [21] assessed a pool trading model in an LEC that considered different home energy management systems (HEMSs) and different consumers. A price-based demand response program (PBDRP) was taken into account. This study included fixed, interruptible, and shiftable loads. The HVAC system was modeled as a controllable load, and the discomfort of the shiftable load was modeled. The objective function included the cost of the LEC transaction with the main grid, the cost of the transaction in the LEC, and the cost of the controllable appliances of the home. The optimization problem model was centralized. In this study, the optimization constraints were divided into two groups: HEMS scheduling and the transaction between the LEC and the main grid. The 24 h schedule was obtained for a 30 min time interval. Ref. [22] evaluated the reduction in peak overload in an LEC that was a university campus in Amsterdam, The Netherlands. The preheating and postcooling with heating pump were optimized to reduce the overloading; also, controlled loads were used as flexibility services. The case study evaluated the behavior of the LEC in winter and summer with a daily study horizon. A fully connected neural network is in charge of the prediction of PV generation and operation of the heating pump and controlled and noncontrolled loads. The time step of these profiles is one hour. The objective function was to minimize the procurement of flexible services. The model was implemented in PYTHON and MATLAB/SIMULINK [41,48]. Ref. [23] evaluated the optimal scheduling of an LEC that embodied various distributed energy systems (DESs), with the objective of minimizing the total expected net energy and CO_2 emission cost. Four study cases were analyzed, where the DESs operated with and without sharing thermal energy and electricity between them, and the grid-connected and island modes were estimated. The four DESs were an office building, a strip mall, a supermarket, and a midrise apartment. The problem was formulated as deterministic and stochastic using a Markovian process with the transition matrix. The results were evaluated using a summer and a winter day. The formulation was an MILP problem and was resolved using branch-and-cut and using the CPLEX solver [45].

Authors [24] determined the optimal minimum operating cost of an EC with the objective of minimizing the energy cost of the entire EC considering the energy cost and the revenues of the participants. The authors considered the Internet of things (IoT) devices necessary to achieve the aim. Each prosumer had a nanogrid system to manage the exchange of energy with the distribution system, the local generation, the management of the storage system, and the home automation system that controlled the connected and disconnected load. Both systems were controlled by a smart energy aware gateway (SEAG), which was the IoT system. It interacted with the local smart meter and shared information with the aggregator and a service provider. The authors also considered that energy was shared among the prosumers and between them and the grid. The time step in this approach was 1 h. The results were obtained using a study case of the University of Calabria Campus in Italy. The formulation was solved as in [23].

Ref. [37] analyzed a smart EC that involved prosumers with renewable generation as PV production and consumers, with the objective of maximizing social welfare. A comparison was made between a centralized and two decentralized approaches. Peer-to-peer (P2P) trading between stakeholders (consumers and prosumers) was carried out. The objective function was the maximization of social welfare. Another study related to the trade of P2P is [10]; the researchers addressed the optimization of the resources of an LEC. In this case, first, each participant optimized their own resources using Lagrange multipliers, and then the results of this optimization were sent to an aggregator. This optimized the operating cost at the community level. ADMM method is used to solve this problem. The objective function of each participant and the community is formulated with Lagrange multipliers. The objective at the community level was to minimize the operating cost; this cost took into account the energy traded with the grid. The objective function for each participant included the cost of the generation, the energy exchanged with the grid, the discharge and charge energy from ESS, and the net load. The formulation was an MIP problem. The problem was formulated in MATLAB [48]. Ref. [32] addressed the optimal operation of an EC that composed of different DESs. The objective was to minimize the total operating cost by taking into account different case studies. As data for the different studies, an EC in the United States was used, which comprised different DESs, such as residential and commercial buildings. The objective was to minimize the operating cost of the EC, taking into account the cost of buying natural gas from the gas station, the cost of purchasing energy from the grid, and the revenues from selling energy to the grid. Ref. [29] assessed the optimization of a multi-nergy district/community with different resources. The objective function was to minimize the operating cost, capacity price, energy import cost, and energy sales revenue, obtaining at the same time a PV generation incentive. The economic analysis was annual, and the operating schedule was for each hour of the day. Ref. [33] minimized the operating cost of an LEC community using a two-stage stochastic MILP. The LEC involved residential load, flexible residential load, and rooftop PV generation. The flexible loads were divided between loads that could be reduced and loads that could be increased, and the periods where these loads could increase or decrease were pre-established. The objective function included the cost of the energy purchased from the grid, the cost of PV energy injected into the grid, the cost of the PV energy sold to the LEC, the cost of the flexible loads that could be reduced, and the cost of the flexible loads that could be increased. The objective function prioritized local consumption, and the study case evaluated the scheduling of 24 h of operation with a time resolution of 15 min. Ref. [9] analyzed the optimization of an HEMS from the point of view of the aggregator. The resources were from an EC that was connected to the main distribution grid. The EC had solar panels, thermal and electrical loads, and a BESS; and the thermal energy storage was electric water heaters (EWHs). The model was a robust optimization, and the formulation took the form of an MILP. In this study, flexible bids were offered to the local market operator (LMO). The uncertainties in energy prices, PV generation, and electrical and thermal loads were modeled through robust optimization. The objective function included the cost of the energy purchased from the grid, the cost of energy imbalances (positive and negative imbalances), the cycling cost of the batteries, and the cost of battery degradation. In addition, the deviation in the electricity prices (positive and negative) was included.

In [11] centralized and decentralized optimization approaches were evaluated. The objective function of the centralized problem was the minimization of the operating cost of the LEC (the energy sold and bought to the grid). The objective function of the decentralized problem was obtained by decomposition of the Lagrangian. Both centralized and decentralized problems were compounded in two stages. An MILP solver was used for the centralized model, and a mixed-integer quadratic programming (MIQP) solver was used for the alternating direction method of multipliers (ADMM) model. All the calculations referred to a time window of 1 day, divided into 96 periods of 15 min each. Ref. [25] addressed the optimization of an EC that comprised a wastewater treatment plant, a hotel complex that included restaurants, and the energy demand of administrative buildings in the southeast of Romania, near the sea. As a local source of electricity generation, the biogas that was obtained from the treatment water of a wastewater treatment plant (WWTP) was used as the fuel for a combustion engine (50 kW) and a PV plant (100 kWp). The objective was to minimize the operating cost of electrical energy to obtaining more local generation than consumed locally, thereby achieving a positive-energy community. The quadratic function of the biogas engine, the cost of start up and shut down, and the cost of energy exchange with the grid were considered. The price of power exchange was the same for the import and export of energy to the grid. Power exchange is considered positive when the power direction is toward the grid, and negative when energy is imported from the grid. The authors only considered an electrical energy balance; the thermal balance was not considered in this study. The model was formulated with a horizon study of 24 h of operation, taking a summer day with high tourist influx as a scenario. Two study cases were evaluated: the power exchange was set to be very close to zero, and the objective function was set to zero. Ref. [18] dealt with the scheduling of a cooperative EC. The approach consisted of two stages: in the first stage, the exchange of energy between the consumers was addressed; in the second stage, the minimization of the energy exchange between the community and the grid was assessed. The stochastic, pessimistic, and optimistic cases of the study were evaluated. All simulations were performed over a 24 h time horizon with a resolution of 30 min. This model was implemented in MATLAB using GUROBI as solver [42,48].

In [38], the willingness of consumers to change their behavior was modeled using a stochastic approach. There was a community manager in charge of making recommendations to consumers to change their consumption patterns. The objective was to match the PV generation with the demand load.

4.2.3. Nonlinear Programming (NLP)

In this type, the objective function and/or constraints are nonlinear. The variables are continuous. These problems can have several local optimal. For solving nonlinear problems, the generalized reduced gradient (GRG) and the quadratic programming (SQP) methods are used. The computational algorithms for NLP are typically iterative in nature. Another characteristic of nonlinear programs is that they can be very hard to solve, there is no guaranteed method of finding a feasible point if the problem embodies nonlinear constraints, and the solution is a local optimum point [39,40].

Researchers [15] presented a short-term memory neural network to forecast the load and distributed generation profiles. It utilizes an elastic net approach to optimally apply a set of feasible distributed resources and demand-side management programs. The optimization technique was a nonlinear constrained optimization that was solved using sequential quadratic programming (SQP) method. The daily operation was programmed on a 15 min basis.

5. Uncertainty Management

Given that renewable generation is one of the main resources in ECs, and variability is its main characteristic, many researchers have evaluated different solutions to address the uncertainty of renewables, including the variability in the load demand.

5.1. Stochastic Optimization

Here, the objective function and/or constraints contain uncertainty. The optimal decision is taken under uncertainty; the formulation can be "wait and see", "here and now", and "chance-constrained optimization". With stochastic programming, the parameters subject to uncertainty or possible errors in their measurement or estimation and whose probability distribution is known can be treated as random variables. Probabilistic measures are necessary, and, on occasion, it is necessary the use a decomposition method to solve the stochastic problem, for example, in a stochastic problem with resources. The probability of occurrence is necessary for modeling different scenarios [39,50].

Ref. [23] designed a stochastic optimization using the Markovian process with a transition matrix to manage the uncertainty. The results showed that by using the stochastic approach, the expected net energy cost was more economical than using the deterministic one. In terms of the computation cost, the deterministic approach required less time than the stochastic approach.

In [37], the authors concluded that with regard to the performance of the model with the stochastic formulation, the matching between the producer and the consumer with similar characteristics was the key to maximizing social welfare in P2P transactions. The renewable generation and load were forecast, and the error of this forecast was considered to model the uncertainty of these parameters using the Laplace distribution. Authors [30] proposed a stochastic MPC that allowed for obtaining more benefits in terms of minimizing operating costs and maximizing self-consumption compared with the deterministic MPC.

In [17], a two-stochastic formulation was used, where the dispatchable generator was a first-stage decision; the EV, ESS, and the cost of the interruptible, shiftable, and reducible loads and the grid imbalances were second-stage variables. Uncertain resources were renewable generators, load profiles, and market prices. A large number of scenarios were generated by Monte Carlo simulation (MCS). The model was performed using TOMLAB in MATLAB [46,48].

5.2. Robust Optimization

The objective function and/or constraints may require uncertainty management. The formulation of an uncertainty set is necessary to characterize the possible outputs of parameters with uncertainty. This set is usually represented through elliptic sets, budgeted uncertainty sets, and box-constrained sets. It is not necessary to use probability functions such as stochastic optimization. A worst-case optimal solution for the parameters with uncertainty is sought. In stochastic optimization, the number of scenarios needed to describe the possible outputs of the scenarios with uncertainty is often very large, which may prove to be more difficult to solve computationally. The number of scenarios does not appear in robust optimization. A larger uncertainty set can lead to very conservative or safe results; but, as consequence, the cost can be very high [50,51].

Ref. [9] formulated a robust optimization in which the uncertainty-prone resources were energy prices, PV production, and electrical and thermal load. The conclusion was that the robust approach allowed minimizing the total operating cost while considering the uncertainty in these factors.

In [35], the uncertainties in demand load, PV generation, and electricity prices were modeled using robust and stochastic optimization. With regard to the robust optimization, in this LEC, the worst-case scenario was considered as an increase in the electricity prices and demand load, and a reduction in the PV generation. The results showed that, using robust optimization to be protected for the worst-case scenario, a higher operating cost was achieved. With a stochastic formulation, effective and economic planning was obtained.

6. Ancillary Services

Many researchers have addressed ECs that offer flexible services to the DSO. This flexibility may be the main objective or one of several objectives, depending on the resources available for the EC. In [15], the authors considered the participation in the DRP, using shiftable and interruptible loads [21]. In future work, they will consider the selection of the demand response program to be an optimization decision, where the solution of the problem selects the most appropriate DRP or the most effective strategy for participating. They propose the use of evolutionary algorithms to achieve this aim.

In [16], the authors, through a mechanism, quantified the flexibility services that the LEC should offer to the grid. One of the contributions was a real-time framework for the flexible services implemented for quantifying the available flexibility capacity, and the distribution of the revenues for the flexible services with CES capacity sharing between the LEC. This was achieved in congruence with the initial investment of the users. To provide this service, load flexibility was used: in this case, HVAC and CES.

In [19], indirect flexibility devices (electric vehicle battery), as in [28], and direct flexibility services (stationary BESS) were addressed. The study contributed to the evaluation of the impact of indirect flexibility on the self-consumption of office buildings and a method to introduce indirect flexibility into the energy management system of a building. Two of the conclusions were that indirect flexibility can increase the self-consumption of the building and that direct flexibility can compensate for the behavior of human actions.

Heating pumps and controlled load were used to reduce the peak overload in [22]. Two of the contributions are that this study optimized the flexibility resources to avoid overloads and modeled the continuous control of flexible devices (heating pump and controlled loads) instead of using the discrete control on/off.

In [26], the challenge was to select the flexible bill that allowed for flexible users and maximized self-consumption. Consumers that provided flexibility to downward and upward energy were used for the DRP. Regarding the results, different case studies were considered: no REC was established (base case), REC was established without flexibility, and REC was established with flexibility. The results showed that the SCR increased by 5.01% when the flexibility in the REC was considered; the same occurred with the SSR, which increased by 2.92%. Thus, it was shown that flexibility impacts the SCR and the SSR. In [27], consumers who reduced their energy according to the DRP target were evaluated. In this study, a trustworthiness rate was determined. According to this value, a consumer is either selected or not to participate in the DRP to reduce energy according to the requirement.

In [31], ancillary services (the participation of the LEC providing the manual frequency restoration reserve (mFRR) or tertiary reserves) were evaluated. The BESS was used to provide flexible services. The results showed that the selection of the BESS parameters in the day-ahead schedule impacted the real-time profitability of the LEC. Additionally, another result was that the participation of the LEC providing mFRR caused an increase in profits. [33] used flexible residential loads; there was a cost to the load that could be decreased and another price to the load that could be increased. This study concluded that flexible loads facilitate the integration of renewable generation into the LEC.

In [9], the DSO procured flexibility services in a local flexibility market. The LMO called for flexibility bids, the aggregator prepared and offered bid services to the LMO, and the LMO informed the aggregator if their bid has been accepted or not. This study contributed a proposal of a local flexibility management strategy that is composed of two products: flexibility bids on the local market, and local constraint support for the DSO in the form of maximum allowed net power and net ramping rate. An adjusted robust optimization was used to model the uncertainty in energy prices, PV production, electrical demand, and thermal consumption. The revenue from the flexibility depended on the level of robustness. In addition, there was a trade-off between the level of robustness and the possibility of being accepted.

In [17], the microgrid/EC participated in DRP. The flexibility in the loads was modeled as direct load control programs, in which consumers voluntarily participated and received monetary compensation if their loads were reduced, disconnected, or shifted.

Table 3 summarizes the ancillary and flexibility services included in the EC operation programs.

Table 3. Ancillary services.

Ref.	Resources	Ancillary Services
[15]	BESS, electric vehicle	DRP: shiftable load, curtailment load
[16]	Shiftable appliances, CES, photovoltaic (PV) panels, HVAC	Load flexibility (HVAC) and CES capacity sharing between LEC and grid aggregator
[19]	Stationary battery, battery electric vehicle, PV modules	Indirect flexibility devices (battery of electric vehicle) and direct flexibility services (stationary battery energy storage system)
[21]	Electric vehicles, Home appliances, PV panel, HVAC	DRP: Interruptible loads and shiftable load
[22]	Photovoltaic generation, heat pump, cooling loads	Reduce peak overloading: heating pumps and controlled load
[26]	PV generation, flexible loads, nonflexible load	Demand response: Flexibility in downward and upward energy
[27]	DG (distribution generator: small hydro, wind, photovoltaic, biomass, fuel cell, cogeneration) and DR consumers and different scale of consumers	DRP: Consumers that reduce their energy according to DR target
[28]	Electric vehicle, PV system	Flexibility using electric vehicles
[35]	Interruptible loads, noninterruptible loads, photovoltaic plant, BESS	Flexible loads: Interruptible load
[30]	Noncontrollable (NCL), controllable loads (CLs), renewable energy sources (RESs), CES	Flexible loads: There is no revenue from flexibility
[31]	BESS, EV, Photovoltaic system	Manual frequency restoration reserve (mFRR) or tertiary reserves: BESS is used to provide flexible services
[33]	Rooftop PV, residential demand, flexible residential loads	Increase and reduction in flexible loads
[9]	PV system (solar panels), BESS, and thermal energy storages: EWH	Flexibility bids to the LMO
[17]	ESS, EV, distpachable generators (DGs), inflexible loads, interruptible loads, reducible loads, shiftable loads	DRP: direct load control programs, voluntary, monetary compensation

7. Future Works and Conclusions

The main contribution of this study are the analysis of the latest research on the mathematical formulation of optimization models for optimal resource scheduling in ECs. Different researchers have modeled the optimization of the resources that belong to different ECs. Several objective functions have been proposed, such as maximizing profits, and minimizing the total operating cost of the community. Self-sufficiency and self-consumption have been used as part of the objective and as indicators of the optimal use of internal resources. Flexibility services have been shown to help increase both indices.

In the reviewed literature, the aim of EC resource scheduling was primarily minimizing operating costs. In addition, the peer-to-peer model has been considered for energy trading among participants.

The most common resources that have been used are PV panels, BESS, EVs, TESs, and HVAC. New resources, equipment, and hybrid systems can be taken into account in future work.

Several researchers have considered uncertainty management in their optimization models. Market prices, renewable energy, and demand load are the resources with uncertainty that were most frequently encountered in the literature. Stochastic optimization using Markovian processes and exponential distributions have been used for uncertainty treatment. Robust optimization has also been used for uncertainty handling; in this case, uncertainty sets have been defined to schedule resources for the worst-case scenario.

Most of the research related to flexibility using DRP has used flexible loads in the form of interruptible loads or shiftable loads. These resources have been predetermined with a capacity depending on their availability and the willingness of the participants. Only a few investigations have included the flexibility service as a variable in the optimization problem, with the aim of obtaining the optimal package of flexibility to include in resource scheduling. Human behavior generates an impact on the operation of ECs; some researchers modeled this factor using stochastic methods. Few researchers haved considered network constraints; some of them simply considered the maximum capacity at the PCC.

Software such as MATLAB and PYTHON have been very present in the development of many optimization approaches.

The distribution of benefits among participants in EC is an issue that needs to be addressed in future studies. The flexibility services that an EC can provide to the system are an open question in the field; provided that most of the present studies refer to participation in DRP, ancillary services such as manual frequency control and downward and upward reserves should be considered.

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Abbreviations, Variables and Parameters

The following abbreviations, variables and parameters are used in this manuscript:

Abbreviations

EC	Energy Community
CEC	Citizen Energy Community
REC	Renewable Energy Community
LEC	Local Energy Community
LMO	Local Market Operator
HEMS	Home Energy Management System
BEMS	Building Energy Management System
CES	Community Energy Storage
ESS	Energy Storage System
BESS	Battery Energy Storage System

EWH	Electric Water Heater
PV	Photovoltaic
TES	Thermal Energy Storage
HVAC	Heating Ventilation and Air Conditioning
EV	Electric Vehicle
WWTP	Wastewater Treatment Plant
MILP	Mixed-Integer Linear Programming
MIQP	Mixed-Integer Quadratic Programming
SQP	Sequential Quadratic Programming
MPC	Model Predictive Control
ADMM	Alternating Direction Method of Multipliers
LP	Linear Programming
NLP	Nonlinear Programming
MPC	Model Predictive Control
MCS	Monte Carlo Simulation
DSO	Distributed System Operator
TSO	Transmisor System Operator
DES	Distributed Energy System
DRP	Demand Response Program
OC	Operating Cost
PBDRP	Price-Based Demand Response Program
LCOS	Levelized Cost of Storage
P2P	Peer-to-Peer
SSR	Self-Sufficiency Rate
SCR	Self-Consumption Rate
Variables	
me_t^{exp}	Energy sold to the grid
mp_t^{imp}	Energy purchased from the grid
pc_t^{ba}	Charge power of the BESS
pd_t^{ba}	Discharge power of BESS
gt_t^{te}	Generation of dispatchable units
gp_t^{pv}	Generation of photovoltaic plants
pi_t^{id}	Load shedding
soc_t^{ba}	State of charge of the battery
edb_t^{ba}	BESS state, binary variable
u_t^{te}	Dispatchable units state, binary variable
Parameters	
p_t^{imp}	Energy purchase prices
p_t^{exp}	Energy sales prices
cr^{id}	Interruptible-load cost
pn_t^{ni}	Essential load
pe^{id}	Nonessential load
ηc, ηd	Charge/discharge efficiency of BESS
soc_{ba}^{min}, soc_{ba}^{max}	Minimum and maximum state of charge of BESS
$soc^{ini,ba}$	Initial state of charge of BESS
pd_{ba}^{min}, pd_{ba}^{max}	Minimum and maximum power of BESS when discharging
pc_{ba}^{min}, pc_{ba}^{max}	Minimum and maximum power of BESS when charging
p_{te}^{min}, p_{te}^{max}	Minimum and maximum power of dispatchable units
mp^{max}	Maximum purchase energy allowed
me^{max}	Maximum sales of energy allowed

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