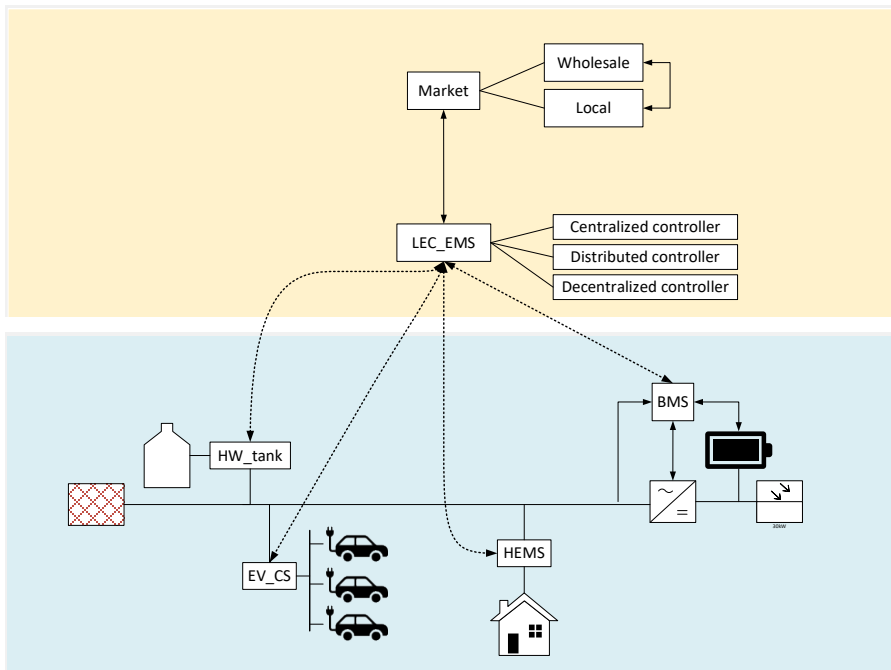




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Project Report

Modelling Approaches for Local Energy Community

Description of selected modelling approaches

Author(s):

Rubi Rana, Merkebu Zenebe Degefa, Kjersti Berg and Markus Löschenbrand

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Rubi Rana, Merkebu Zenebe Degefa, Kjersti Berg and Markus Löschenbrand

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SUMMARY

Due to the absence of well documented experiences from implementations of Local Energy Communities (LECs), it is very difficult to infer implications of increased LEC integrations for the distribution network as well as for the wider society. To conduct quantifiable assessment of different control architectures, LEC types and market frameworks in the FINE project, a flexible and comprehensive LEC modelling, and simulation approach is being established.

Modelling LECs and the environment they operate in can involve the co-modelling of different domains such as power system, control, market, and communication. In addition, one can imagine different levels of autonomy in terms of the Energy Management System (EMS) which can be community level (LEC EMS) or down to component level such as Battery EMS. The modelling approaches which focus on market-based activation of flexibility and EMS decision making are likely to face uncertain aspects such as customer behaviour. In this report, the different LEC modelling approaches in the reviewed literature are presented together with a selected modelling approach outlined for the FINE project.

PREPARED BY

Rubi Rana

SIGNATURE

Rubi Rana
 Rubi Rana (Sep 30, 2021 15:20 GMT+2)

CHECKED BY

Maren Istad

SIGNATURE

Maren Istad
 Maren Istad (Sep 30, 2021 21:33 GMT+2)

APPROVED BY

Knut Samdal

SIGNATURE

Knut Samdal
 Knut Samdal (Oct 8, 2021 08:17 GMT+2)

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Terminology

The following tables contain the terms and abbreviations that are used throughout this document.

Term	Explanation
Stakeholder	Participants involved for example: prosumers, distribution system operator, community manager, retailer and market operator.
Agent	An agent is “a software (or hardware) entity (modelling of stakeholders) that is capable to make scheduling decisions.
Component	Devices such as battery, photovoltaics, water heater etc
Local market	Individual consumers enter into agreements to purchase electricity from a power supplier of their choice. Norway's end-user market consists of about one-third household customers, one-third industry and one-third medium-sized consumers such as hotels and chain stores.
Wholesale market	Large volumes are bought and sold by power producers, brokers, power suppliers, energy companies and large industrial customers. The wholesale market consists of several markets where bids are submitted and where prices are determined such as the day-ahead market, the continuous intraday market and the balancing markets.
Energy trading	Energy trading is organised with the objective of ensuring that power always flows to where its value is greatest, i.e. from low-price areas to high-price areas.
Prosumers	Own any kind of renewable-based generation assets and/or electricity storage etc.
Community manager	Central entity for managing the optimal operation of community assets and acts as an interface between community and distribution system operator
Distribution system operator	A central entity solves the optimization problem across the scheduling horizon with the goal of minimizing the total cost of supplying power to the consumers subject to network constraints.

Abbreviation	Explanation
LEC	Local Energy Community
DSO	Distribution System Operator
EMS	Energy Management System
REC	Renewable Energy Community
CEC	Citizen energy community
FINE	Flexible Integration of Local Energy Communities into the Norwegian Electricity Distribution System
EV	Electric Vehicle
PV	Photo Voltaic
BESS	Battery Energy Storage System
P2P	Peer-to-peer
ADMM	Alternating Direction Method of Multipliers
P2PMO	Peer-to-peer market operator
MIQP	Mixed Integer Quadratic Programming
NBS	Nash Bargaining Solution
PCC	Point of Common Coupling
MAS	Multi-Agent System
DER	Distributed Energy Resource
JADE	Java Agent Development Framework
TCP	Transmission Control Protocol
HELICS	Hierarchical Engine for Large-scale Infrastructure Co-Simulation
RC	Resistance-Capacitance
OCHRE	Operational, Controllable, High-resolution Residential Energy
HEMS	Home Energy Management System
NVE	Norwegian Water Resources and Energy Directorate
LC	Local Controller

1 Introduction

The emergence of local energy communities (LECs) will likely create new dynamics in the operation and planning of distribution networks by aggregating and modifying distributed customer loads at central energy management system. To study the techno-economic benefits and drawbacks of LECs in the Norwegian power system, a research project 'Flexible Integration of Local Energy Communities into the Norwegian Electricity Distribution System (FINE)' is initiated. Among the activities in the FINE project, modelling of LECs and the environment they operate is central to run simulation studies to understand LEC-DSO operational interaction, to analyse distribution network planning with LEC and to study different market architectures for harnessing LEC flexibility potential. As part of this effort, this report will set the stage by reviewing LEC modelling approaches in prominent publications and outlining the selected modelling approach that will be followed in the FINE project. Moreover, this report presents the first simulation implementation to concretize the modelling approach.

In general, modelling and simulation are indispensable for planning, design and operation of electrical energy systems. As LECs are new concepts being introduced in the power distribution system, there does not exist adequate data to perform impact analysis in the coming ten-twenty years. Hence, modelling and simulation of LECs and their operation is essential to study and plan LECs themselves and the distribution network, to recommend the right regulatory measures and to design market architectures.

As there is no universally adopted definition of LEC, the FINE project has attempted to formulate a definition reviewing prominent definitions in the literature. To define the scope of the modelling activities, the project level LEC definition is presented in this section. In addition, the LEC modelling practices must be relevant to expected LEC configurations in the Norwegian power system. Hence, selected reference LEC configurations are outlined in this section to guide the LEC modelling approaches.

1.1 Definition of a LEC

The European Union has issued two directives with official definitions: renewable energy community (REC) [1] and citizen energy community (CEC) [2]. These definitions are described more thoroughly in [3]. From these definitions and the review of existing energy communities in [4], a LEC has been conceptualized. The following five criteria are considered fundamental for a LEC:

1. **Locality:** The community should have a large proportion of local investment and ownership and it should be managed locally. The community is located within a defined geographical area, typically in the distribution grid.
2. **Energy sustainability:** The community, or its members, fully or partially owns renewable energy generation, energy storage and / or electric vehicle chargers, or other relevant infrastructure. These assets are community shared and / or located at a single customer.
3. **Community engagement:** The majority of the community participants are active members of the community, i.e. they invest in energy related assets and provide flexible demand options. The main objective of the community is not to make profit, but to provide environmental, economic or social community benefits for its members/shareholders and/or the local area where it operates. The community participants may be natural persons, small and medium-sized enterprises or local authorities, including municipalities.
4. **Information and communications technology:** The community has (to some degree) smart meters, communication, control and energy management system(s) installed. This can enable flexible operation and optimization of the local system, and the interaction with the larger power system.

5. **Transactions:** The community allows financial transactions related to energy amongst its members. This can potentially be implemented via local energy markets, but such are not mandatory. This includes transactions between the community and the larger power system.

1.2 Reference LECs

In the FINE project, LECs are divided into three types:

1. Neighbourhood in urban area
2. Rural area with weak grid (e.g. small or distant islands)
3. Industry/small-medium enterprise cluster

Figure 1.1 shows the first reference LEC, which is a neighbourhood cooperative in an urban area. The cooperative consists of three apartment buildings and a common garage with an electric vehicle (EV) charging station. There might be an electric boiler or heat pump, but this is optional (illustrated by stippled lines).

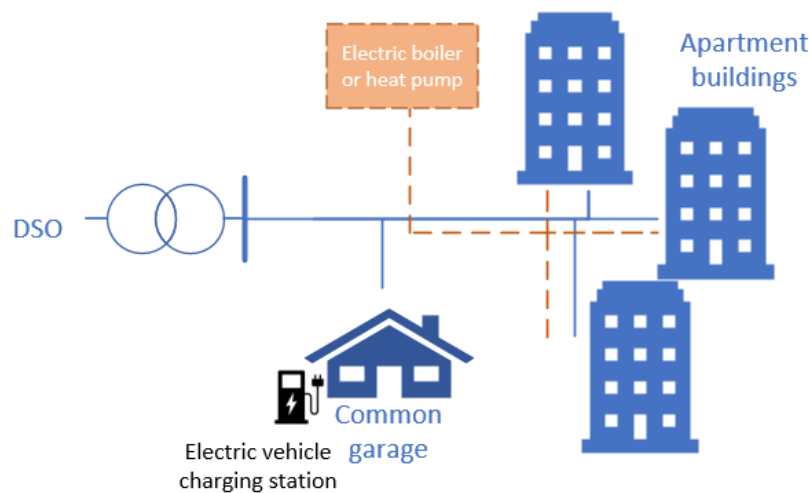


Figure 1.1: LEC – Cooperative in urban area.

Figure 1.2 shows the second reference LEC, which is in a rural area with a weak grid. The members of the LEC are cabins, where some have photo-voltaic (PV) panels and some have EVs. There is a community owned wind turbine and a community battery energy storage system (BESS). This reference LEC can be modelled with or without grid connection.

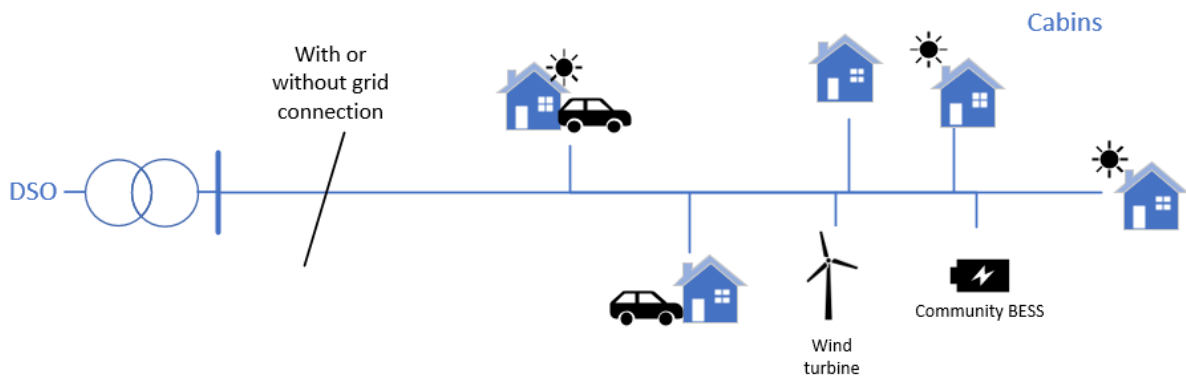


Figure 1.2: LEC – rural area with cabins in weak grid.

Figure 1.3 shows the third reference LEC, which is an industry/small-medium enterprise cluster in a harbour area. The members of the LEC are a port with shore power facility, small industry/enterprise, warehouses and charging stations for heavy EVs. There is not sufficient grid capacity for future electrification (for the industry/enterprise and shore power). There might also be hydrogen production in the harbour, and thermal storage for heating and cooling. These are optional, as illustrated by stippled lines.

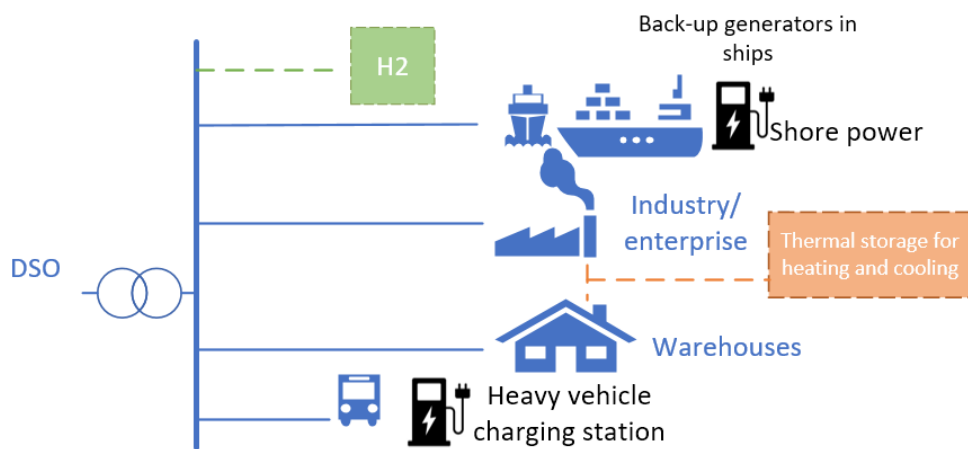


Figure 1.3: LEC – industry / enterprise cluster in harbour area.

2 Review of LEC modelling approaches

The operation of a LEC requires the implementation of an energy management system (EMS) for the optimal exploitation of the available resources. The focus on the EMS can be the day-ahead scheduling, real time operation, or both. Further, the scheduling function can be either structured as a centralized, distributed or decentralised optimization framework. In the reviewed literature, different structures of LEC, energy management systems (EMS), market mechanisms and modelling approaches are described. Besides, different simulation platforms are deployed. In this section, a comprehensive review of these approaches is presented together with our own reflection on relevance to LEC modelling in the FINE project.

2.1 Market structures of LEC

Different categories of LEC structures can be distinguished in literature depending on the degree of decentralization of the LEC. The main categories are classified into community-based structure and Peer-to-Peer (P2P) structure as described in the following subsections.

2.1.1 Community-based market

A community-based structure is when a community of prosumers operates collaboratively to optimize their assets and trade their lack or excess of collective energy. To coordinate prosumers, to provide services to the distribution system operator (DSO), and to interface with different existing markets, a non-profit virtual node called a community manager as shown in Figure 2.1 is introduced in [5]. This structure can readily be applied to micro/mini-grids or to a group of neighbouring prosumers that are geographically close. Nevertheless, more generally, a community is to be based on members who share common interests and goals: for instance, a group of members willing to share green energy, though they are not at the same location. Hence, the community-based structure design is the enhancement of involvement and cooperation between peers.

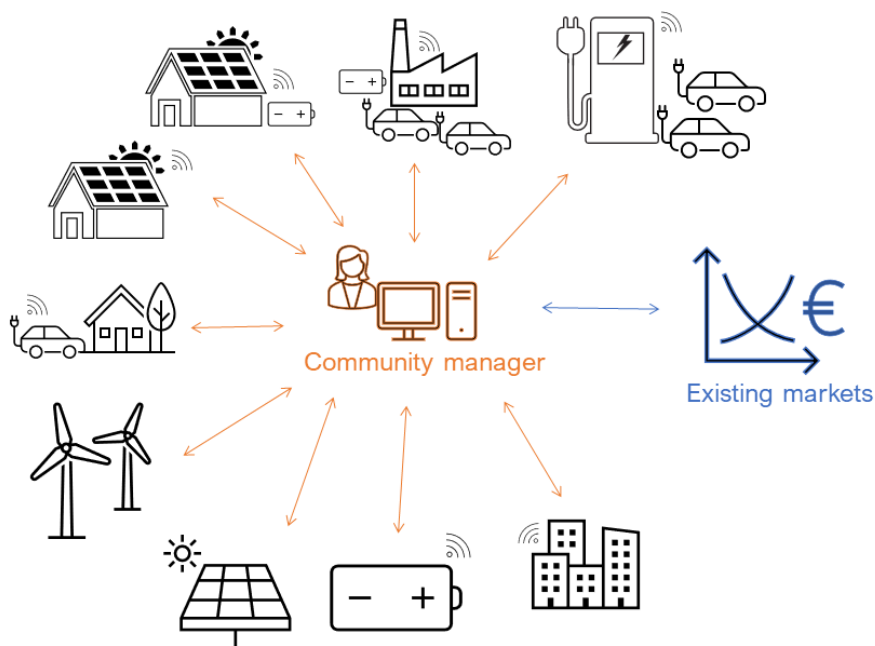


Figure 2.1: Illustration of community-based market.

Energy management of community-based LEC

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

- 1) **Centralized:** A single central node with EMS, which is characterized by a high-performance computing unit managing the assets owned by the prosumers. This central node performs computations to calculate optimal reference signals while considering all the prosumer's assets in one optimization problem. Each of the prosumer's asset uses a local controller (LC) in order to communicate and directly interact with the central node as shown in Figure 2.2. Central node sends reference signals to LC.
- 2) **Decentralized:** Unlike a centralized optimization framework, each prosumer is considered autonomous in a decentralized optimization problem and has its own EMS. With this thought, the centralized optimization problem can be broken down into N subproblems that can be solved independently by each prosumer EMS. However, there is still a need for a central node that ensures the power balance among prosumers, i.e., to sell their surplus energy to other prosumers or the electric network. To achieve this, the alternating direction method of multipliers (ADMM) is a decomposition-coordination procedure. The solutions to small local subproblems are coordinated to find a solution to a significant global problem. ADMM is an iterative procedure where prosumer EMS solves its subproblem to optimize its assets and sends the solution to the central node. Central node checks for the power balance and the final calculated optimal commands from Prosumers EMS are dispatched to LC as shown in Figure 2.3.

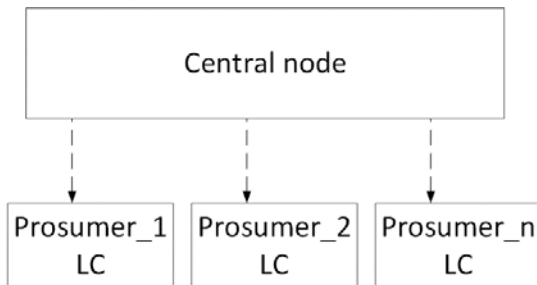


Figure 2.2: Centralised framework.

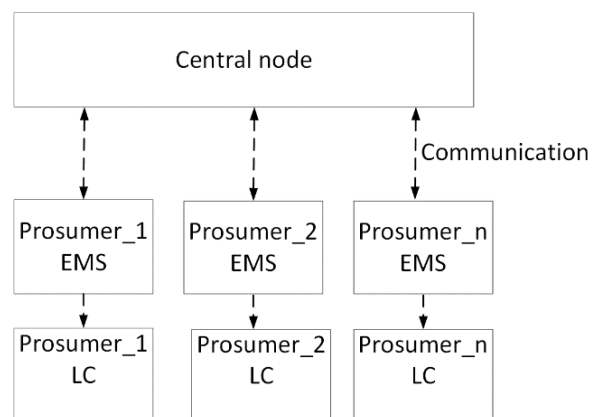


Figure 2.3: Decentralised framework.

In community-based LEC, the prosumer agents collectively act as assets of the community, and the community manager agent takes the responsibility of coordinating collective assets. The community manager can interact with different markets and the DSO. The tasks and responsibilities with different objectives and constraints for different agents reported in [5], [6], [7] is discussed below and in Table 2.1.

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 has to find 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 to preserve fairness among the prosumers, for instance, to prevent strategic behavior, in ref. [5] a community may choose to penalize the prosumer contributing the most to the import by an additional fee. Each member is, therefore, 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 maximum imported energy. The community manager can play the role of local market operator, including the tasks related with market clearing and settlement [6].

In [8], a cooperative strategy in a community of prosumers to maximize the benefits of each prosumer and the whole community is proposed. This cooperative strategy is called an augmented energy management model [9] for prosumers. This model considers controlled and uncontrolled generation and consumption and the prosumer's ability in two ways:

1. to plan the power consumption day-ahead;
2. to manage 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 the intended consumption, and help each other by compensating deviations. The proposed approach tries to improve the power system and enable a prosumer society that takes into account each prosumer's comfort.

A design of a community-based LEC is proposed in [6] where the members are allowed to trade energy between 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 takes part in the determination of the local market price while deciding its own scheduling problem under uncertainty concerning renewable energy generation and storage. In the energy community discussed in [7], each prosumer and its assets are connected to a community manager. The community manager optimizes the cost of the community with a dispatch model while having the constraint to satisfy the heat and electricity demand. The community manager can control the prosumers' assets and decide if the prosumers should import/export from/to the main electric network or exchange energy locally.

Table 2.1: Literature survey for community-based LEC.

Reference	[6]	[5]	[7]		
Framework	Decentralised	Decentralised	Centralised		
Stakeholder	DSO, Community Manager, Prosumers	DSO, Community Manager, Prosumers	DSO, Prosumers		
Component	PV, BESS in one community	PV, BESS in multiple communities	PV, BESS, Thermal energy storage system, Heatpumps, Demand response		
EMS agents	Prosumer Agent	Community Manager Agent	Prosumer Agent		
	Community Manager Agent	Prosumer Agent	Community Manager Agent		
	<u>Objective</u> minimize the cost of the energy supply. <u>Constraints</u> <ul style="list-style-type: none"> • BESS operation • Energy balance • PV limits • DSO contract limit¹ <u>Algorithm</u> ADMM	<u>Settlement Mechanism</u> <ul style="list-style-type: none"> • gives tentative price to prosumers. • gathers all the tentative commitments from prosumers and check if the energy balances. 	<u>Objective</u> Minimize costs by finding the optimal power setpoints for each asset <u>Constraints</u> <ul style="list-style-type: none"> • BESS operation • Power balance • Community energy exchange • Energy exchanges with the DSO² <u>Algorithm</u> ADMM	<u>Objectives</u> <ul style="list-style-type: none"> • minimize the costs of importing • maximize the revenues from exporting energy in day-ahead. • peak shaving services³ 	<u>Objective</u> minimize cost of community ⁴ <u>Constraints</u> <ul style="list-style-type: none"> • Electricity and heating balance • Assets power/energy capacity. • BESS and thermal energy system operation • Internal energy exchange cost
Test Network	A residential neighbourhood in the city of Amsterdam, the Netherlands. Data of ten households from the neighbourhood is used for running the simulation for one day.	A setup of 15 prosumers. The data was originally collected from households in Australia.	The case study is carried out on a district in Gothenburg, Sweden. The district has 41 buildings including houses, multi-family dwellings and services buildings.		

¹ 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

² Energy each prosumer has to respectively import, or export, from outside the community

³ By minimizing the maximum imported energy by adding a penalty coefficient

⁴ Summation of assets operating cost, cost for imports from the outer electric network, local energy exchange cost exporting to outer electric network.

2.1.2 Peer-to-Peer based market

In situations where there are many prosumers with conflicting interests, it would be quite challenging either to capture such conflicting interests in the decision-making process of each participant or to motivate them to cooperate for achieving the goals of community-based structure. 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 as illustrated in Figure 2.4. There can be a separate entity called Peer-to-Peer Market Operator (P2PMO) responsible for the execution of energy trading [10], but this does not always exist [11].

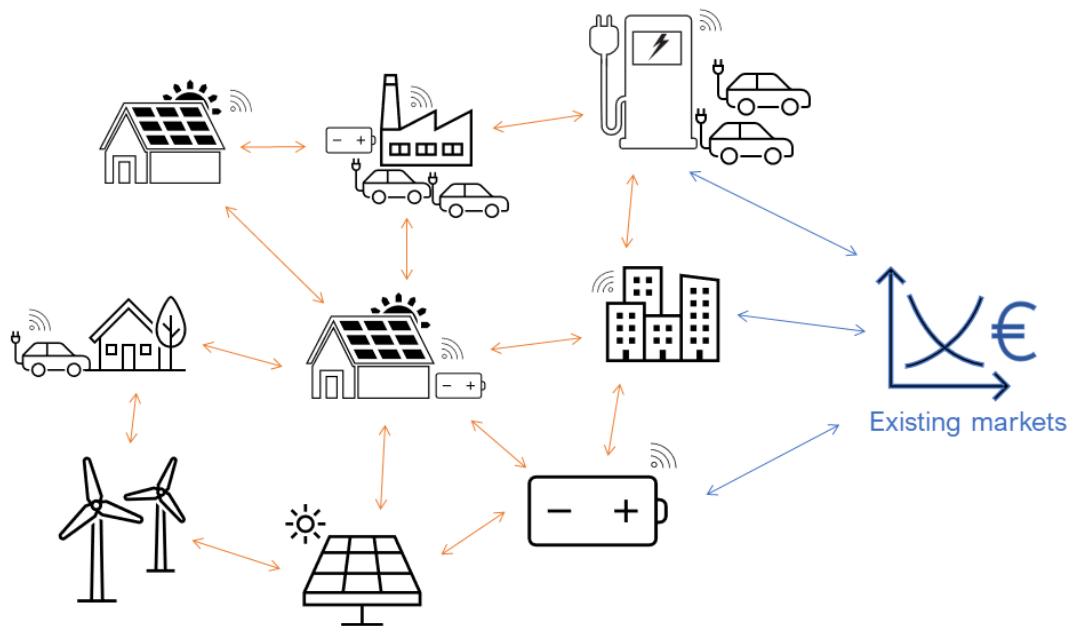


Figure 2.4: Illustration of P2P market.

Energy management of Peer-to-Peer based LEC:

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

- 1) **Fully distributed:** The fully distributed nature of the optimization framework implies that the ADMM algorithm is solved at the individual prosumer EMS level. There is no central node (Figure 2.6) to check the power balance. Prosumer EMS communicates with the neighboring EMS and solves the optimization problem while considering power exchange information from other prosumers EMS. The use of a distributed approach limits the information that every prosumer needs to communicate.
- 2) **Partially distributed:** The partially distributed approach is a presence of one central node (to check the power balance) and the other nodes can act in a distributed manner (to calculate reference commands for LC) (Figure 2.5).

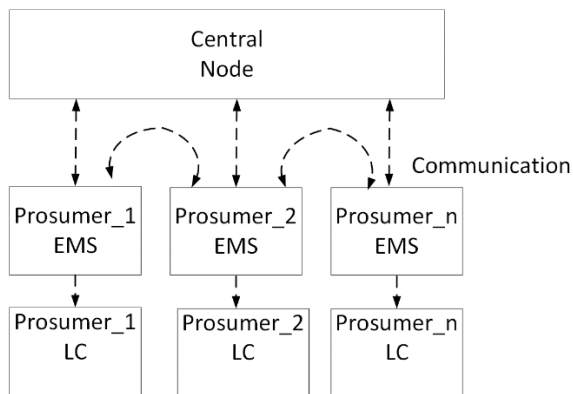


Figure 2.5: Partially distributed framework.

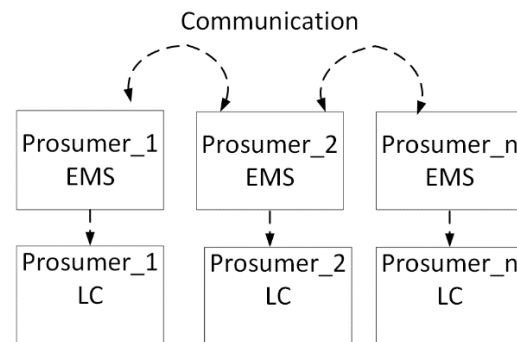


Figure 2.6: Fully distributed framework.

In this structure, three agents, such as prosumer agent, market mechanism agent, and DSO agent, are needed. P2P LEC model is considered more autonomous with more dispersed communication infrastructure than the community-based model. The prosumer agents optimize their assets and also can directly communicate with other prosumer agents. The market mechanism agent can handle clearing the market and system stability eliminating the need for 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 [5], [6], [11], [12] is discussed in detail below and also elaborated with the objective and constraints in Table 2.3.

Prosumer Agent

A prosumer agent is an EMS, as discussed in Section 2.1.1. All the prosumers agent in a community are connected through the bidirectional power and communication links, and a whole community is connected to the upstream electric network via a one point of common coupling point [10]. Smart meters are installed at each prosumer. Smart meter measures the prosumer's generation, consumption, and energy transaction with other prosumers or with the electric network.

Market Mechanism Agent

A market mechanism agent assists with energy trading in a P2P market. This software platform, enables the information exchange among prosumers and also assists DSO to monitor and control the distribution network.

DSO Agent

The DSO agent 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. DSO send a signal to 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 electric network at a specific time due to the huge risk of creating voltage problems in the network. If the transaction is approved, the extra cost associated with the network constraints are allocated to the users involved in the matched transaction [12].

In [11], the authors proposed a fully distributed framework with no central coordinator or market mechanism. The grid meter positioned at the point of common coupling with the electric network 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 every 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. Moreover, a predefined time-varying price profile of the energy exchanges with the electric network is assumed.

In [12], the authors presented a partially distributed architecture where a central coordinator ensures that energy is exchanged between prosumers without violating the network constraints and that prosumers can still capture the economic benefits. The authors proposed a novel methodology which embeds voltage and loss sensitivity coefficients to validate the energy transactions. Moreover, transactions will be charged with extra costs associated with losses.

Ref. [13] proposed a P2P energy market platform based on the new concept of multi-class EMS to coordinate trading between prosumers. The P2P platform minimizes costs associated with power losses and battery depreciation while providing added value by accounting for the prosumers' individual preferences for the source/destination of the energy they consume/produce.

Table 2.2: Literature survey for P2P LEC structure.

Ref.	Framework	Stakeholder	Component	Energy Management System		Test Network
[11]	Distributed	DSO, Prosumer	PV, Battery	Prosumer Agent <u>Objective</u> Minimizing the energy procurement cost of the LEC considering the power loss in the electric network. <u>Constraints</u> <ul style="list-style-type: none"> • BESS operation • Power balance with network losses • Loss estimation • Coordination constraint 5 <u>Algorithm</u> ADMM		Two LV feeders. Five prosumers are connected to each feeder.
[12]	Partially distributed	DSO, Market Agent, Prosumer	PV, Battery	Prosumer Agent <u>Objective</u> Optimise self - consumption <u>Constraints</u> <ul style="list-style-type: none"> • BESS operation • Energy balance 	DSO Agent <u>Objective</u> To evaluate voltage variation and line congestion using <ul style="list-style-type: none"> • Voltage sensitivity coefficients • Power transfer distribution factors • Loss sensitivity factors 	U.K. LV electric network comprising one feeder, hundred households.
[13]	Decentralised	Wholesale Electricity Market, P2P Platform Agent, Prosumer	PV, Battery	P2P Platform Agent <u>Objective</u> Minimize losses between the main and distribution electric network. <u>Constraints</u> <ul style="list-style-type: none"> • Power Flow <u>Algorithm</u> ADMM	Prosumer Agent <u>Objective</u> Minimise the operational cost <u>Constraints</u> <ul style="list-style-type: none"> • BESS depreciation • BESS operation • Renewable source • Power balance 	IEEE European Low Voltage Test Feeder, with 55 prosumers.

2.1.3 Review of LEC simulation platforms

ADMM-based clearing process [6], as explained in Section 2.1.1, is analyzed in terms of scalability and convergence by performing simulations within a Python 3.7 environment, using CVXPY to model the subproblems with ECOS as a solver. The computer used for the optimization has a CPU Intel Core i7 10510U 2.30 GHz and 8 GB of RAM. In [12], four schemes such as Local Market P2P, static active power curtailment, tripping, droop-based active curtailment is simulated using OpenDSS software. In [13], to achieve agreement between the prosumers and the market platform agent, the ADMM algorithm is run for 300 iterations at each trading interval. The optimization sub-problems were solved using IBM's CPLEX solver in

5 Coordination between the sales and purchase decisions of prosumer with respect to other prosumers.

MATLAB on an Intel Core i7-6500U CPU with 8GB of RAM. In [14], different operation scenarios of multi-microgrid energy management optimization model have been carried out in the MATLAB environment using the IBM ILOG CPLEX LP solver on an Intel Core 2 Duo 3.00 GHz running Windows 7. In [15], eight LECs under study and the distribution network are modeled using MATLAB/Simulink, including a model of the electric network, the RESs, and various flexibilities, such as energy storage systems. As the underlying optimization method of the Simulink models, an optimal power flow is computed under the LEC assets and the distribution network constraints. All optimizations are conducted using the Gurobi optimization solver.

Various LEC simulation platforms found in literature has been briefly described in Table 2.3.

Table 2.3: LEC solvers and tools used for implementing EMS.

Ref.	Solvers/Tools
[6]	Python 3.7 environment, using CVXPY to model the subproblems with ECOS as a solver.
[12]	OpenDSS software
[11]	AIMMS Developer modelling environment and tested by using the Cplex V12.8 solver. MIQP (mixed integer quadratic programming)
[13]	The optimisation sub-problems were solved using IBM's CPLEX solver in MATLAB, on an Intel Core i7-6500U CPU with 8GB of RAM.
[14]	MATLAB environment using the IBM ILOG CPLEX LP solver on an Intel Core 2 Duo 3.00 GHz running Windows 7
[15]	The eight LECs under study as well as the distribution network are modeled using MATLAB/Simulink All optimizations are conducted using the Gurobi optimization solver.

2.1.4 Review of LEC market mechanism

From a market perspective, prosumers are defined only by their energy trades within and outside the community. A market layer at the community level allows the prosumers of the community to share their excess or lack of energy. The market layer envisages trades between the community, as a whole, and the DSO. Table 2.4 briefly describes the market mechanism found in the literature.

Ref. [11] 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 optimization 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 prosumer. In [12], continuous double auction market mechanism is used, which is very well suited for P2P exchanges. It should be noted that in continuous double auction comprising bidders with reasonable goals (i.e., participants only trade at a profit), trades are always Pareto-improving. That is, the continuous double auction moves towards an allocation that is Pareto efficient. As such, the continuous double auction tends towards a highly efficient allocation of energy.

In [13], 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. Ref. [15] presents a Nash bargaining solution (NBS) approach to offer a fair and financial reimbursement for changing the operation objectives of such 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.

Table 2.4: LEC market platforms/mechanism.

Ref.	Market mechanism
[11]	No additional framework matching is done using ADMM.
[12]	Continuous Double Auction
[13]	A platform agent is introduced to act as an auctioneer and to allow energy trading between the prosumers and the wholesale electricity market (e.g. Uber)
[15]	Nash bargaining equilibrium

2.1.5 Comparison of market structures

Both the peer-to-peer and community-based market structures have advantages and challenges as discussed in Table 2.5.

Table 2.5: Advantages and challenges of LEC structures for different stakeholders.

LEC structure	Main advantages	Main challenges
Peer-to-Peer (P2P)	<ul style="list-style-type: none"> Total freedom of choice and autonomy, empowering the active consumers. Energy use aligned with each prosumer's preference (e.g. cost, green, local, etc) 	<ul style="list-style-type: none"> Investment and maintenance of ICT infrastructure. Scalability problem concerning the negotiation process discussed in [16] Predicting system behaviour by DSO, because of the lack of centralized control.
Community-based	<ul style="list-style-type: none"> Enhancing the relationship and involvement of community members, because of sharing a common good (i.e. energy) Mobilizing social cooperation in community members Potential new services for DSO provided by the community manager 	<ul style="list-style-type: none"> Reaching the preferences of energy use for all community members at all time. Having a fair and unbiased energy sharing among community members

2.2 Microgrids

In this section, a review of the energy management of microgrids is presented. 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 point of common coupling (PCC), which has the ability to operate in islanded mode. LECs do not necessarily have one PCC nor the ability to be islanded. Furthermore, as described by the definition of a LEC (in Section 1.1), the LEC often has a greater motivation and participation from the community members.

In [14], centralized controller, which would be owned and operated by the partnership with prosumers, controls the BESS and calculates their electricity costs using the optimization framework. As a result of this coordinated control scheme, the prosumers in the microgrid share their resources (PV and BESS) to reduce their electricity cost substantially. To model different objectives of DSO and microgrids, a coordinated decentralised bilevel problem with DSO in the upper level and microgrids in the lower level is formulated in [17]. At the upper level DSO guarantee the power flows and voltage levels while minimizing the operational cost. At the lower level microgrids optimize its own objective of minimizing the operational costs as given in Table 2.6.

Table 2.6: Operational cost in [17].

Operational cost of microgrid	Operation cost of DSO
<ul style="list-style-type: none"> • the operation costs of assets and the cost of purchasing electricity from the DSO • the revenues of a microgrid result from selling electricity to microgrid consumers and the electric network. 	<ul style="list-style-type: none"> • operation costs of DSO-owned assets and the cost of purchasing electricity from microgrids and the connected high voltage system • the revenues include selling electricity to the high voltage system, DSO consumers, and microgrids

The EMS in [18] has a hierarchical decentralized system of system architecture; therefore, a bi-level optimization model is developed. Energy management is achieved at two levels:

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

Provided with a schedule of power exchange and trading from DSO, the energy management of each microgrid aims to minimize the daily operating cost. In [19], author proposed a transactive energy control framework. They introduced an entity called system coordinator, similar to an independent operator in electricity markets who only manages the energy trading through the electric network. Thus, 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 optimizes the allocation of the bids received and provided feedback regarding successful energy transactions.

The details of objective, constraints for [14], [17], [18], [19] is discussed in Table 2.7.

Table 2.7: Literature Survey for Microgrids.

Ref.	Framework	Stakeholder	Component	Energy Management System		Test Network
[18]	System of Systems	DSO controller, ₁ microgrid central controller, ₂ microgrid	wind, PV, BESS, diesel generator	Microgrid central controller	DSO controller	3 microgrids are built on 3 islands owned by the same investor.
				<u>Objective</u> minimise the daily operating cost <u>Constraints</u> <ul style="list-style-type: none"> • Wind, PV operation • Diesel generator • BESS • Power balance 	<u>Objective</u> coordinating energy exchange between microgrids <u>Constraints</u> <ul style="list-style-type: none"> • Power Flow Constraints • Voltage limits • Active and Reactive Power limits 	
[17]	Decentralised	DSO controller, ₁ microgrid central controller, ₂ microgrid	microturbine PV, wind turbine	Microgrid_central controller	DSO controller	Modified IEEE 33-bus distribution system with 3 microgrids
				<u>Objective</u> Minimise the daily operating cost <u>Constraints</u> <ul style="list-style-type: none"> • Microturbine operation • Redispatch cost • Power balance 	<u>Objective</u> Minimise the daily operating cost <u>Constraints</u> <ul style="list-style-type: none"> • Power Flow • Voltage limits • Microturbine operation • Redispatch cost • Power balance 	
[14]	Centralized	DSO, microgrid owners	BESS, PV	Centralized Controller		A network with one hundred microgrids is considered.
				<u>Objective</u> net cost of electricity for the corresponding microgrids <u>Constraints</u> <ul style="list-style-type: none"> • Power Exchange • BESS operation • Island mode operation • Peak shaving operation • Fair power exchange operation 		
[19]	Transactive Energy Control	Microgrid operator, system coordinator, High voltage system	PV, conventional generating units	Microgrid Operator	System Coordinator	A total of five microgrids are included, and the IEEE 123
				<u>Objective</u> minimize the total procurement cost <u>Constraints</u> <ul style="list-style-type: none"> • Power balance • ramping limits • active and reactive power generation limits 	<u>Objective</u> minimize the procurement cost from high voltage system and max. social welfare of energy transaction among microgrids. <u>Constraints</u> <ul style="list-style-type: none"> • branch power flow limit • nodal voltage magnitude limit • nodal power injection 	

2.3 Modelling approaches

To simulate a complete system with EMS of different stakeholders two modelling approaches can be used as described below.

2.3.1 Agent based modelling

Agent-based modelling and simulation (ABMS) is a relatively new approach to modelling systems composed of autonomous, interacting agents. Agent-based modelling is a way to model the dynamics of complex systems and complex adaptive systems. Such systems often self-organize themselves and create emergent order. Agent-based models also include models of behaviour (human or otherwise) and are used to observe the collective effects of agent behaviours and interactions [20]. The idea of agent-based modelling is quite timely due to the current decentralization in power systems. Previously, the multiagent system (MAS) in hierarchical control has been applied in microgrids. Bidirectional information and energy interaction in the microgrids can be achieved by using the distinct features of MAS, such as autonomy, communication, and coordination. Under the MAS environment, individual agents can determine power control strategies for entities such as distributed energy resources (DERs) or loads. During the whole process, communication and coordination are the most critical factors and the entire decision-making process. The operation of MAS relies on the communication links, as the open communication infrastructures, Ethernet, worldwide interoperability for microwave access (WiMAX), and wireless fidelity (Wi-Fi) can be used for communication links of electric network [21]. The implementation of these agents has been discussed in several literature as described in Table 2.8.

Table 2.8: Agent based modelling literature.

Ref.	Modelled agent	Simulator for modelling	Communication between agents	Communication between agents and simulator
[22]	BESS, a micro-gas turbine, a controllable load	Real-time simulator named Opal-RT	16-bit freescale microcontrollers, ZigBee modules	Interface boards using a controller area network protocol
[23]	Substation, bus, feeder, load, generator	Internet Technology Based Power System Simulator	Java Agent Development Framework (JADE), Java Universal Network/Graph Framework	
[24]	Microgrid	MATLAB	JADE	
[25]	Microgrid	MATLAB/Simulink	JADE	MACSimJX, acts a middleware between Simulink models and the agents
[26]	Feeder	Actual 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

2.3.2 Co-simulation

Co-simulation consists of the theory and techniques to enable global simulation of a coupled system via the composition of simulators. Co-simulation addresses the challenge that models of individual partial solution cannot be exchanged or integrated easily due to the specialized tools deployed and the needed specialized expertise. An alternative to co-simulation is co-modelling where models are described in a unified language [27]. Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) is employed in [28] to model interactions between the prosumer homes, the market, and the electric distribution network. The modelled entities and the modelling platforms used are presented in Table 2.9. 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 as illustrated in Figure 2.7.

Table 2.9: Model entities and platforms.

Entities	Platform
A house model	Thermal resistance-capacitance (RC) model (The operational, controllable, high-resolution residential energy (OCHRE) model is a new tool specifically designed for co-simulation applications.)
A house controller	foresee™
An energy orders broker	An intermediary between the market solver and the home controller. It is meant to represent a self-executing smart contract that could be hosted on a blockchain ledger.
The Market Solver	PLEXOS, FESTIV
The Grid Simulator	OpenDSS

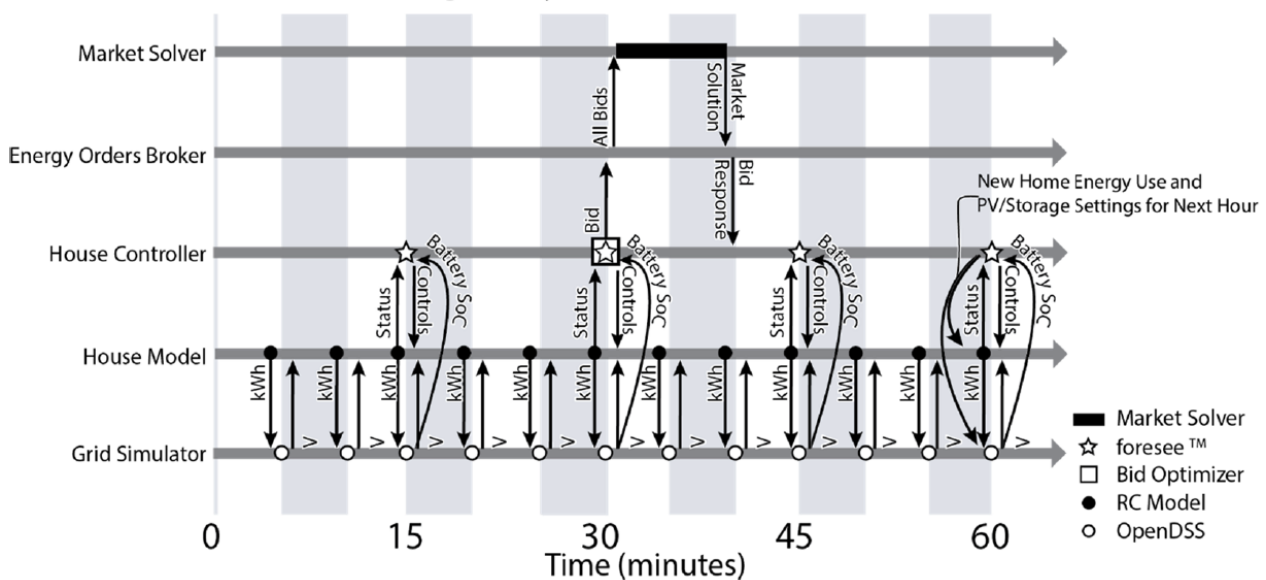


Figure 2.7: Timing of key events in each hour of the HILICS co-simulation. [28]

In [29], 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 as illustrated in Figure 2.8.

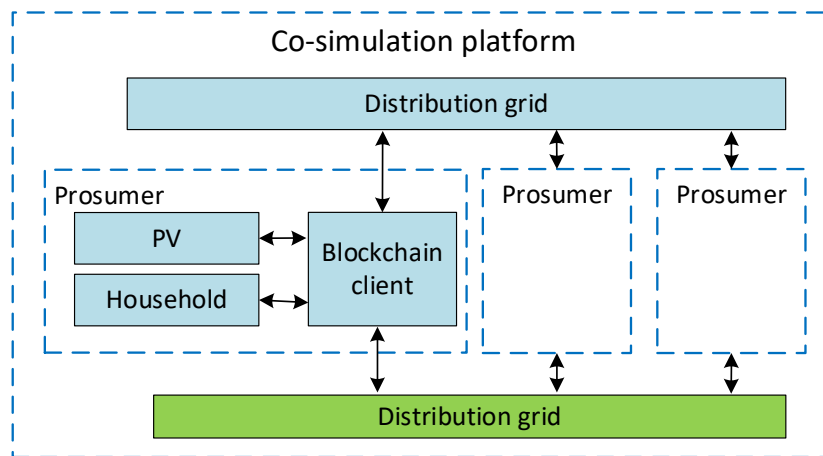


Figure 2.8: Overview of the co-simulation framework, orange blocks represent mosaik simulators. The blue block at the bottom represents the live blockchain shared between all the participants [29].

2.4 Proposed community-based LEC framework for modelling

In this section, a summary of three LEC modelling approaches is presented. Essentially the modelling approaches are distinct in terms of the EMS framework. The EMS frameworks include decentralized framework with and without P2P interaction and distributed framework in community-based LEC.

2.4.1 Decentralised framework

Figure 2.9 shows a LEC with four layers, i.e., physical layer, controller layer, market layer, and DSO. The controller layer, market layer, and DSO layer are arranged in a decentralized framework to manage 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 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. At the LEC level, the objective is to balance the power of small prosumers with community charging stations, community BESS, residential prosumers, or consumers within each LEC. Thus, community charging stations and community BESS receive charge/discharge commands from LEC_EMS. The home energy management system (HEMS) of residential households interacts with LEC EMS, as shown in Figure 2.10. LEC EMS gives scheduling signals to HEMS, which in turn gives the same signals to appliances.

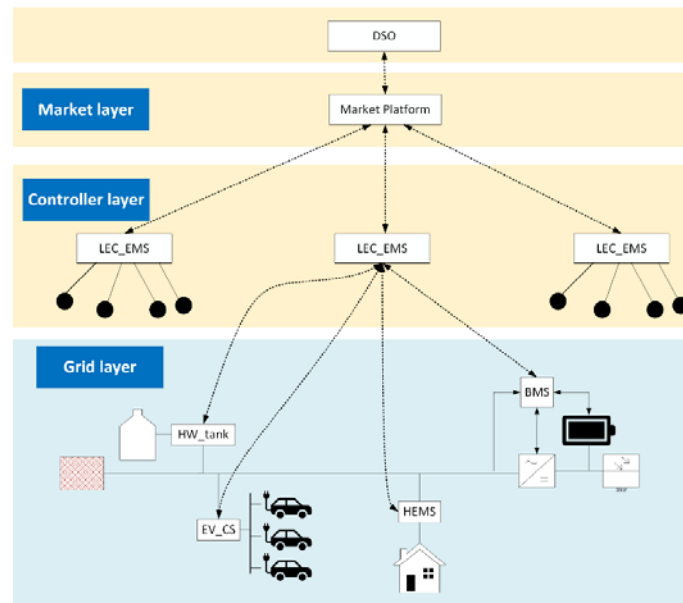


Figure 2.9: Decentralised framework.

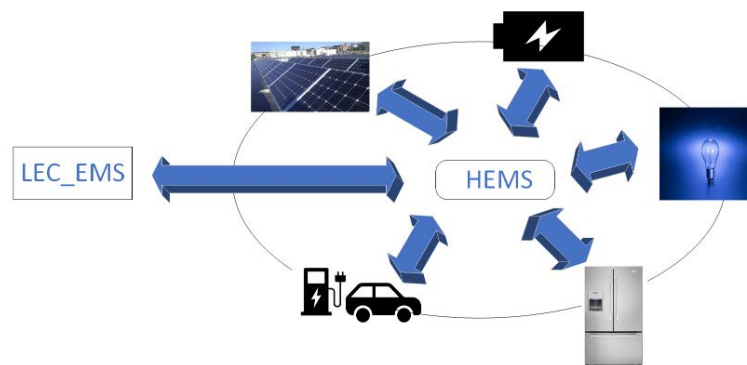


Figure 2.10: Interaction between LEC_EMS and HEMS.

2.4.2 Decentralised framework with P2P market within LEC

As shown in Figure 2.11, there is a physical layer, two controller layers, a market layer, and a DSO layer in this framework. Two controller layers are needed because this framework manages energy at two levels; the LEC level, and the HEMS level. Residential consumers/prosumers optimize their assets using HEMS, which generates command signals, and sends them back to individual appliances. There is still interaction with LEC_EMS, which is responsible for giving certain upper limits to the prosumers and maintaining fairness among the prosumers. From a market perspective, there are three potential markets in this framework:

1. Prosumers or members of the collective share their excess or lack of energy (HEMS and HEMS interaction in Figure 2.11)
2. Trades between the community, as a whole, and the DSO (LEC_EMS and DSO interaction in Figure 2.11)
3. The community can share their energy managed by the market platform (LEC_EMS and Market Platform interaction in Figure 2.11).

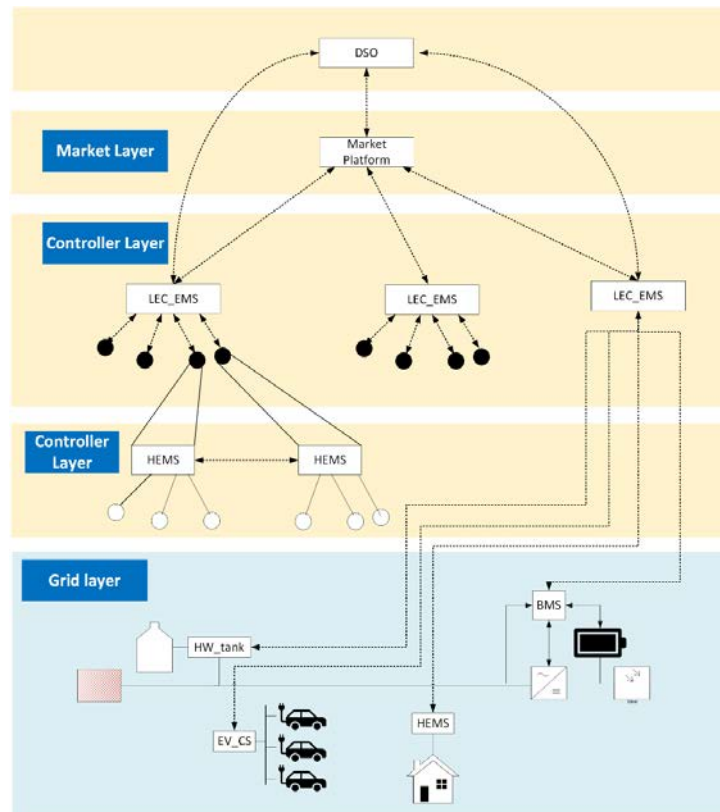


Figure 2.11 Interaction between LEC_EMS, HEMS and different layers in decentralized framework

2.4.3 Distributed framework

In this framework, as shown in Figure 2.12, there are only two layers: the physical layer and the controller. In distributed framework, every LEC EMS communicates with other LEC_EMS through a communication network to achieve the global control objectives. The communication network is sparse, and every agent communicates with a few other agents (neighbors). A lack of a supervisory agent characterizes a distributed framework. However, it consists of a simultaneous negotiation over the price and energy of multi-bilateral trades along with a predefined trading scheme. Moreover, community charging stations and community battery storage systems receive charge/discharge commands, and residential households receive scheduling signals for the HEMS.

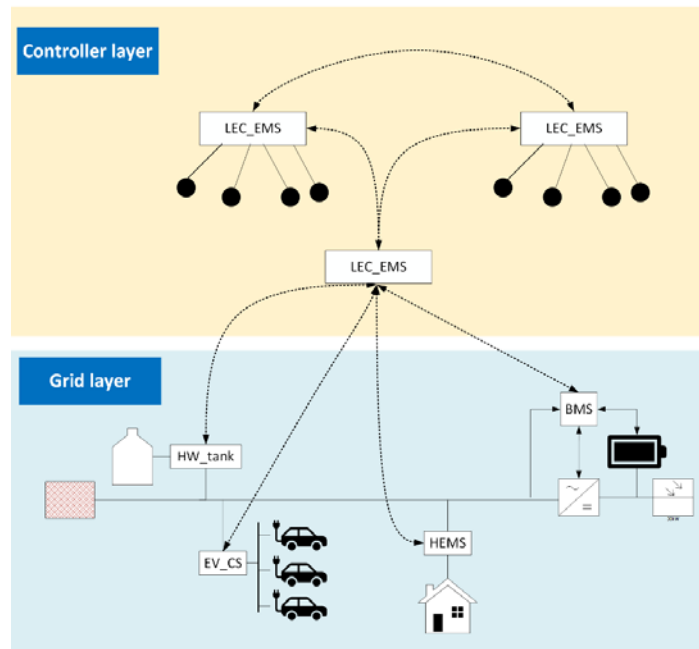


Figure 2.12 Interaction between LEC_EMS and different layers in distributed framework

3 Deep Reinforcement Learning in LECs – overview of the state of the art

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. Autonomous agents such as LEC_EMS, prosumers, home energy management systems (HEMS), DSO models, aggregators and similar have been explored in literature using deep reinforcement learning. Additional uncertainties and more localized storage capacities also have the potential to further increase this trend from traditional control models to deep reinforcement learning, which will be explored in this section.

3.1 Introduction to Reinforcement Learning

Reinforcement learning is a special form of dynamic optimization that uses function approximations for the expectations of future outcomes of a dynamic system [30], [31]. Thus, it is also being referred to as approximate dynamic programming.

The mentioned approximation concerns the future state of an optimization problem. Assuming the task is to optimally schedule charging of a battery in a microgrid, the expectation of future outcomes would include the system (e.g. expectations of future consumption and generation in the microgrid) as well as the impact of the decision to be optimized on such (e.g. what is the value of storing regarding minimizing the cost of electric network feed-in, etc.) as illustrated in Figure 3.1.

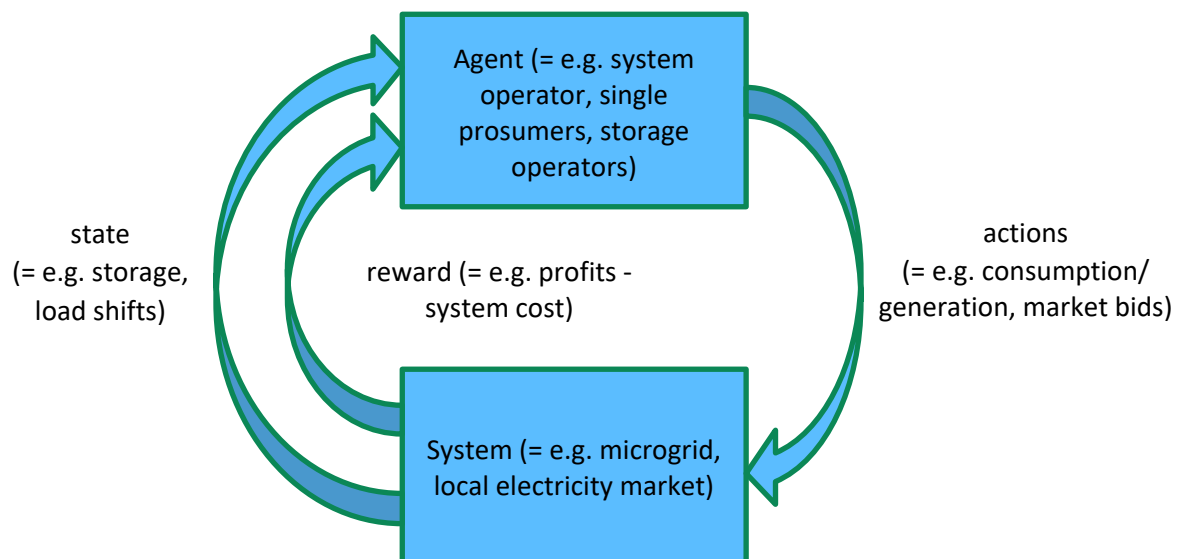


Figure 3.1: Agent-environment interaction in agent based modelling.

Usually the decision process is formulated as a Markov decision process and discounted to require the algorithm to prefer pay-off now over 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 neural networks. Power systems is no exception to this.

3.2 Introduction to Deep Learning

Deep learning is a subcategory of machine learning, where non-linear functions are represented via differentiable stacks of layers, 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.

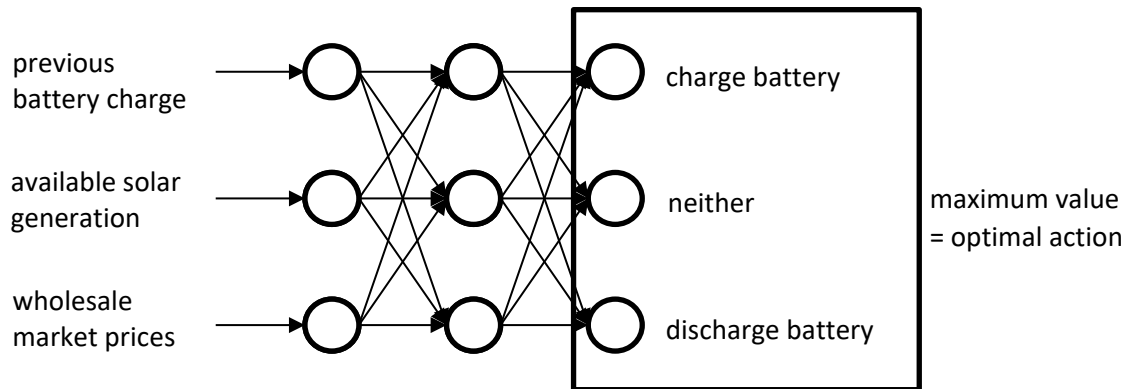


Figure 3.2: Backpropagation Neural Network for battery charge-discharge decision.

3.3 Introduction to Q-Learning

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 [32]. 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 Figure 3.2). 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 LECs is given in the following:

- Ref. [33], which applies reinforcement learning on a decentralized energy management system and a utility function representation for demand response. Ref. [34] approaches a similar task, but focusing on the generation side over the demand side.
- Ref. [35] applies Q-Learning on charging management of fleets of single or aggregated EVs. Ref. [36] does similar but focusing on a single-household level and thus also includes home appliances.
- Ref. [37] adds competition to Q-Learning frameworks by having several agents solve subsystems and interact with each other in a Stackelberg framework. A similar transactional focus is shown by ref. [38] which implements market trading in a microgrid via Q-Learning agents. In similar context, ref. [39] considers Q-Learning agents interacting within a single building.

4 Description of the LEC model

The complete LEC model shall include the adequate representations for the components, primary controllers, EMS, the market environment, and the distribution network the LEC is connected to and operating within.

Full scale models of LECs and their operating environment are likely to traverse across multiple domains such as: electrical domain, market domain, controller domain and possibly ICT domain. However, in the FINE project the purpose of such model is to generate power exchange timeseries data to the DSO-LEC coupling point from relevant LEC architectures and also to simulate and study impact of different market architectures. Hence, essentially detail attention will be given to the electrical and market models while adequate considerations will be given to control and ICT domains.

Usually, the phasor model is designed for system-level analysis of power systems, while conventional distribution electric networks are described as passive elements. Nevertheless, the power system is becoming more dynamic and oscillatory due to the increasing number of actors such as EVs, storage systems and/or other DERs. Hence, the usual approaches of neglecting or averaging of high-time resolution transient is no longer sufficient to represent the operational dynamics in the distribution system [40].

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 electricity network. 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 [41]. This entails that there is a need for different level of model details and time resolution for market, controller, and electric grid component models.

4.1 The electric network

The level of details in the electrical network component models essentially depends on the network services the LEC is assumed to provide to the DSO and TSO, as well as the power quality requirements one envisions to impose on the LEC operation. As the FINE project mainly focuses on the interaction of LEC and the surrounding distribution network, the LEC ancillary service provisioning capabilities to the surrounding distribution network is given the utmost attention. In principle, the service provisioning capability of a LEC is limited by the capability of the individual components within the LEC. However, as stated above, the focus is mainly local services such as power quality and peak shaving. There might also be a need to study the services a LEC can provide to the TSO, and how this impacts the local distribution network.

The statutory voltage limits in Norway are monitored by the Norwegian Water Resources and Energy Directorate (NVE) and specified in Regulation on power system quality of supply⁶. The network companies are required to keep the steady state voltage in LV networks within $\pm 10\%$. There are also voltage quality regulations different from the CENELEC standard for voltage characteristics of electricity supplied by public electricity networks (EN 50160). The maximum number of voltage changes per 24 hours are limited in Norway as shown in Figure 4.1

⁶ <https://lovdata.no/dokument/SF/forskrift/2004-11-30-1557>

Table 4.1: Single rapid voltage change limitations within 24 hours. [42]

Voltage levels	Limits
$0.23 \leq U \leq 35 \text{ kV}$	$\Delta U_{\text{steady state}} \geq 3 \% / \leq 12$
$35 \text{ kV} < U$	$\Delta U_{\text{steady state}} \geq 3 \% / \leq 12$
$0.23 \leq U \leq 35 \text{ kV}$	$\Delta U_{\text{max}} \geq 5 \% / \leq 24$
$35 \text{ kV} < U$	$\Delta U_{\text{max}} \geq 5 \% / \leq 24$

Hence keeping statutory voltage limits and assuring voltage variation limits within a day can be considered services expected by the DSO from a LEC. In addition, flexibility and energy products outlined in Table 4.2 can be sought for by the DSO connecting a LEC.

Table 4.2: Generalized product definitions for load participation in ancillary services, energy, and capacity market. [43]

Product Type	General description	Physical Requirements			
		How fast to respond	Length of response	Time to fully respond	How often called
Regulation	Response to random unscheduled deviations in scheduled net load	30 seconds	Energy neutral in 15 minutes	5 minutes	Continuous within the specified bid period
Contingency	Rapid and immediate response to a loss in supply	1 minute	≤ 30 minutes	≤ 10 minutes	\leq Once per day
Flexibility*	Additional load following reserve for large unforecasted wind/solar ramps	5 minutes	1 hour	20 minutes	Continuous within the specified bid period
Energy*	Shed or shift energy consumption over time	5 minutes	≥ 1 hour	10 minutes	1-2 times per day with 4-8 hour ahead notification
Capacity	Ability to serve as an alternative to generation	Top 20 hours coincident with balancing authority area system peak per month.			

*Flexibility and Shifting/shedding energy are the relevant services in case of LEC-DSO interaction.

Based on the services expected from a LEC, as specified in this section, the level of modelling detail needs can be illustrated as shown in Figure 4.1. The modelling needs in the FINE project for power system components such as converters, battery storage systems, on-load tap changers, lines, transformers and loads are going to be satisfied by average value models and phasor models.

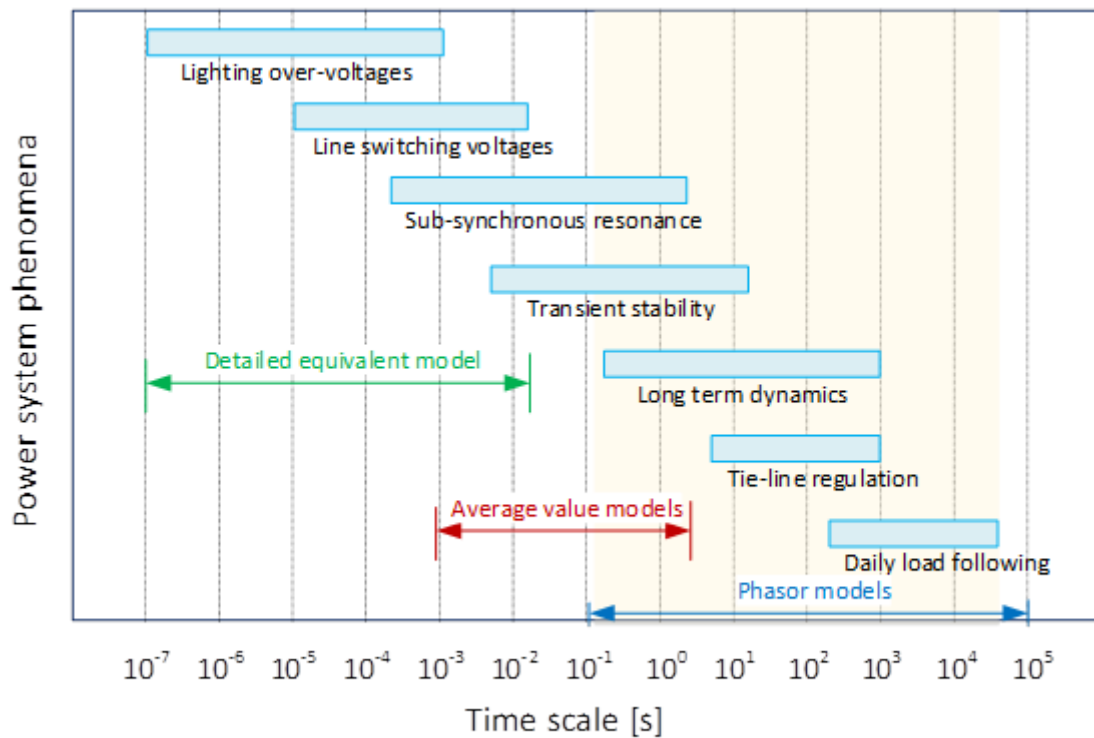


Figure 4.1: Time frames of power system phenomena and power system components modelling needs.

4.2 The energy management

In general, EMSs schedule dispatchable generators and flexible loads as well as scheduling charging and discharging for BESS within a specified period of time. Devices such as BESS, smart homes, LECs as well as distribution systems may have their respective EMSs. Although the environment the EMSs are operating in varies as we move from distribution system to individual devices, they can potentially be envisioned to operate autonomously, scheduling their operation achieving specified objectives such as loss minimization or energy cost minimization.

In this project, autonomous EMSs are envisioned at household level. Large community level storage systems within a LEC can also participate autonomously in a specified within-a-LEC local market environment. Another important aspect is the delegation of energy management to a third party, for example, with which an individual house within a LEC can delegate its energy management to LEC_EMS or aggregating actors while the other households within the same LEC run their own HEMS.

In FINE project, mainly LEC_EMS will be developed, and potentially autonomous household level and large storage systems and large flexible loads may have their own autonomous EMS.

4.3 The market platform

The modelling approach to be followed in this project needs to be flexible enough to accommodate different types of market architectures. The entity which will participate in some form of market architecture or contractual schemes are the EMSs. Therefore, decoupling the electric network model from the EMS algorithm is essential.

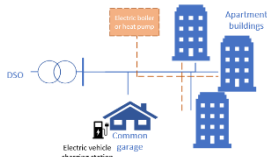
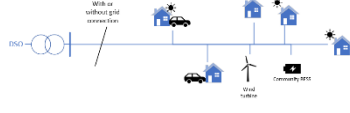
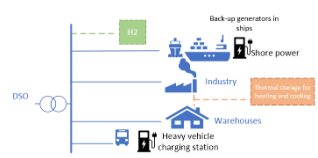
The modelling approach is expected to accommodate the following market transactions related interactions:

1. LEC_EMS to wholesale market interaction for objective such as energy arbitrage.
2. LEC_EMS to DSO contractual agreement, responding to DSO signals such as capacity based pricing, incentives or indicative guiding signals such as traffic light
3. One LEC_EMS to another LEC_EMS interaction in local P2P market
4. LEC_EMS making transaction with other actors such as aggregators
5. Within the LEC market transactions

4.4 Reference LECs and modelling

In section 1, descriptions of selected reference LEC types are presented. These reference LECs are to be developed further during the FINE project. Nevertheless, the reference LECs outlined here will guide modelling approaches and data specifications. The modelling needs of the three selected LECs are described in Table 4.3.

Table 4.3: Outline of modelling needs and possible modelling tools for selected reference LECs.

	LEC - Cooperative in urban area	LEC - Rural area with weak grid	LEC - Industry/enterprise cluster in harbour area
			
Electric network model needs	<p><i>Platform: Matlab Simscape</i></p> <p>Lines, transformers, EV battery, EV charging station load and household/apartment load.</p> <p>Thermal models of hotwater tank and building heating needs (<i>optional</i>).</p>	<p><i>Platform: Matlab Simscape</i></p> <p>Lines, transformers, EV battery, EV charging station load, PV generation, stationary battery storage and household/cabin load.</p>	<p><i>Platform: Matlab Simscape</i></p> <p>Lines, transformers, EV battery, EV charging station load, ferry charging station load/ship shore power load, Hydrogen fuel cell (<i>optional</i>) and industrial/enterprise load.</p> <p>Models of thermal storage (<i>optional</i>).</p>
LEC EMS model needs	<p><i>Platform: Python</i></p> <p>LEC Multi-Energy Management System, Building EMS, Charge station EMS, Hot water tank EMS</p>	<p><i>Platform: Python</i></p> <p>LEC Electrical Energy Management System</p>	<p><i>Platform: Python</i></p> <p>LEC Multi-Energy Management, Hydrogen storage EMS and Thermal storage EMS</p>
Market platforms	<p><i>Platform: Agent platform</i></p> <p>Wholesale market and DSO signal</p>	<p><i>Platform: Agent platform</i></p> <p>Wholesale market, DSO signal, peer-to-peer market</p>	<p><i>Platform: Agent platform</i></p> <p>Wholesale market and DSO signal</p>

5 First simulation results

A simple simulation is implemented to showcase a possible implementation of LEC models with the power system they are connected to. The model has an electric model implemented in Matlab Simulink and a LEC_EMS implemented in python as it is illustrated in Figure 5.1. In this implementation there is no market simulation implemented. However, a day-ahead market price signal is streamed from a timeseries data file.

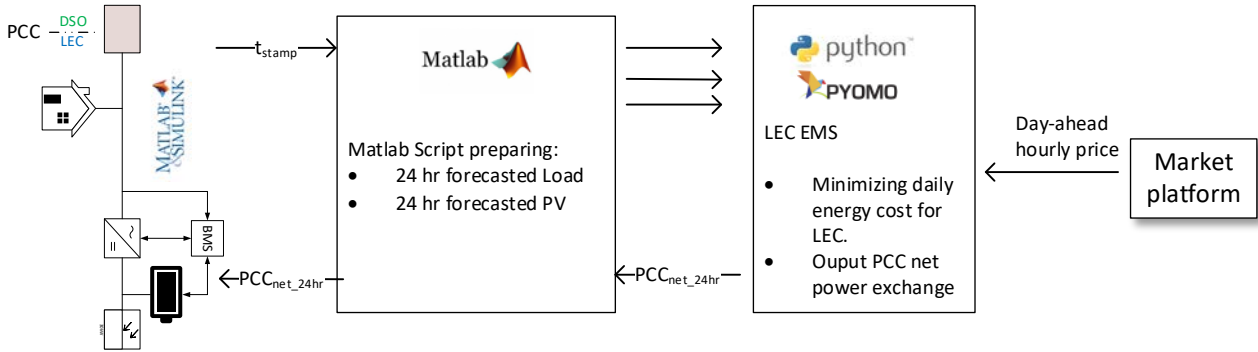


Figure 5.1: LEC modelling coupling physical electric network, energy management system and market price signal.

In this first implementation there is no forecasting tool. Load, PV generation and day-ahead market price timeseries profiles are used as deterministic simulation. There are two scenarios implemented in this simulation:

1. LEC EMS objective of Maximize Self-Consumption. (LEC-MSc)
2. LEC EMS objective of Maximize Profit from Energy Arbitrage. (LEC-MPEA)

The mathematical formulation of both the objectives and constraints are described below:

1.
$$\min \sum_t (p_{\text{import}}^t)$$
2.
$$\min \sum_t ((C_{\text{spot}}^t) \cdot p_{\text{import}}^t)$$

s.t

$$p_{\text{out}}^t + P_{\text{PV}}^t + p_{\text{import}}^t = P_{\text{load}}^t + p_{\text{in}}^t, \forall t$$

$$p_{\text{out}}^t \leq P_{\text{bat,max}}, \forall t$$

$$p_{\text{in}}^t \leq P_{\text{bat,max}}, \forall t$$

$$\sum_t p_{\text{in}}^t - \sum_t p_{\text{out}}^t = 0$$

$$e_{\text{SoC}}^t = 0.5 \cdot E_{\text{bat}}, t = 0$$

$$e_{\text{SoC}}^t = e_{\text{SoC}}^{t-1} + p_{\text{in}}^{t-1} \cdot \eta_{\text{bat}} - \frac{1}{\eta_{\text{bat}}} \cdot p_{\text{out}}^{t-1}, \forall t > 0$$

$$e_{\text{SoC}}^t \leq E_{\text{bat}}, \forall t$$

$$p_{\text{in}}^t, p_{\text{out}}^t, e_{\text{SoC}}^t \geq 0, \forall t$$

where

- C_{spot}^t is the spot price in hour t given in (NOK/kWh)
- p_{import}^t is the average power imported by the customer in hour t given in (kWh/h)
- p_{in}^t is the average charging rate by the battery in hour t given in (kWh/h)
- p_{out}^t is the average discharging rate by the battery in hour t given in (kWh/h)
- e_{SoC}^t is the State of Charge (SoC) of the battery in hour t given in kWh
- P_{PV}^t is the average power generated by the PV in hour t given in (kWh/h)
- P_{load}^t is the average load demand by the customer in hour t given in (kWh/h)
- $P_{\text{bat,max}}$ is the maximum charging/discharging rate of the battery
- E_{bat} is the maximum energy capacity of the battery in kWh
- η_{bat} is the charging and discharging efficiency of the battery

The first 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 Figure 5.2 and the resulting impact on voltage level is presented in Figure 5.3. The simulation results shows that active engagement of LEC_EMS, especially with energy arbitrage, results in creating stochastic load profile with new peaks and potentially power quality related challenges.

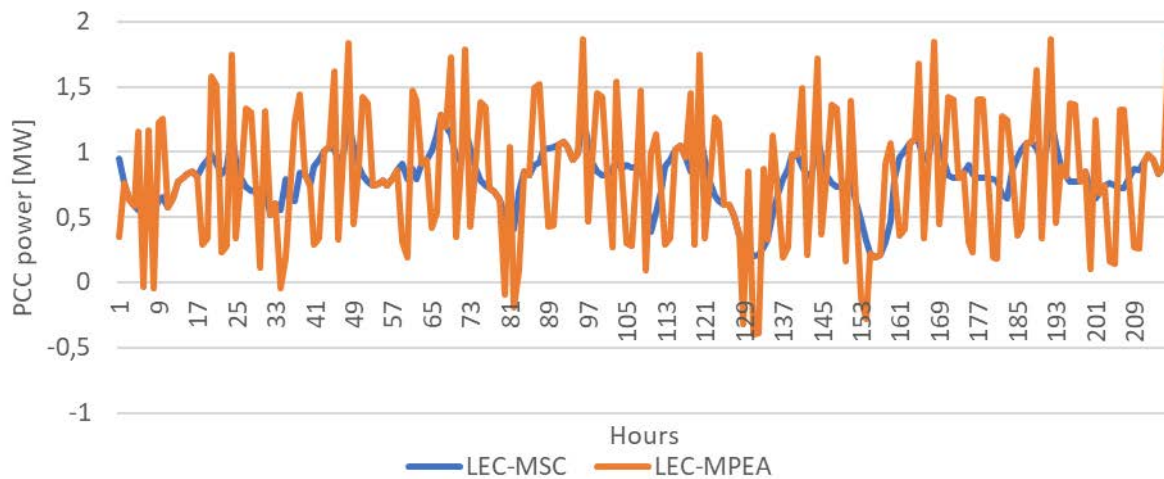


Figure 5.2: Impact of LEC operation with energy arbitrage on PCC power.

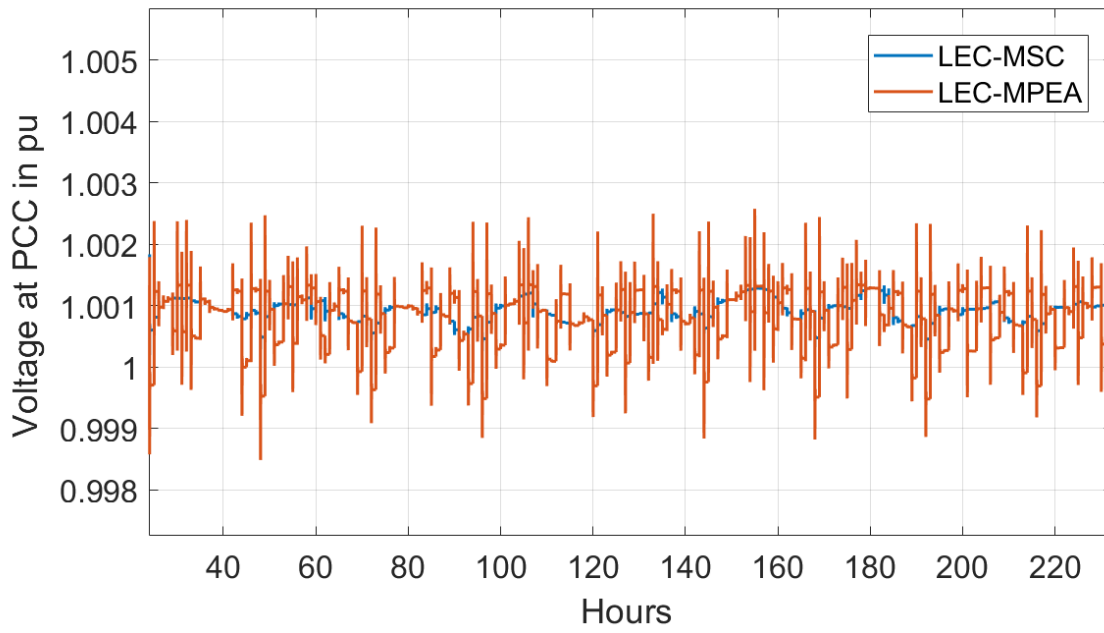


Figure 5.3 Impact of LEC operation with energy arbitrage on PCC voltage

6 Conclusion

LEC modelling can traverse both multiple domains such as control, market and power system as well as multiple energy systems such as thermal and electrical energy. Hence, the LEC modelling approaches should be flexible enough to simulate/ represent different configurations of domains and energy vectors (i.e. electric and thermal). In the FINE project, a step-by-step approach to modelling and simulation is devised as shown in Table 6.1.

Table 6.1: Implementation phases for modelling and simulation of LEC in the FINE project.

Phases of implementation	Activities	Comments
Phase#1	Standard test network (e.g. CIGRE MV and LV network) Define three LEC types Consider single price Real-time simulation	The use of standard test networks
Phase#2	Phase#1 with real network	The use of realistic Norwegian distribution network
Phase#3	Include DSO signal (e.g. traffic light) or incentive	Include price mechanism for activating flexibility
Phase#4	Include local (peer-to-peer) market and decentralized controller	Implement local market

While modelling LECs and their operating environment, one has to consider the following aspects:

1. Representation of customers which are not members of the LEC but reside at the same geographic location.
2. Representation of the freedom of LEC_EMS to directly participate in market frameworks or delegating it to other stakeholders such as aggregators.
3. Representation of multiple market frameworks and interactions among stakeholders.
4. Incorporation of diverse objectives in the LEC_EMS including economic, environmental, and other quantifiable sustainability factors.

Based on an evaluation of the available literature, the FINE project will implement and evaluate decentralized framework with both wholesale and local market as well as distributed framework for LEC_EMS. Market platforms will be implemented by applying agent-based modelling approach. As it is outlined in Table 6.1, the model developments and simulation implementation are planned to be carried out step-by-step increasing complexity and comprehensiveness.

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