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Modelling and Simulation Approaches for Local Energy Community Integrated Distribution Networks

RUBI RANA[1], **KJERSTI BERG**[2], **MERKEBU Z. DEGEFA**[1], **AND MARKUS LÖSCHENBRAND**[1]
[1]SINTEF Energy Research, 7465 Trondheim, Norway
[2]Department of Electric Power Engineering, NTNU, 7491 Trondheim, Norway

Corresponding author: Rubi Rana (rubi.rana@sintef.no)

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ABSTRACT Due to the absence of studies of local energy communities (LECs) where the grid is represented, it is very difficult to infer implications of increased LEC integration for the distribution grid as well as for the wider society. Therefore, this paper aims to investigate holistic modelling and simulation approaches of LECs. To conduct a quantifiable assessment of different control architectures, LEC types and market frameworks, a flexible and comprehensive LEC modelling and simulation approach is needed. Modelling LECs and the environment they operate in involves a holistic approach consisting of different layers: market, controller, and grid. The controller layer is relevant both for the overall energy management system of the LEC and the controllers of single components in a LEC. In this paper, the different LEC modelling approaches in the reviewed literature are presented, several multilayered concepts for LECs are proposed, and a case study is presented to illustrate a holistic simulation where the different layers interact.

INDEX TERMS Battery energy storage system, community manager, distribution system operator, energy management system, prosumers, photovoltaic, local energy community.

I. INTRODUCTION

Local energy communities (LECs) are new concepts being introduced in the power distribution system over the past ten years. As of yet, there is no established definition of a LEC, but the EU has issued two official definitions on Renewable Energy Community [1] and Citizen Energy Community [2]. The two community types have in common that their primary purpose is to provide environmental, economic or social community benefits for its members or the local areas where they operate rather than financial profits [3]. Both also require that the community is effectively controlled by shareholders or members [4]. LECs can make distribution networks more dynamic and oscillatory due to the increasing number of actors such as electric vehicles (EVs), battery energy storage systems (BESS) and other distributed energy resources (DERs). Hence, the usual approaches of neglecting or averaging high-time resolution transients is no longer sufficient to represent the operational dynamics in the distribution system [5].

For real-time price-based activation of demand response, hourly price signals can be adequate. However, an hourly lag time between price signals is not capable of reflecting the actual real-time supply/demand situation regarding power flow and voltage situations in the distribution grid. There are real-time constraints of seconds and minutes in relation to requirements, such as power quality requirements, which must be considered by a controller [6]. This entails that there is a need for a different level of model detail and time-resolution for market, controller, and electric grid component models.

A holistic model of a LEC is needed to perform simulations on LECs that can provide insight on how they will affect the distribution grid. 'Holistic' refers to the system level modelling of LEC integrated power system, including the relevant domains such as power, control, market and communication. Such a holistic model should include the adequate representations of the individual components in the LEC, their primary controllers, the energy management system (EMS)

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of the LEC, the market, and the distribution grid the LEC is connected to and operating within. Hence, full scale models of LECs and their operating environment are likely to traverse across multiple domains such as the electrical, market, controller and possibly ICT domains.

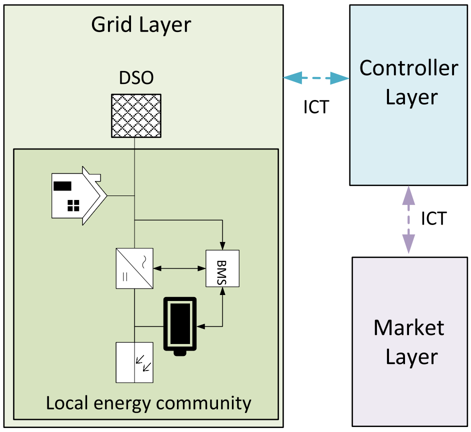


FIGURE 1. General schematic of holistic LEC integrated distribution network.

This paper aims to investigate the holistic modelling and simulation approaches of LECs. To achieve this, there is a need to review literature for all the three domains, i.e., market, controller, and grid as discussed earlier and seen in Fig. 1. Existing literature has presented a comprehensive review of challenges, opportunities, and modelling needs for the market layer as mentioned in [7]. However, the literature on markets often approximates or generally neglects grid and controller layers. [7]–[9].This paper aims at connecting these three layers into a single work and model.

In general, existing applications of communities are mainly focused on economic operation and energy management to control the point of common coupling (PCC) power or optimise energy interaction among communities or prosumers. There is ongoing research on energy communities; but the literature lacks consideration for distribution networks. Since microgrids can be similar to LECs and are a more mature field, some microgrid literature is reviewed in this paper to see how the distribution network is represented.

Inspired by microgrid literature and filling the gaps of distribution network representation and LEC, holistic models are proposed, and a case study is presented in this paper. The aim of presenting a case study is to give readers an overview of how the economic operation of LEC and its impact can be studied in a distribution network with basic tools such as MATLAB and Python.

Specific contributions include:

- Investigating the modelling requirements for LECs through literature review.
- Developing holistic models for LECs in a distribution grid.
- Presenting a holistic simulation case study for a LEC.

The paper is organised in the following way: Section II provides an overview of literature related to holistic simulation of LECs. Section III describes proposed holistic models for LECs. Section IV shows the results of a holistic simulation case study of a LEC. Section V gives a brief discussion. Finally paper is concluded in Section VI.

II. LITERATURE REVIEW

We divide the literature review into four separate, but related areas:

- Literature on EMS in LECs which does not consider network. This includes community-based and peer-to-peer (P2P) market structures.
- Literature on EMS in LECs which considers network.
- Solvers, tools, market clearing algorithms and test networks used in literature.
- Literature on EMS in microgrids, including agent-based modelling and EMS using reinforcement learning.

A. ENERGY MANAGEMENT WITHOUT CONSIDERING NETWORK

The operation of a LEC requires the implementation of an EMS for the optimal exploitation of the available resources. The focus of the EMS can be day-ahead scheduling, real time operation, or both. Further, the scheduling function can be either structured as a centralised, distributed or decentralised optimisation framework.

Different categories of LEC market structures can be identified in literature depending on the degree of decentralisation of the LEC. The main categories are classified into community-based and P2P.

1) ENERGY MANAGEMENT IN A COMMUNITY-BASED MARKET STRUCTURE

A community-based structure is a framework wherein a community operates collaboratively to optimise their assets and trade their lack or excess of collective energy. A non-profit virtual node called a community manager is introduced in [10] to coordinate member assets, provide services to the distribution system operator (DSO), and interface with different existing markets.

More generally, a community should be based on members who share common interests and goals: for instance, a group of members willing to share green energy even though they are not at the same location. As a result, the community-based structure design is the enhancement of involvement and cooperation between peers.

For a community-based LEC, the scheduling function can be structured as either a centralised or decentralised optimisation framework, as described below:

- Centralised: This framework consists of a single central node with an EMS, which is characterised by a high-performance computing unit managing the assets of the prosumer. This central node performs computations to calculate optimal reference signals while considering all the members' assets in one

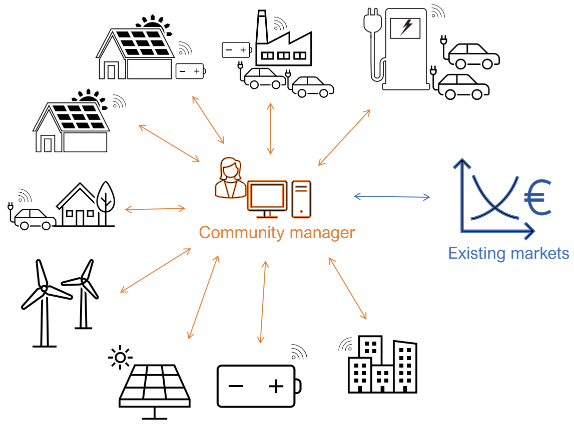


FIGURE 2. **Community-based market structure.**

optimisation problem. Each asset uses a local controller (LC) in order to communicate and directly interact with the central node as shown in Fig. 4(a). The central node sends reference signals to the LC.

- Partially Decentralised: Unlike a centralised optimisation framework, each prosumer is considered autonomous and has its own EMS in a decentralised optimisation problem. Therefore, the centralised optimisation problem can be broken down into N subproblems that can be solved independently by each prosumer EMS. Methods for solving decomposable optimization problems that involve several prosumers use a derivative-based approach, such as distributed gradient descent (DGD), wherein individual prosumers can can use a local, step-wise update of their optimization variable in proportion to the gradient of their objective function [11], [12]. However, such methods generally require a variable step size for optimal convergence as iterations proceed [13], and correctly choosing the step size can make the algorithm more complex. More importantly, the gradient-based methods only work over differentiable functions, and a wide variety of prosumer-based models include mixed integer objectives/constraints (i.e. MIPs), as well as absolute, max functions, etc.. This therefore makes derivative-based methods impractical for the proposed objectives of this manuscript. However, sub-gradient-based methods can also minimize non-differentiable convex functions by using sub-gradients instead of gradients. However, such methods rely on their individual/specific rules of optimal step-size selection, which differ from gradient-based approaches and have a significant impact on the optimality/sub-optimality of the solutions [14]. The coupling constraints, found in the proposed scheduling algorithms of manuscript, can be handled using dual decomposition, which then allows for an iterative and decentralized update of the primal and dual variables for optimality. In particular, methods such as dual-ascent can be used for this purpose; however, dual-ascent requires very strong assumptions on the objectives, such as strict convexity to guarantee convergence. In contrast, Alternating Direction Method of Multipliers (ADMM) algorithms have been widely described in the literature. ADMM is known to have more relaxed convergence requirements [15], and is therefore more commonly used for objectives where the prosumer EMS solves its subproblem in order to optimise its assets, and sends the solution to the central node. The central node checks the power balance, and the final optimal commands calculated from the prosumer EMS' are dispatched to the LC as shown in Fig. 4(b).

In the community-based market structure, the prosumer agents collectively act as community assets, and the community manager agent is responsible for coordinating collective assets. The community manager can interact with different markets and the DSO agent. The tasks and responsibilities with different objectives and constraints for different agents reported in [10], [16], [17] is discussed below:

- Prosumer Agent: A prosumer agent refers to the EMS used by the prosumer to plan off-line (in advance) the intended power consumption. Each prosumer is in charge of optimizing its set of assets and finding the optimal power set-points for each asset.
- Community Manager Agent: Collaborative systems are prone to dishonest behaviors whenever one or more participants behave strategically. The community manager agent has the task of preserving fairness among the prosumers, for instance, to prevent strategic behavior in [10] a community, and may choose to penalise the prosumer contributing the most to the import by an additional fee. Therefore, each member is pushed to decrease its import as this fee increases. The community manager can coordinate with the prosumers to provide peak shaving services by minimizing the imported energy. The community manager can play the role of a local market operator, including the tasks related with market clearing and settlement as described below [16]:
    - providing tentative price to prosumers
    - gathering all the tentative commitments from prosumers and check if the energy balances
    - minimising the costs of importing, maximise the revenues from exporting energy in day-ahead.

[18] proposes a cooperative strategy in a community of prosumers in order to maximise the benefits of each prosumer and the whole community. This cooperative strategy is called an augmented energy management model [19] for prosumers. This model considers controlled and uncontrolled generation and consumption as well as the prosumer's ability in two ways:

- planning the power consumption day-ahead;
- managing real-time deviations from the planned consumption.

The model can be applied to the energy management of prosumer communities by allowing the prosumers to coordinate their power consumption plan, manage the deviations from

TABLE 1. Energy management system characteristics for community-based structures.

Ref.	characteristics
[10]	• BESS operation • Power balance • Community energy trading • DSO energy trading[1]
[16]	• BESS operation • Energy balance • PV limits • DSO contract limit[2]
[17]	• Electricity and heating balance • Assets power/energy capacity • BESS and thermal energy system operation • Internal energy exchange cost
[19]	• PV operation • Controllable appliance operation • BESS operation • Power balance
[20]	• PV operation • Vanadium redox flow battery operation • EV operation
[21]	• Power balance • EV operation • Water heater • BESS operation • PV operation

the intended consumption, and help each other by compensating deviations.

A design of a community-based LEC is proposed [16], where the members are allowed to trade energy with each other through a local pool. The price is set on a day-ahead basis under the coordination of a community manager. Moreover, every agent participates in determining the local market price while deciding its own scheduling problem under uncertainty concerning renewable energy generation and storage. In the energy community discussed in [17], each prosumer and its assets are connected to a community manager. The community manager optimises the cost of the community with a dispatch model while having the constraint on satisfying the heat and electricity demand. The community manager can control the prosumers' assets and decide if the prosumers should import/export from/to the outer grid or exchange energy locally.

In [20], a LEC is proposed to provide manual frequency restoration reserves with a two-stage model. The first stage is performed day-ahead, when the energy community management center estimates the amount of flexible capacities available for frequency restoration reserves provision. In the second stage, the real-time scheduling of the community is performed for each hour, taking into account the assigned and activated amount of reserve power.

In [21], a mixed integer linear programming optimisation model is performed on a neighborhood consisting of 30 consumers with different amounts of flexible resources to test grid tariffs' impact on power peak reduction. Tab. 3 gives an overview of the characteristics of EMS models found in the literature. The type of optimisation and scheduling structure is shown in Tab. 2.

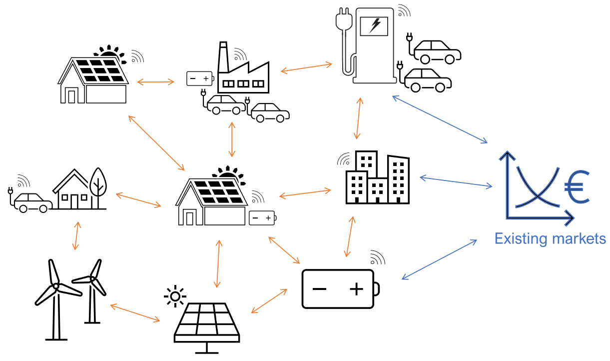


FIGURE 3. P2P market structure.

2) ENERGY MANAGEMENT IN A P2P MARKET STRUCTURE

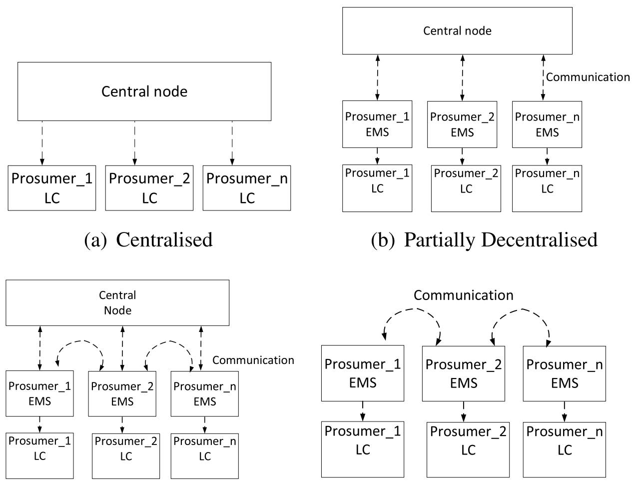
In situations involving multiple prosumers with conflicting interests, it can be quite challenging to either capture such conflicting interests in the decision-making process of each participant or motivate them to cooperate to achieve the goals of community. This leads to the second LEC structure, where trades are conducted bilaterally (i.e., prosumers interconnect directly with each other), and there is no community manager. There can be a separate entity called P2P Market Operator (P2PMO) responsible for the execution of energy trading [22], but this is not always the case [23].

For a P2P-based LEC, the scheduling function can be either structured as a decentralised or distributed optimisation framework. The different distributed optimisation frameworks are described below:

- Partially distributed: An improvement to the conventional ADMM was initially proposed in [27], which uses a consensus-based approach for a fully distributed update of primal and dual variables at each prosumer. However, this requires additional auxiliary variables and constraints to be included in the optimization framework [28], as well as the communication of the iteration wise solutions of each prosumer with all its neighbors. The partially distributed approach has one central node to check the power balance and the other nodes can act in a distributed manner to calculate reference commands for the LC (Fig. 4(c)).
- Fully distributed: The fully distributed nature of the optimisation framework implies that the optimisation problem is solved at the individual prosumer EMS level (most commonly using ADMM). There is no central node (Fig. 4(d)) [29] to check the power balance. The prosumer EMS communicates with the neighbouring EMS and solves the optimisation problem while considering power exchange information from other

[1] Energy each prosumer has to respectively import, or export, from outside the community.

[2] Each community member or prosumer agent has a contract with the DSO which limits the amount of power that can be exchanged through its point of common coupling.



(a) Centralised (b) Partially Decentralised (c) Partially Distributed (d) Fully Distributed

FIGURE 4. Structure of scheduling function.

TABLE 2. Energy management system algorithm and optimisation type.

Ref.	Scheduling structure	Algorithm	Optimisation type	
[10]	Decentralised	ADMM	Quadratic programming	Community
[16]	Decentralised	ADMM	Linear programming	Community
[17]	Centralised	✗	Mixed integer linear programming	Community
[19]	Partially distributed	ADMM	Mixed integer quadratic programming	Community
[20]	Centralised	✗	Mixed integer quadratic programming	Community
[21]	Centralised	✗	Mixed integer linear programming	Community
[24]	Centralised	✗	Mixed integer linear programming	Peer to Peer
[25]	Decentralised	ADMM	Linear programming	Peer to Peer
[26]	Partially distributed	ADMM	Mixed integer linear programming	Peer to Peer
[23]	Fully distributed	ADMM	Mixed integer quadratic	Peer to Peer

prosumers EMS. The use of a distributed approach limits the information that every prosumer needs to communicate.

In the P2P market structure, two agents are described in literature: the prosumer agent and the market mechanism agent. The P2P LEC model is considered more autonomous with more dispersed communication infrastructure needs than the community-based model. The prosumer agents optimise their assets and can also communicate directly with other prosumer agents. The market mechanism agent can look into clearing the market and system stability, thereby eliminating the need for a DSO. However, if the market mechanism agent role is limited to market clearing, the DSO agent will validate the energy flows while considering system stability. The role of all the agents reported in the literature [22], [23], [25], [26] is discussed in detail below.

- Prosumer Agent: A prosumer agent is an EMS, as discussed in Section II-A1. All the prosumer agents in a community are connected through the bidirectional power and communication links, and a whole community is connected to the upstream distribution grid via one grid connection point [22]. Smart meters are installed at each prosumer. The smart meter measures the prosumer's generation, consumption, and energy transaction with other prosumers or with the distribution grid. The objective of the prosumer agent is to optimise its assets to find the optimal power setpoints for each asset in view of the respective cost function.
- Market Mechanism Agent: A market mechanism agent assists with energy trading in a P2P market using continuous double auction in a community. This software platform enables the information exchange among prosumers and also assists the DSO in monitoring and controlling the distribution grid. The market mechanism agent has the objective of minimizing losses between the main grid and distribution grid.

In [23], the authors proposed a fully distributed framework with no central coordinator or market mechanism. The meter positioned at the point of common coupling with the external distribution grid is bidirectional, and measures the energy exchanged in each time interval. Furthermore, a distributed procedure is implemented at the prosumer EMS, limiting the information that each prosumer needs to communicate. A distributed approach plans the optimal use of the LEC energy resources, with particular reference to the BESS units, and calculates the prices of the energy transactions between prosumers. It is assumed that the costs of exchanges with the utility grid are predefined, although they vary according to the time of day. Reference [25] proposed a P2P energy market platform based on the new concept of multi-class EMS to coordinate trading between prosumers. The P2P platform minimises costs associated with power losses and battery degradation, while providing added value by accounting for the prosumers' individual preferences for the source/destination of the energy they consume/produce. The authors in [24] presented an optimization formulation that considers demand side management and P2P transactions to obtain the optimal social welfare costs of the community.

In regards to considering the grid, as described in [7], most of the peer-to-peer markets consider DC approximations of the distribution grid. Notable exceptions using AC formulations include [30], which focuses on deriving locational marginal prices for uncertain renewable and electric storage; [31], which iterates between optimal power flow and a market clearing model in order to find an equilibrium for both; [32], which incorporates grid services via a centralized peer-to-peer trading system; and [33], which iterates between the grid problem and a bi-level game-theoretic framework in order to find an equilibrium solution.

Furthermore, an alternative to markets that still conducts exchange peer-to-peer is presented in [34], which models the interactions of multiple decision makers within a micro grid.

Tab. 3 gives an overview of the characteristics of EMS models found in the literature.

TABLE 3. Energy management system characteristics for P2P structures.

Ref.	Characteristics
[23]	• BESS operation • Power balance • Power flexibility • Coordination constraint between the sales and purchase decisions of prosumers
[24]	• Market transaction operation • BESS operation • PV operation
[25]	• BESS degradation • BESS operation • PV operation • Power balance considering maximum allocated power injection from grid • Power flow
[26]	• BESS operation • Energy balance
[30]	• BESS operation • PV operation • Power flow
[31]	• Power flexibility • Coordination constraint between the sales and purchase decisions of prosumers • Market transaction operation
[32]	• Power flow • Power balance considering maximum allocated power injection from grid
[33]	• Power flow • Power flexibility • PV operation • Wind turbine operation • Coordination constraint between the sales and purchase decisions of prosumers
[34]	• BESS operation • PV operation • Coordination constraint between the sales and purchase decisions of prosumers

TABLE 4. Literature discussing impact on distribution network.

Ref.	Market Structure	Network Representation: Steady State	Network Representation: Dynamic State	
[10]	LEC	✗	✗	EMS of LEC without network
[23]	LEC	✗	✗	
[16]	LEC	✗	✗	
[17]	LEC	✗	✗	
[25]	LEC	✗	✗	
[20]	LEC	✗	✗	
[21]	LEC	✗	✗	
[24]	LEC	✗	✗	
[26]	LEC	✓	✗	EMS of LEC with network
[35]	LEC	✓	✗	
[36]	Prosumer interaction	✗	✓	
[37]	Prosumer interaction	✗	✓	
[38]	Prosumer interaction	✗	✓	
[39]	Microgrid	✗	✗	EMS of microgrid
[40]	Microgrid	✓	✗	
[41]	Microgrid	✗	✗	
[42]	Microgrid	✗	✗	
[43]	Microgrid	✗	✓	
[44]	Microgrid	✗	✓	
[45]	Microgrid	✗	✓	
[46]	Microgrid	✗	✓	
[47]	Microgrid	✗	✓	

B. ENERGY MANAGEMENT CONSIDERING NETWORK

As shown in Tab. 4, very little literature on LEC focuses on capturing the network's high time resolution dynamics. The literature is here divided into steady and dynamic states, where steady state is defined as studies with an hourly time scale, while dynamic state is defined as studies with a time scale of minutes and seconds.

In [26], the authors present a partially distributed architecture wherein a central coordinator ensures that energy is exchanged between prosumers without violating the network constraints, while still enabling prosumers to capture the economic benefits. The authors propose a novel methodology based on a sensitivity analysis in order to internalise the external cost linked with the energy exchange and evaluate the impact of the transactions on the network. The authors model a DSO agent that validates the transactions using a network permission structure based on the network's features and sensitivity coefficients. Every time prosumers are matched, voltage variation and line congestion are evaluated. The DSO computes a signal for each household that informs them if they can still participate in the market without causing problems in the network. For instance, one prosumer could be blocked from injecting power into the grid at a specific time due to the risk of creating voltage problems in the network. If the transaction is approved, the extra cost associated with the network constraints is allocated to the users involved in the matched transaction. The authors of [35] analyse the impact and challenges of local P2P trading interactions to the physical grid operation, as well as more specific effects on power flows, voltage variations, and system losses.

These papers do not study high-resolution dynamics. To study the dynamics of network, the authors of [36] develop a co-simulation framework with OpenDSS and a blockchain-based P2P market (double-auction) agent to analyse the impacts on low and medium voltage distribution networks. An alternative to co-simulation is co-modelling, wherein models are described in a unified language [48]. Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) is employed in [37] to model interactions between the prosumer homes, the market, and the electric distribution grid. The modelled entities are a house (model and controller), an energy orders broker, a market and a grid. The house model is made from the OCHRE (Operational, controllable, high-resolution residential energy model) tool, the house controller is made by foresee, the market solver is PLEXOS and FESTIV, and OpenDSS is used as a grid simulator. The HELICS modelling approach is used to assign a federate to each entity to model and control the timing of communication and data transfer between them.

In [38], the Mosaik co-simulation tool, which is designed for steady state simulators with discrete time steps, is used to establish a unifying simulation of market clearing rules, and the electric network ensuring economic incentives are aligned with physical constraints. A co-simulation framework is proposed to handle a variety of DERs and market designs capable of handling complex device specific constraints, and a high-level scripting language for blockchain smart contracts.

C. SOLVERS, TOOLS, MARKET AND TEST NETWORKS

There are different solvers and tools used to study LECs in literature. In [16], the ADMM-based clearing process is analysed in terms of scalability and convergence by performing simulations within a Python 3.7 environment, using CVXPY[3] to model the subproblems. In [26], local market P2P, static active power curtailment, tripping, and droop-based active curtailment are simulated using OpenDSS[4] software. In [25], the ADMM algorithm is run for 300 iterations at each trading interval in order to achieve agreement between the prosumers and the market platform agent. In [39], different operation scenarios of a multi-microgrid energy management optimisation model have been carried out in the MATLAB environment. In [49], eight LECs under study and the distribution network are modelled using MATLAB/Simulink, including a model of the electric power grid, the renewable energy sources, and various flexibility resources, such as energy storage systems. This work, along with Simulink models, computes an optimal power flow that considers the constraints of the heterogeneous LEC assets and the distribution network. A summary of the solvers and tools used in literature is given in Tab. 5.

TABLE 5. LEC solvers and tools used for implementing EMS.

Ref.	Solvers/Tools
[16]	Python 3.7 environment, using CVXPY to model the subproblems with ECOS as a solver. The computer used for the optimisation has a CPU Intel Core i7 10510U 2.30 GHz and 8 GB of RAM.
[26]	OpenDSS software
[23]	AIMMS Developer modelling environment and tested by using the CPLEX V12.8 solver. MIQP (mixed integer quadratic programming)
[25]	The optimisation sub-problems were solved using IBM's CPLEX solver in MATLAB on an Intel Core i7-6500U CPU with 8GB of RAM.
[39]	MATLAB environment using the IBM ILOG CPLEX LP solver on an Intel Core 2 Duo 3.00 GHz running Windows 7
[49]	MATLAB/Simulink. All optimisations are conducted using the Gurobi optimisation solver.

Market clearing is handled in different ways in the literature. Reference [23] is an example of a fully distributed LEC framework. Each prosumer is equipped with a local bidirectional meter that measures the energy that the specific prosumer exchanges with the internal network in each time interval. There is no market platform for achieving trading among prosumers, and the distributed approach is based on the ADMM. The optimisation is performed iteratively. At each ADMM iteration, the power bought or sold by each prosumer calculated in the previous iteration is made known to all prosumers. In [26], a continuous double auction market mechanism is used, which is very well suited for P2P exchanges. It should be noted that in a continuous double auction comprising bidders with reasonable goals (i.e., participants only trade at a profit), trades are always Pareto-improving. The continuous double auction tends towards a highly efficient allocation of energy. In [25], the proposed P2P energy market platform allows small-scale prosumers to trade energy with one another and the wholesale market. The proposed P2P energy market platform operates in a distribution network to incentivise local prosumer energy balancing, while accounting for the costs associated with importing energy from the main electric network. Through the P2P market, prosumers can trade energy with one another and the wholesale market. However, small-scale prosumers may not wish to be exposed to fluctuating wholesale energy prices. Thus, retail suppliers could act within the P2P platform on prosumers' behalf, based on their energy preferences. Reference [49] presents a Nash bargaining solution (NBS) approach to offer a fair and financial reimbursement for changing the operation objectives of LECs. A bargaining problem represents a situation in which there is a conflict of interest between multiple agents on how to share a fixed sum of resources.

Tab. 6 shows the different test networks used in literature for implementing EMS.

[3]Python-embedded modelling language for convex optimization problems. It relies on the open-source solvers ECOS, OSQP, and SCS.

[4]https://sourceforge.net/projects/electricdss/

D. ENERGY MANAGEMENT IN MICROGRIDS

Microgrids have been subject to research for several years and are a more mature field than LECs. It is, however, essential to distinguish a microgrid from a LEC. A microgrid often describes the physical structure of a grid with one PCC, which has the ability to operate in islanded mode. This section describes microgrid literature considering energy management, agent-based modelling and reinforcement learning. In [39], the DSO and the prosumers in a microgrid create a partnership where they own and operate a centralised controller that controls a battery energy storage system (BESS), and calculates the electricity costs using an optimisation framework. As a result of this coordinated control scheme, the prosumers in the microgrid share their resources (photovoltaics (PV) and BESS) in order to reduce their electricity cost substantially.

To model different objectives of the DSO and microgrids, a coordinated decentralised bilevel problem with DSO in the upper level and microgrids in the lower level is formulated in [40]. At the upper level, the DSO guarantees the power flows and voltage levels while minimising the operational cost. At the lower level, microgrids optimise their own objective of minimising the operational costs.

The energy management system (EMS) in [41] has a hierarchical decentralised system of system architecture; therefore, a bi-level optimisation model is developed. Energy management is achieved at two levels:

- energy management at the level of individual microgrids
- energy management at the DSO level through coordinating energy exchange between microgrids and energy trading with the distribution networks.

TABLE 6. Test networks in LEC literature.

Ref	LEC Structure	Stakeholders	Components	Test Network
[10]	Community-based	DSO, Community Manager, Prosumers	PV, BESS	A setup of 15 prosumers. The data was originally collected from households in Australia.
[16]	Community-based	DSO, Community Manager, Prosumers	PV, community BESS	A residential neighbourhood in the city of Amsterdam, the Netherlands. Data of ten households is used for running the simulation over one day.
[17]	Community-based	DSO, Prosumers	Auxiliary heat pumps, thermal energy storage, PV, BESS	The case study is carried out on a district in Gothenburg, Sweden. The district is a mix of 41 buildings including houses, multi-family dwellings and services buildings.
[19]	Community-based	Prosumers, Community Manager	PV, BESS, controllable appliances	37 households at various locations across Japan.
[20]	Community-based	Prosumers, Community Manager, balancing service provider, TSO	PV, BESS, EVs	A hypothetical LEC with 50 households. This community has a 100kW PV system as well as DERs, including a 50kW/200kWh BESS and 10 EVs.
[23]	P2P-based	DSO, Prosumers	PV, BESS	Two low-voltage feeders. Five prosumers are connected to each feeder.
[26]	P2P-based	DSO, Market Agent, Prosumer	PV, BESS	UK low-voltage network comprising one feeder with 100 households.
[25]	P2P-based	Wholesale electricity market, P2P Platform Agent, Prosumer	PV, BESS	IEEE European Low Voltage Test Feeder with 55 prosumers.
[24]	P2P-based	Prosumers, Retailer	PV, BESS	A LEC with 10 prosumers
[21]	P2P-based and Community-based	Prosumers, DSO	PV, BESS, water heater, EV	Load data for 30 households in Steinkjer, Norway. Mostly apartments with an average power consumption between 0.64-3.5 kW, a pre-school and a grocery store with an average consumption between 10-31 kW.

Provided with a schedule of power exchange and trading from DSO, the energy management of each microgrid aims to minimise the daily operating cost.

In [42], the authors propose a transactive energy control framework. They introduce an entity called the system coordinator, similar to an independent operator in electricity markets who only manages the energy trading through the electric network. Therefore, the privacy of individual microgrids is protected since the system coordinator does not have access to the data of individual microgrids. The individual microgrid operators and system coordinator will interact through bidirectional communication to efficiently manage resources. Within the framework, respective microgrid operators submit price bids to the system coordinator with their preferences to trade energy among various microgrids. At the same time, the system coordinator optimises the allocation of the bids received and provides feedback regarding successful energy transactions.

The idea of agent-based modelling is quite timely due to the current decentralisation in power systems.

The multi-agent system (MAS) in hierarchical control has been applied in microgrids. Under the MAS environment, individual agents can determine power control strategies for entities such as DERs or loads.

The implementation of these agents has been discussed in previous literature, which is summarised in Table 7.

E. ENERGY MANAGEMENT OF AUTONOMOUS AGENTS USING REINFORCEMENT LEARNING

Due to a resurgence of deep learning, non-linear control algorithms have gained scientific ground in recent years. The main advantage of deep learning over comparable non-linear methods is better problem scalability and robustness to uncertainties. Reinforcement learning is a special form of dynamic optimisation that uses function approximations for the expectations of future outcomes of a dynamic system [50], [51]. Therefore, it is also being referred to as approximate dynamic programming. The mentioned approximation concerns the future state of an optimisation problem. For example, if we assume the task to optimally schedule charging of a battery in an LEC, the expectation of future outcomes would include the system (e.g. expectations of future consumption and generation in the LEC) as well as the impact of the decision to be optimised on the system (e.g. what is the value of storage regarding minimizing the cost of grid feed-in, etc.) as illustrated in Fig. 5.

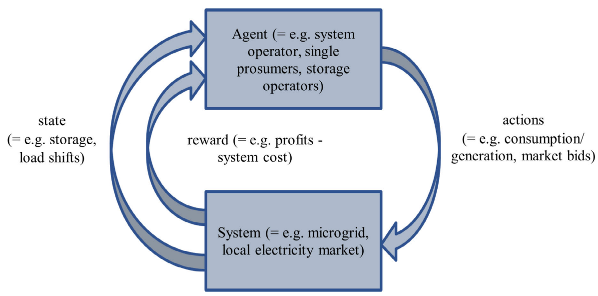


FIGURE 5. Agent-environment interaction in agent-based modelling.

Usually the decision process is formulated as a Markov decision process and discounted in order to require the algorithm to prefer pay-off now compared to future pay-offs. The approximations used are functions that can be linear, polynomial or non-linear. In recent years, literature has shifted towards using non-linear approximators in the form of deep

TABLE 7. Agent-based modelling literature.

Ref.	Modelled agent	Simulator for modelling	Communication between agents	Communication between agents and simulator
[43]	BESS, micro-gas turbine, smart load	Opal-RT (Real-time simulator)	16-bit freescale microcontrollers, ZigBee modules (communication protocol for a wireless personal area network)	Interface boards using a controller area network protocol
[44]	Substation, bus, feeder, load agent, generator	Internet Technology Based Power System Simulator (InterPSS)	Java Agent Development Framework (JADE), Java Universal Network/Graph Framework	N/A
[45]	Microgrid	MATLAB	JADE	N/A
[46]	Microgrid	Simulink	JADE	MACSimJX, acts as a middleware between Simulink models and the agents
[47]	Feeder agent	Substations	Transmission Control Protocol (TCP) communication network	Protocols defined by standard IEC 61850, ie, MMS and GOOSE that are suitable for communication systems used in power substations

neural networks. Applications in power systems are no exception to this trend.

Deep learning is a subcategory of machine learning, where non-linear functions are represented via differentiable stacks of layers, and are most commonly composed of linear regression layers and non-linear activation layers. Training of such networks is conducted via "backpropagation", i.e. calculating the gradients to real data sets starting at the last layer towards the first.

Even though the technique does not have its origin in deep-learning, the state of the art of Q-Learning comes in form of deep Q-Learning [52]. In such systems, the approximator is used as a "lookup table" in order to select the optimal action from a discrete set of actions (see example in Fig. 6). In deep Q-Learning, a neural network acts as a mapping of the current state to the most optimal state. Training of the neural network is conducted via backpropagation based on boot-strapped scenarios. Examples of literature concerning microgrids is given in Tab. 8.

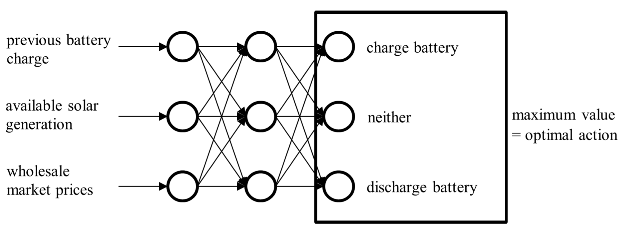


FIGURE 6. Q-neural network "lookup table" for a battery charge-discharge decision.

In addition to using a function approximation to both evaluate and then decide on the optimal policy whilst adding an exploration noise, it is also possible to dynamically approximate a stochastic policy, i.e. a decision process. Compared to Q-Learning, which can be referred to as "off-policy", these techniques are termed "on-policy" [60]. Recent examples of this from the domain of LECs are the use of "soft-actor critic" to coordinate flexible units with renewables within buildings [61], coordination of HVAC units via "deep deterministic policy gradient" [62] and optimal

TABLE 8. Energy management system literature based on deep reinforcement learning.

Ref.	Contribution
[53]	Applies reinforcement learning on a decentralised EMS and a utility function representation for demand response
[54]	Focuses on the generation side
[55]	Applies Q-Learning on charging management of fleets of single or aggregated EVs
[56]	Focuses on a single-household level and thus also includes home appliances
[57]	Adds competition to Q-Learning frameworks by having several agents solve subsystems and interact with each other in a Stackelberg framework
[58]	Implements market trading in a microgrid via Q-Learning agents
[59]	Considers Q-Learning agents interacting within a single building

scheduling of residential appliances via "trust-region policy optimization" [63].

The interaction problem of several such agents on wholesale electricity markets has been presented in [64]–[66].

III. MODEL TOPOLOGIES

As discussed above, the mentioned agents have to be nested in more holistic control algorithms that consider distribution grids and market interactions whilst independently making their control decisions. In Section II we outline the lack of studies on such models, here we attempt to conceptualize multi-layer topologies of these LEC models.

A. MODELING REQUIREMENTS FOR LEC

As described earlier, a holistic study of LECs should include three layers: grid, controller and market. These layers are described in more detail in this subsection.

1) GRID LAYER

The grid layer contains the electric grid models of each component in the LEC, including the grid itself. Here, analyses like the power flow analysis are important to assess voltage levels and overloading lines or transformers. This layer is essential to study the impact on the distribution grid.

The level of details in the electrical grid component models depends on the grid services the LEC is assumed to provide to the DSO, as well as the power quality requirements that are imposed on the LEC operation. In principle, the service provisioning capability of a LEC is limited by the capability of the individual components within the LEC. Typical services that a LEC might provide to the DSO include peak shaving and voltage control to improve power quality.

2) CONTROLLER LAYER

The controller layer consists of two layers: the primary controllers, which are managing the operation of single components locally, and the secondary controllers, which are managing the energy flow on a higher level. One example of a primary controller is a battery management system (BMS), which keeps the battery within its operating limits. An example of a secondary controller is a HEMS, which controls the energy flow within a house.

In general, EMS schedule generators and flexible loads, as well as the charging and discharging of BESS within a specified period of time. EMSs can be found at several levels: individual components (such as BESS), at a household level (HEMS), at a LEC level, and at the distribution system level.

3) MARKET LAYER

The market layer consists of a market platform that sends price signals to the LEC EMS. The work presented in this paper aims to follow a modelling approach that is flexible enough to accommodate different market architectures. The entity that will participate in some form of market architecture or contractual schemes is the EMS. Therefore, decoupling the grid models from the EMS algorithms is essential.

B. PROPOSED HOLISTIC MODEL FOR LEC

This section presents three proposed LEC modelling approaches. All three approaches have community-based market structures. The modelling approaches are distinct in terms of the controller layer: the first framework has a decentralised scheduling function, the second has a distributed scheduling function, and the third has a decentralised scheduling function with a P2P market within the LEC.

1) DECENTRALISED FRAMEWORK

Fig. 7 shows the framework with the three layers: grid, controller, and market. The layers are arranged in a decentralised framework to manage the energy. The controller layer is divided into two parts to distinguish between the primary controllers (at an individual level) and the secondary controllers (managing the energy). The market platform in the market layer attempts to coordinate multiple LECs to achieve a performance better than operating uncoordinated individual LECs. This objective is realised through coordinating an energy exchange between LECs and energy trading with the distribution network. The market platform interacts with the DSO and coordinates participating LECs in the system. Individual LECs are independently managed and operated by LEC_EMS, and they can choose to join the multiple LEC system.

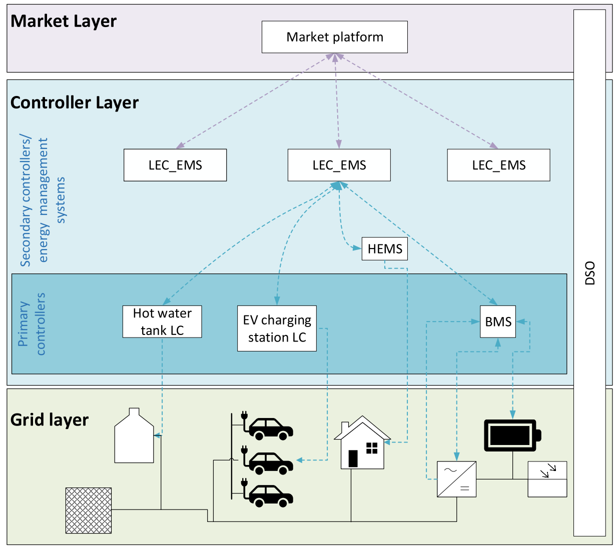


FIGURE 7. Decentralised framework.

The LEC_EMS communicates with the HEMS, and local controllers, such as hot water tanks, EV charging stations, and BESS. The HEMS can either receive scheduling signals from the LEC_EMS, or operate on its own and send signals back to the LEC_EMS.

As such, agents incorporating the grid layer as well as market interactions into the control of DERs do not necessarily have to be sophisticated. We show this through the example given in the following section, which demonstrates how to implement this practically via a linear optimisation algorithm.

2) DISTRIBUTED FRAMEWORK

In this framework, as shown in Fig. 8, there are only two layers: grid and controller. In this distributed framework, each LEC_EMS communicates with other LEC_EMSs through a cyber network to achieve the objectives. The communication network is sparse, and every agent communicates with a few other agents (neighbours). Distributed frameworks are characterised by a lack of a supervisory agent. However, it consists of a simultaneous negotiation over the price and energy of multi-bilateral trades along with a predefined trading scheme. Moreover, community EV charging stations and community BESS receive charge/discharge commands, and residential households receive scheduling signals for the HEMS.

3) DECENTRALISED FRAMEWORK WITH P2P-MARKET WITHIN LEC

As shown in Fig. 9, this framework is based on the decentralised framework described in III-B1. The main difference is that in this framework, HEMS can communicate and trade among themselves. Residential prosumers opti-

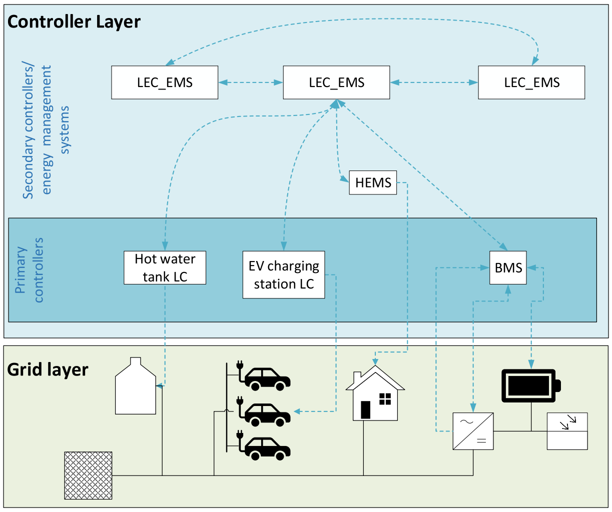


FIGURE 8. Distributed framework.

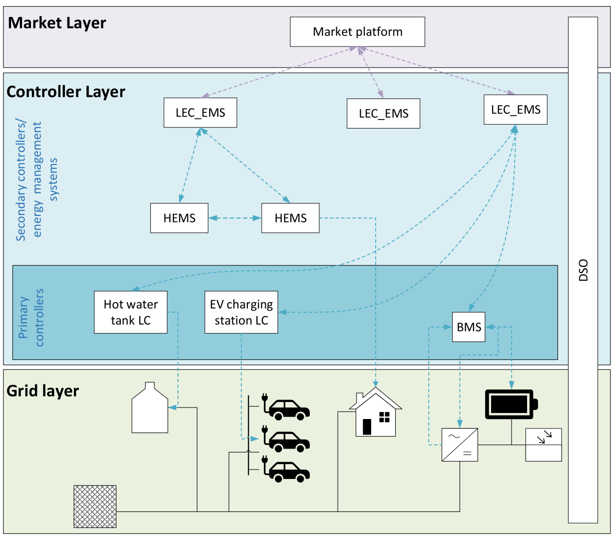


FIGURE 9. Decentralised framework with market within LEC.

mise their assets using HEMS, generate command signals, and send them back to individual appliances. There is still interaction with the LEC_EMS, which is responsible for setting upper limits for the prosumers and maintaining fairness among the prosumers. From a market perspective, there are three potential markets in this framework: energy trades between prosumers and members of the community, trades between the community as a whole and the DSO; and trades within the community managed by the market platform.

Irrespective of the chosen methodology, a holistic approach does not necessarily entail high model complexity and related efforts. This is shown by the following section, which presents an illustrative example on how to set up a simple test bed implementation of such a proposed holistic model.

IV. A PRACTICAL EXAMPLE

A holistic model of LEC integrated electric power distribution network entails the modelling of the different domains such as power, market, control domains and their real-time interaction. The purpose of such simulation is to illustrate the system dynamics as whole without losing important details in the respective domains.

4) ABOUT THE MODEL/SETUP

The model has an electric grid model implemented in MATLAB Simulink and a LEC_EMS implemented in Python as it is illustrated in Fig. 10.

The PV-battery system is modelled as a three-phase dynamic load in MATLAB simulink. After the net timeseries load is computed with the python optimization script the active and reactive power is given as reference to the network model in the simulink. The dynamic load is connected to a MV/LV transformer which is then further connected to a MV line modelled as a three phase PI section line. Hence, the network model is a simple single feeder system of load, transformer, and line. The simulation of the model is run with the interest of steady state system evaluations and hence no dynamic states are simulated. The time step in the simulation is 100 μ s and the time step for load profiles and price signal are hourly. In this implementation there is no market simulation, but a day-ahead hourly market price signal is streamed from a timeseries data file to represent a price signal. The LEC formed with different customers having BESS, PV and residential load is assumed here to be connected to the rest of the electric power distribution network through the MV/LV transformer. Load, PV generation and day-ahead market price timeseries profiles are used as deterministic simulation. The implementation approximately represent the decentralised framework presented in Fig. 7.

The load for households is based on the measured energy consumed by an anonymised household located in the county Trøndelag, Norway. The rating for the BESS is given below:

- Energy capacity: 1.2 MWh
- Charging/discharging rate: 0.6 MW
- Efficiency when charging/discharging: 95 %

There are two scenarios implemented in this simulation:

- LEC_EMS has the objective to maximise self-consumption (LEC-MSC).
- LEC_EMS has the objective to maximise profit from energy arbitrage (LEC-MPEA).

$$min \sum_{t} \left(\left(C^{t}_{spot} \right) p^{t}_{import} \right) \tag{1a}$$

$$p^{t}_{out} + P^{t}_{PV} + p^{t}_{import} = P^{t}_{load} + p^{t}_{in}, \ \forall \ t \tag{1b}$$

$$p^{t}_{out} \leq P_{bat,\ max} \ \forall \ t \tag{1c}$$

$$p^{t}_{in} \leq P_{bat,\ max}, \ \ \forall \ t \tag{1d}$$

$$\sum_{t} p^{t}_{in} - \sum_{t} p^{t}_{out} = 0 \tag{1e}$$

$$e^{t}_{SoC} = 0.5 * E_{bat}, \ \ t = 0 \tag{1f}$$

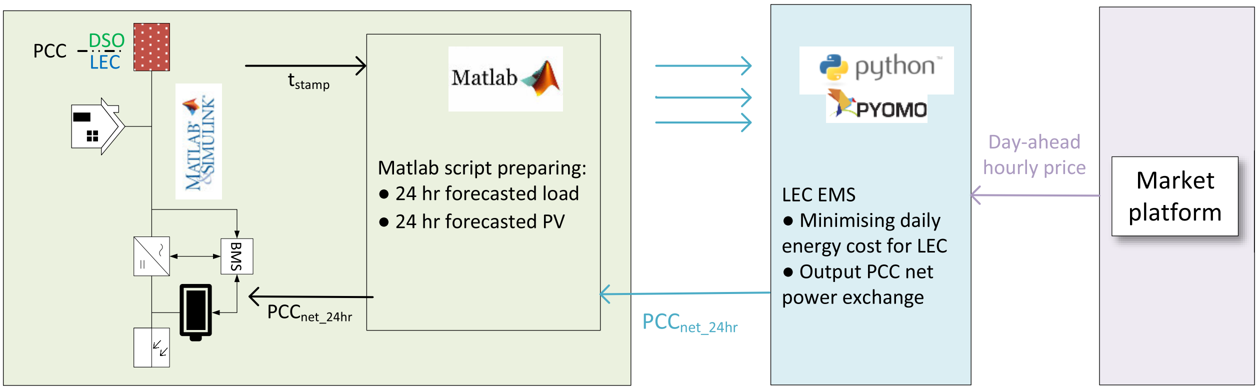


FIGURE 10. The setup of the case study.

$$e_{SoC}^{t} = e_{SoC}^{t-1} + p_{in}^{t}\sqrt{\eta_{bat}} - \frac{1}{\sqrt{\eta_{bat}}}p_{out}^{t} \quad \forall\, t > 0 \qquad (1g)$$

$$e_{SoC}^{t} \leq E_{bat}, \ \forall\, t \qquad (1h)$$

$$p_{in}^{t},\ p_{out}^{t},\ e_{SoC}^{t} \ \geq 0,\ \forall t \qquad (1i)$$

The corresponding notation is the following:

- C_{spot}^{t} spot price in hour t [NOK/MWh]
- p_{import}^{t} average feed-in in hour t [MWh/h]
- p_{in}^{t} average charging rate by the BESS in hour t [MWh/h]
- p_{out}^{t} average discharge in hour t [MWh/h]
- e_{SoC}^{t} state of charge in hour t [MWh]
- P_{PV}^{t} average PV generation in hour t [MWh/h]
- P_{load}^{t} average customer load demand in hour t [MWh/h]
- $P_{bat,\ max}$ maximum charging/discharging rate[MW]
- E_{bat} maximum energy storage capacity [MWh]
- η_{bat} charging/discharging efficiency [%]

The constraint in (1b) ensures that power balance is fulfilled, while the constraints in (1c), (1d) impose a limit on charging and discharging power of BESS. Constraint (1g) forces the state-of-energy at every interval to have the value that it had at the previous interval plus the actual amount of energy that is transferred to the BESS if it is charging at that interval minus the energy that is subtracted if the BESS is discharging during that interval. Constraint (1h) limits the state-of-energy of the BESS to be less than the BESS capacity. The constraint in (1f) ensures that the BESS is 50 percent charged at the start, while the constraint in (1e) ensures that the BESS state of energy in the final hour is the same as in the first hour, i.e. 50 %.

$$min \sum_{t} \left(p_{import}^{t}\right) \qquad (2a)$$

$$s.t\ (1b - 1i) \qquad (2b)$$

LEC modelling couples physical grid, energy management system and market price signal.

The power system components are modelled in MATLAB Simulink to sufficiently represent their dynamic operating conditions. The Python scripts however are used as EMS engines with optimisation capability. The MATLAB Engine API for Python is used to link the Python scripts with the Simulink model of the physical system. The Simulink models can be customised based on the operational dynamics of interest.

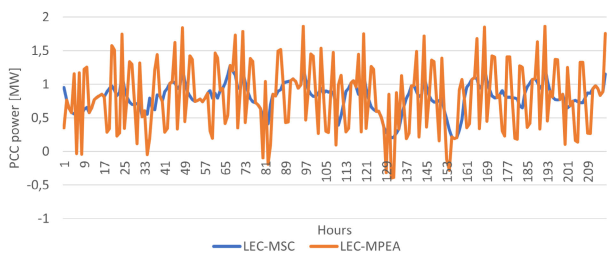


FIGURE 11. Impact of LEC operation with energy arbitrage on PCC power.

5) RESULTS

The simulation results indicate how the power exchange and voltage level at the PCC is affected as the LEC_EMS operates under different objective functions. The LEC-MPEA scenario represents a situation where LEC_EMS actively responds to the price signal. The fluctuation in power exchange is presented in Fig. 11 and the resulting impact on voltage level is presented in Fig. 12. The simulation results shows that active engagement of LEC-MSC, especially with energy arbitrage, results in creating a fluctuating load profile with new peaks and potentially power quality related challenges.

V. DISCUSSION

The LEC EMS can be operated in a centralised, decentralised or distributed manner. From the literature, it is clear that in cases of different ownership of DERs (P2P-based LECs), where several decisions should be taken locally, centralised control is very difficult. Therefore, decentralised and distributed approaches are adopted. For a community-based LECs, a mostly centralised or decentralised approach is implemented.

The existing applications of LECs are mainly focused on economic operation and energy management to control the PCC power or optimise energy interaction among LECs or prosumers. Research on energy communities is ongoing;

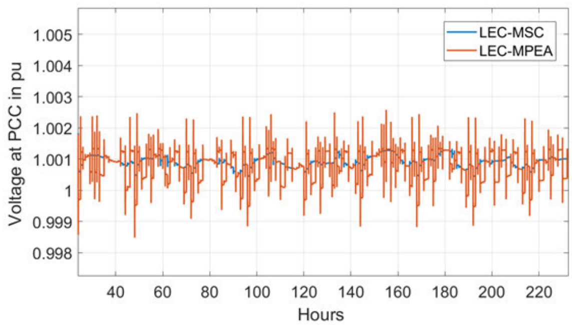


FIGURE 12. Impact of LEC operation with energy arbitrage on PCC voltage.

hence literature lacks the consideration of distribution networks in their investigation.

To model and simulate LEC-integrated distribution networks, it is important to consider the three layers: the market, controller and grid layer. The grid layer is essential for studying the impact on the distribution grid. The controller layer is essential for managing the energy flow and participating in market frameworks. The market layer is essential for sending price signals to the controller layer. Based on these identified needs through literature survey, we propose three frameworks for LECs and discuss the interaction between individual layers. We detail the controller layer and proposed primary and secondary control,

Autonomous agents such as LEC EMS, prosumers, HEMS, DSO models, and aggregators can be modelled via deep reinforcement learning. Additional uncertainties and more localised storage capacities also have the potential to further increase this trend from traditional control models to deep reinforcement learning.

VI. CONCLUSION

Modelling and simulation of LECs and their operation is essential for studying and planning LECs integrated in the distribution network, recommending the right regulatory measures and designing market architectures. The aim of this paper was to do a literature review of a LEC integrated in a distribution network. The literature review touched upon all the representative domains (grid, controller, and market) of an LEC integration in a distribution network, unlike existing reviews. The review found that the grid layer is missing in most simulation studies concerning LECs. In addition, this paper proposes three different frameworks needed for LEC integration based on the literature studies, and illustrates an implementation of one of the frameworks with a case study. Future work will include detailing the signals exchanged between individual domains or stakeholders, and expanding on the frameworks depending on scenarios for regulation.

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RUBI RANA received the M.E. degree in power systems from Thapar University, India, in 2016, and the Ph.D. degree from the Indian Institute of Technology, Delhi, India, in 2021. She is currently a Research Scientist at SINTEF Energy Research. Her research interests include planning the operation and expansion of distribution networks, electric vehicle charging infrastructure, microgrids, and optimization.

KJERSTI BERG received the M.Sc. degree in energy and environmental engineering from the Norwegian University of Science and Technology (NTNU), Trondheim, Norway, in 2017, where she is currently pursuing the Ph.D. degree in electric power engineering. From May 2017 to May 2021, she worked at SINTEF Energy Research, mostly in projects related to battery energy storage systems and power quality in the distribution grid. Her research interest includes the integration of local energy communities into the Norwegian electricity distribution grid.

MERKEBU Z. DEGEFA received the M.Sc. degree in electrical engineering, in 2010, and the Ph.D. degree in power systems and high-voltage engineering from Aalto University, Espoo, Finland, in 2015. He is currently a Research Scientist at SINTEF Energy Research. He has authored more than 50 scientific papers. His research interests include the development of advance operational functions for active distribution systems, laboratory-based testing, the development of ancillary services, and load and flexibility modeling.

MARKUS LÖSCHENBRAND received the M.Sc. degree in supply chain management from the Vienna University of Economics and Business (WU Vienna), in 2015, and the Ph.D. degree from the Norwegian University of Science and Technology (NTNU), Trondheim, Norway, in 2019. He is currently a Research Scientist at SINTEF Energy Research, Trondheim. His research interests include renewable energy, economics, game theory, optimization, probabilistic programming, and machine learning.