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Review article

A systematic review of machine learning techniques related to local energy communities

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ABSTRACT

In recent years, digitalisation has rendered machine learning a key tool for improving processes in several sectors, as in the case of electrical power systems. Machine learning algorithms are data-driven models based on statistical learning theory and employed as a tool to exploit the data generated by the power system and its users. Energy communities are emerging as novel organisations for consumers and prosumers in the distribution grid. These communities may operate differently depending on their objectives and the potential service the community wants to offer to the distribution system operator. This paper presents the conceptualisation of a local energy community on the basis of a review of 25 energy community projects. Furthermore, an extensive literature review of machine learning algorithms for local energy community applications was conducted, and these algorithms were categorised according to forecasting, storage optimisation, energy management systems, power stability and quality, security, and energy transactions. The main algorithms reported in the literature were analysed and classified as supervised, unsupervised, and reinforcement learning algorithms. The findings demonstrate the manner in which supervised learning can provide accurate models for forecasting tasks. Similarly, reinforcement learning presents interesting capabilities in terms of control-related applications.

1. Introduction

Recent technological developments in renewable energy have enabled a shift in the energy generation capacity closer to the consumption. This evolution has led to a decentralisation process that is required for the coordination of generation and demand in electric power systems. A part of this process involves the management of a greater number of active consumers and so-called prosumers, i.e., consumers who also produce electricity in the grid. Consequently, the energy sector is transitioning towards a more decentralised control owing to these prosumers and active consumers, who cooperate for the management and control of storage systems and flexible demand. A resulting framework attempting to solve the challenges associated with this decentralisation is that of local energy communities (LECs) representing local, self-organising entities that operate autonomously or semi-autonomously within an electricity grid [1]. The shift towards a more community-focused approach from a traditionally centralised power system is further amplified by the increasing digitalisation of these systems, for example, in terms of the metering and control of energy. In this context, recently popularised technologies such as distributed ledgers [2], big data applications and artificial intelligence have shown promising results for shaping the future of decentralised power systems [3].

This paper focuses on the recently growing field of machine learning, which is a subcategory of the research field of artificial intelligence. Machine learning is based on the development of computer systems that can learn from data without explicitly following instructions. This learning is achieved via algorithms and statistical models to analyse and draw inferences from the data patterns. In several research fields such as those of medicine and finance, machine learning has been used to solve high-complexity problems. Moreover, community-based power systems are no exception to the advent of machine learning [4]. This study aims to discover a relationship between the operation of LECs and

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existing machine learning algorithms on the basis of recent research reported in the literature.

1.1. Research questions and contributions

This study aims to provide a systematic review on the state-of-the-art of machine learning that are applicable for LECs. Towards this end, an in-depth discussion and conceptualisation has been provided to answer the following question: ***'what constitutes as a local energy community?'***; the LEC characteristics have been defined from the perspective of European electricity systems. Following this general conceptualisation, an extensive review was conducted on the basis of the previously derived characteristics of LECs to answer the following question: ***'which machine learning literature is related to local energy communities'***. Eventually, an answer has been presented to the following question: ***'what future trends and conclusions can be drawn from machine learning utilised in local energy communities?'***.

In summary, the contributions of this paper are as follows:

1. A conceptualisation of LECs from a European perspective
2. An extensive review of state-of-the-art machine learning literature associated with LECs
3. Detailed applications of machine learning methods within LECs
4. An evaluation of and the future outlook on machine learning methods that are utilised in LECs

1.2. Outline

This paper is structured as follows: In Section 2, LEC definitions within regulatory frameworks and existing community-based energy projects are presented. Furthermore, the criteria for conceptualising an LEC are explored in detail. In Section 3 a meta-review of the associated literature, aiming to better contextualise the present work with respect to the existing literature reviews, is presented. In Section 4, an initial overview of the different machine learning tasks and techniques are listed. Furthermore, the different practical applications of machine learning in LECs have been analysed, and a structured evaluation of these applications is presented in Section 5. Finally, a summary of the main research findings as well as an outline of current developments, potential trends in the future, and suggestions for further research direction are presented in Section 6.

2. Local energy communities

Although it has been indirectly defined in literature, for example, the general definition within the regulatory framework of the European Union (EU) for energy communities, to the best of the authors' knowledge, no direct definition of LEC has been reported in the relevant literature. To close this research gap, the authors of this study analysed 25 existing community-based energy projects on the basis of two EU regulatory definitions of energy communities. Accordingly, a definition of an LEC is presented in this study. This definition serves as the foundation for the identification of the areas of application for machine learning methods.

2.1. Classification of local energy communities

In the existing literature, an LEC has been perceived mainly as a technical rather than a structural concept. However, the definition of an LEC extends beyond purely technical, social, and organisational aspects [5]. In a study [6], the authors analysed different approaches and terms for the integration of local energy systems into a larger centralised energy system. They investigated community microgrids, virtual power plants, energy hubs, prosumer community groups, community energy systems, and integrated community energy systems. Subsequently, the authors introduced a comprehensive concept for integrated community energy systems, which is similar to the concept of LEC and is presented in Section 2.2. In another study [7], the authors defined 'clean energy communities' as social and organisational structures that are formed to achieve the specific goals of its members, primarily in terms of clean energy production, consumption, supply, and distribution. They analysed the long-term dynamics and possible pathways of the transition from centralised to decentralised systems in the energy sector as well as the co-evolution of energy systems and energy communities. This study aims to explore the manner in which different machine learning techniques can assist in the operation of LECs and optimisation of their local energy systems. As presented in the following sections, the foundation for a framework for LECs has been established on the basis of two different definitions within the EU regulatory framework and analyses of 25 existing community-based energy projects.

2.1.1. Regulatory definitions

As mentioned, the EU has issued two directives with official definitions that are proximate to those of LECs: 'Renewable Energy Community' (REC) [8] and 'Citizen Energy Community' (CEC) [9]. These definitions are listed in Table 1. Member states must revise national laws to comply with the EU rules, and therefore, they must develop national-level definitions for citizen and renewable energy communities.

The specific differences between citizen and renewable energy communities are further explored in detail in the literature [1]. The authors explored renewable energy communities to showcase certain characteristics that are not inherited by the citizen energy communities: a specific geographical scope owing to the required proximity to renewable energy projects, a more restricted membership, i.e., participants cannot join the renewable energy community as their primary economic activity, a need for autonomy from individual participants or stakeholders, and the possibility of grid control by enterprises located in the proximity of the renewable energy project. Furthermore, unlike the renewable energy community, a citizen energy community generally follows technology-neutral policies, and thus, it incorporates both renewable and conventional sources of electrical energy.

2.1.2. Existing energy community projects

A review of functional energy communities in Europe was performed to identify the characteristics of an LEC. The following keywords were used to search for energy community projects (Oct. 2020): 'energy community', 'renewable energy community', 'citizen energy community', 'local energy market', 'electric energy community', 'microgrid', 'renewable energy market', 'local energy system', 'micro energy system', 'zero emission neighbourhood', 'smart neighbourhood', and 'micro markets'. This search resulted in approximately 200 projects, 60 of which were investigated in more detail in this study. For a project to be included in the review, it had to: (a) fit the definitions of citizen and/or renewable energy communities, (b) focus on electrical energy systems, and (c) possess sufficient information regarding the structure, stakeholders, technology, and motivation of the project. By applying these criteria, the initial number of 60 projects was reduced to the 25 projects that are listed in Table 2. The research findings on the structure, stakeholders, technology, and motivation of the 25 projects are detailed herein.

Structure

In terms of composition, an energy community can be distinguished by its physical and organisational structure. The physical structure involves the geographical area and location of the grid as well as the electrical grid topology. In contrast, an energy community's organisational structure can be categorised into seven types, as described in the relevant literature [1]: energy cooperatives, limited partnerships, community trusts and foundations, housing associations, non-profit customer-owned enterprises, public–private partnerships and public

Table 1
Comparison of definitions of renewable and citizen energy community.

Renewable energy community [8]	Citizen energy community [9]
(a) "which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity";	(a) "is based on voluntary and open participation and is effectively controlled by members or shareholders that are natural persons, local authorities, including municipalities, or small enterprises";
(b) "the shareholders or members of which are natural persons, SMEs [small and medium-sized enterprises] or local authorities, including municipalities"; and	(b) "has for its primary purpose to provide environmental, economic, or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits"; and
(c) "the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits"	(c) "may engage in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders"

Table 2
Existing energy community projects.

Project	Country	Motivation	Participants
BeauVent [1]	Belgium	Increase renewable energy production	>5000
Courant d'Air [10]	Belgium	Provide renewable energy to consumers	>2000
Ecopower [11]	Belgium	Increase renewable and local energy production	56,000
Svalin Energy Collective [12]	Denmark	Increase renewable and local energy production, reduce climate impact	20 households
Cornwall Local Energy Market [13]	England	Test market-based flexibility provision, reduce climate impact	100 households, 100 businesses
Larsmo Vindkraft Ab [14]	Finland	Increase renewable and local energy production, lower costs	200
Enercoop [15]	France	Increase renewable energy production, lower costs	92,000
Fermes de Figeac [16]	France	Increased income for members	321
Jühnde Bioenergiedorf [17]	Germany	Local solutions for solving climate change	660
Elektrizitätswerke Schönau [18]	Germany	Increase renewable energy production, energy democratisation	185,000
Sprakebüll Village [19]	Germany	Increase renewable energy production, self-sufficiency	247
Wildspoldsried microgrid [20]	Germany	Self-sufficiency with renewable energy, research on microgrids	2500
Aran Islands Energy Cooperative [14]	Ireland	Self-sufficiency with renewable energy, research on microgrids	100 stakeholders
Erris Energy Community [21]	Ireland	Energy efficiency, increase renewable energy production, community aspect	Unspecified
Amelander Energie Coöperatie [22]	Netherlands	Self-sufficiency, increase renewable energy production	286
Brattøra [23]	Norway	Energy efficiency, positive energy block	3 office buildings
Elnett21 [24]	Norway	Reduce fossil fuels in transport and enterprises, avoid grid congestion	Port, airport, businesses
Spoldzielnia Nasza Energia [1]	Poland	Energy independency, lower costs	300
Slupsk pilot [1]	Poland	Energy poverty, reduce air pollution	200 households
Edinburgh Community Solar [25]	Scotland	Reduce climate change, energy poverty, energy security	540
Isle of Eigg [26]	Scotland	Increase renewable energy, lower costs	96
BRF Lyckansberg [27]	Sweden	Local renewable energy production, export surplus electricity	85 apartments
Farmarenergi Eslöv [28]	Sweden	Reduce fossil fuels	9 farmers
Simris Energy System [29]	Sweden	Increase renewable and local energy production, avoid congestion	140 households
Quartierstrom [30]	Switzerland	Local market to balance power from renewable energy	37 households

utility companies. A review of the 25 community projects revealed numerous organisational structures. Certain projects, such as *Svalin* [1] and the *Isle of Eigg* [31] are organised in collectives through citizen engagement with the social aspects of sharing at its core. Other projects were registered as companies owned by local citizens, such as *Amelander* [32] and *Jühnde* [1]. As displayed in Table 2, the number of members in these projects greatly vary, with three members in *Brattøra* [23], and 56,000 members in *Ecopower* [11]. Furthermore, a few of these projects have emerged from scientific research and are not initiated by citizen participants.

In certain studies [32,33], researchers investigated the importance of social and organisational aspects in energy communities. Reportedly, factors such as a shared vision, the level of activity in the community, the type of organisation, and the organisation's affiliations on local, regional, or national levels can significantly influence the success of the energy community.

Stakeholders

Stakeholders in an energy community can either serve as active participants forming the energy community or passive actors with invested interests in the project. Within the 25 aforementioned projects, the stakeholders comprise citizens, municipalities, technology providers, distribution system operators (DSOs), universities, local businesses, energy generation companies, and housing associations. In addition to the aforementioned examples, the relevant literature [34] lists research centres, consultancies, information and communications technology (ICT), telecommunication companies, utilities and engineering service providers, retail companies, transmission system operators (TSOs), industry organisations, real estate developers, energy service providers, public utilities, energy cooperatives, and transport solution companies as potential stakeholders.

Generation, load, storage and flexible resources

For the reviewed projects, the typical generation technologies in energy communities comprise photovoltaic (PV) panels, wind turbines, small-scale hydropower plants, and combined heat and power plants. Additionally, thermal energy systems for heat production are incorporated in most of the reviewed communities, typically through combined heat and power generation, or geothermal and solar heating. Energy storage for back-up or other grid services was realised through either diesel generators or battery-based energy storage systems. These generation and storage technologies can be observed either at the household level or as shared assets in the community. The various types of load sources in these 25 reviewed energy community projects were categorised as households, prosumers, office buildings, industry/farms, and public buildings. The yearly load demands of these categories differ on daily and seasonal scales. Typical flexible resources available within load categories comprise electric vehicles (EVs), heat pumps, and water boilers. Optimal control of these flexible resources and energy storage systems is crucial to minimise the energy costs of the community.

An energy management system will be required by the community to control its flexible resources, through which the community can ultimately decide the period and manner of energy utilisation, thereby lowering the overall energy costs.

Motivation and benefits

The energy community projects, reviewed in this study, address environmental concerns and the related goal of increasing the share of renewable energy, which comprise the core motivation for establishing an energy community. For example, both *BeauVent* [1] and *Sprakebüll* [19] aimed to achieve 100% renewable energy production in the community, whereas *Svalin* [12] aimed to consume renewable energy that was entirely produced locally. Similarly, the common motivation behind energy community projects involves further investment in sustainable energy infrastructure for the community [1]. Furthermore, several projects such as *Amelander* [22], *Aran* [14] and *Wildpoldsried microgrid* [20] have highlighted the importance of self-sufficiency. Such requirements for self-sufficiency may be motivated by economics, security of supply (especially relevant in energy communities, which are microgrids), or a demand for greater transparency regarding the origin of the consumed electricity.

The economic incentives of communities typically lead to reduced wholesale market expenses owing to increased self-consumption of locally produced energy, revenue generation through feed-in of excess power generation, or a reduction in costs to the DSO owing to a lowered peak power consumption (caused by load shifting). Certain energy communities provide balancing and frequency control services to the TSO, such as the *Cornwall Local Energy Market* [13] and *Wildpolsried microgrid* [20].

2.2. Definition of a local energy community

As detailed in Section 2.1, the regulatory definitions and review of existing energy community projects facilitate the establishment of a definition of an LEC. This definition can be achieved by incorporating the five criteria that are fundamental to an energy community, which can be referred to as an LEC:

1. **Locality**: The community should possess a large proportion of local investment and ownership and be managed locally. A community is located within a defined geographical area and is typically connected at the distribution-grid level.
2. **Energy sustainability**: The community or its members fully or partially own the process of renewable energy generation, energy storage, EV chargers, or other relevant assets or infrastructure. These assets and infrastructure are shared by the community; from an energy system perspective, they are established at a single customer location.
3. **Community engagement**: Most of the participants are active members of the community, i.e., they are invested in the energy-related assets and provide flexible demand options. The main objective of the community is not profit-oriented; however, it aims to provide environmental, economic, or social benefits for its members/shareholders and/or the local area where it operates. The community participants may be individuals, small- and medium-sized enterprises, or local authorities, including municipalities.
4. **ICT**: The community possesses ICT infrastructure of varying degrees. Typically, this includes smart meters and communication, control, and energy management systems. Such infrastructure can enable the flexible operation and optimisation of the local system and facilitate interaction with national power systems in the form of transmission grids and wholesale electricity markets.
5. **Transactions**: The community allows for energy-related financial transactions amongst its members. This feature is generally implemented in local energy markets; however, such a feature is not mandatory. The transactions conducted not only consist of local transactions but also include transactions between the community and the national power system, for example, via wholesale electricity markets.

Criteria 1, 2, and 3 are closely related to the definitions of citizen and renewable energy communities. Criterion 4 indicates that an energy community must exercise some degree of ICT technology for the control of assets, communication amongst its members, and data collection. According to Criterion 5, a mechanism is required to share the energy-related costs and benefits amongst the members in the community. Table 3 depicts the relationship between the criteria defined for the applications, which are further detailed in Section 5.

To summarise this definition, an LEC is illustrated in Fig. 1 as a part of the larger power system.

3. Associated literature reviews

On the basis of the definition of an LEC provided in Section 2.2, a recent body of literature reviews associated with the topic has been identified, as listed in Table 4. The associated literature reviews were selected according to their relevance to the topic of LECs by considering the commonalities in the fundamental criteria established in the previous section. The exception to this has been reported in several studies [50–52], which possesses no direct relation but relates tangentially to locality and ICT infrastructure. The associated methods are explored in detail in the following section.

A range of literature reviews specialise in topics related to LEC; however, they do not specifically focus on local applications. Within the topic of forecasting, in a review [35] recurrent neural network models focusing on the specific problem of solar power forecasting were analysed with data from the South Korean power grid. Furthermore, an overview of deep learning in renewable electricity forecasting has been reported [37]. A review [39] specifically focused on time-series drift in terms of flexibility in power system flexibility, whereas another review [40] explored load forecasting from short to long term periods. Most of reviews of energy management systems highlight the topic of locality, except for the review [48] which presents a general view on reinforcement learning and its application in problems concerning power system control, and excluding the review [42] that explores energy storage and EVs. With regard to the protection, stability and quality of power systems, none of the reviews consider locality. In a review [50], methods such as support vector machines, neural networks and genetic algorithms were analysed in the context of fault detection. Moreover, deep learning has been analysed in the context of power quality [51]. Furthermore, the review [52] explores applications of machine learning in reliability assessment and control (specifically on the topics of security assessment, emergency control, preventive control, error measurement and power flow predictions). Most reviews of machine learning in smart grids do not consider locality. The emerging importance of machine learning and autonomous control in power systems has been reported [53]; although the review was not specifically focused on decentralised solutions, the reported topics were strongly related to such solutions. Furthermore, machine learning in smart grids has been analysed with a focus on data and data security [54]. The relevance of artificial intelligence to sustainable energy systems has been investigated in a general context [56]. In a review [55] machine learning in power systems has been investigated with a focus on topics such as forecasting, failure analysis, demand side management, and cyber security. Additionally, a review of the last decade of machine learning in power systems has been established [4].

The remaining related literature reviews focus on the subcategories of the field of machine learning. Reinforcement learning is a core topic in studies that focus on control aspects. The Markov decision process, i.e., the heating and storage of heat in water boilers, has been explored, and Q-learning has been identified as the state-of-the-art for dealing with control in such decision processes [43]. Researches [44]

Table 3
Value matrix criteria—applications.

Application	Locality	Energy sustainability	Community	ICT	Transactions
Forecasting	Generates information for short-term planning of the resources in the LEC	The individual and community assets are optimally managed by having information of future DER and related asset behaviour (such as storage)	Individuals can better coordinate with better prediction on their demand and supply	A condition for data security in forecasting systems	Energy and price forecasting provides operational inputs allowing the LEC to conduct an optimised economic dispatch
Storage optimisation	Enables localised storage as a grid asset, increases self-consumption of local renewable resources in the LEC		Storage assets are coordinated with other assets in the community and investments can be shared	Automated control of the storage system and associated information streams	
Demand response	Decentralised demand response becomes a feasible asset in the power system	Time-flexible demand can increase the consumption of intermittent renewable energy in the community	Demand response can be aggregated and coordinated with other community members	Local assets interact with the larger power grid via wholesale markets. e.g. as virtual power plants	Local assets interact with the larger power grid via wholesale markets, e.g. in form of virtual power plants
Energy management system	Decentralised coordination of resources	More optimal coordination provides more efficient utilisation of renewable energy and lowers emissions	Provides the sense of common welfare and a central coordination point within an LEC	Data storage and monitoring systems constitute the core of an EMS	
Power quality, stability and security	Practices that secure proper functioning and handling of the equipment owned in the LEC	Towards energy sustainability goals, energy generated and dispatched from LEC has to comply with the quality standards of power grids	Akin to centralised power systems, in decentralised systems such as LEC, the grid remains a shared asset	Grid data collection, maintenance and security	-
Energy transactions	Transactions are moved to the local level, consumers and prosumers financially interact with each other within an LEC	Local markets trade mainly local, renewable generation	Transactions within a community lead to higher level of self-consumption	LEC members are able to make better informed decisions about the sourcing of their energy supply; because to information sensitivity, transactions must also be secure	Local markets are integrated into wholesale markets and also have to provide proper supply/demand on balancing and regulating markets

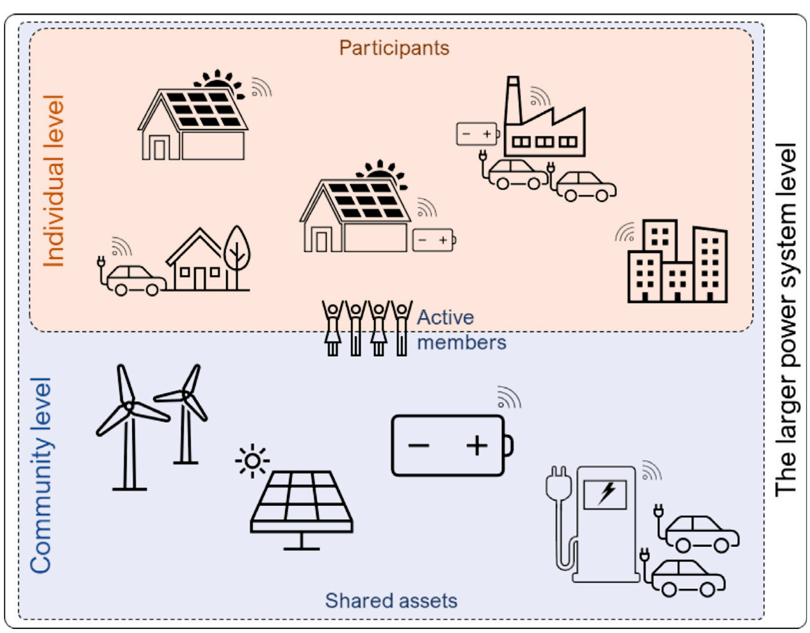

Fig. 1. Visualisation of a local energy community in the larger power system. The local energy community consists of two levels: the community and the individual level. The individual level consists of the participants in the community, such as residential consumers, prosumers, and enterprises. The participants own individual assets such as EVs, PV panels and batteries. Moreover, the ICT infrastructure, such as smart meters and energy management systems, are also incorporated into this system. The community level consists of shared assets, such as community-owned PV panels, wind turbines, batteries and charging stations for EVs.

approached the topic from the perspective of building management and discussed the real-world challenges involved in the implementation of reinforcement-learning frameworks. Similarly, control problems in buildings have been addressed through reinforcement learning, focusing on demand response control [45] and the latter focusing on its practical applications [46]. Another literature review focusing on the

Table 4
Literature reviews on machine learning applied on associated topics.

Source	Year	Topic	Locality	Energy sustainability	Community engagement	ICT	Transactions
Forecasting							
[35]	2019	PV generation forecasting	x	✓	x	x	x
[36]	2019	PV generation forecasting	✓	✓	x	x	x
[37]	2019	Renewable energy forecasting	x	✓	x	x	x
[38]	2019	Load prediction with smart meter data	✓	✓	x	✓	x
[39]	2020	Forecasting of flexible resources	x	✓	x	x	x
[40]	2020	Load forecasting	x	✓	x	x	x
Energy management system							
[41]	2020	Battery state estimation	✓	✓	x	✓	x
[42]	2020	Battery control methods	x	x	✓	x	✓
[43]	2018	Water heater control	✓	x	✓	x	x
[44]	2019	Energy management systems of buildings	✓	✓	✓	x	x
[45]	2021	Energy management of appliances in buildings	✓	x	✓	x	x
[46]	2019	Demand response control	✓	x	✓	x	x
[47]	2020	Demand response	✓	x	✓	x	x
[48]	2019	General control problems in power systems	x	x	✓	x	✓
[49]	2020	EV flexibility	✓	x	✓	x	x
Power system protection, stability and quality							
[50]	2017	Fault detection	∼	x	x	∼	x
[51]	2019	Power quality analysis	x	x	x	∼	x
[52]	2020	Reliability assessment and control	x	x	x	∼	x
Machine learning in smart grids							
[53]	2019	Role of machine learning in power systems	x	x	x	✓	x
[54]	2019	Machine learning in smart grids	x	x	x	✓	x
[55]	2020	Machine learning in smart grids	x	✓	✓	✓	x
[4]	2020	Deep learning in smart grids	x	✓	x	✓	✓
[56]	2020	Sustainable development	x	✓	x	x	x
[57]	2020	Distributed smart grids	✓	x	✓	x	x
[*]	–	Local energy communities	✓	✓	✓	✓	✓

* this paper, ✓related, ∼ tangentially related.

subcategory of supervised learning has been reported [41], focusing on methods dealing with battery state estimations, namely Markov process- based methodologies such as Kalman filters.

Compared to these sources, literature reviews focusing on local applications and considering multiple subcategories of machine learning focus on specific problems. A review of applications, utilising smart meter data, such as load forecasting and related issues, including screening for energy theft and demand response forecasting, has been reported in the literature [38]. Additionally, solar energy predictions in microgrids have been surveyed [36], and the demand response and associated methods for operation, prediction, and segmentation have been highlighted [47]. Finally, a method for charging demand prediction of electric vehicles have been reported in literature [49].

In terms of the existing literature, a prior research has been reported, which is most relevant to this study [57]. However, the prior research focuses on single assets, especially energy management systems, whereas the present study focuses on energy communities, especially LECs, as an integrative unit. Although these approaches overlap, the research presented herein will dive deeper into specific applications such as agent-based coordination and classification from a communal perspective.

4. Machine learning methods

This section provides a short introduction to machine learning and its main categories as well as the main topics related to LECs, which were revealed in literature review performed in Section 3.

Popularised by a study [58], machine learning algorithms are traditionally classified into three main categories: *(a) Supervised Learning*, *(b) Unsupervised Learning*, and *(c) Reinforcement Learning*. The three categories, with their respective associated algorithms, are illustrate in Fig. 2. The essence of these classifications lies in the interaction of the algorithms with the data and environment. A comprehensive review of these methods and associated concepts have been reported in [59].

Supervised Learning algorithms are supplied with knowledge pertaining to the data in the form of so-called labels and are used to predict new and unknown data labels. This process can occur in the form of tasks such as classification, where labels represent categories, and regression tasks where the labels represent the values to be predicted. In this study, the regression tasks are referred from traditional linear regression, advanced models such as Lasso regression, or Ridge regression to models such as support vector machines, a method that can be fit on nonlinear data sets. In the context of LECs, regression methods are primarily used to predict and forecast of uncertain parameters. This forecast applies to both the demand side (e.g. household loads or utilisation of devices) and the supply side (e.g. available PV capacity) [60,61]. However, classification problems rely on prediction tasks for categorical or qualitative outputs [59]. Consequently, classification methods are generally used in scenarios wherein the problem involves the detection of specific cases in datasets on the basis of historical examples. The main applications of such methods related to LECs comprise fault detection and error classification [62].

Finally, probabilistic tasks refer to methods that consider uncertainty in the data not only to optimise the expected value but also to infer the distribution of such uncertainty. A simple example is provided by the probabilistic form of regression, such as Bayesian regression. Applications of probabilistic methods in LECs include the fitting of stochastic processes or determination of the parameters of distributions for renewable energy installations, household loads, or usage patterns of electric vehicles and electric devices.

Deep learning, commonly referred to as a neural network, can perform any of the aforementioned tasks. These methods employ function approximations consisting of stacks of differentiable linear regression ‘layers’ and nonlinear ‘activation functions’. Hence, neural networks are built with different configurations of layers to solve the problem and handle the nonlinearities of such problems. Such models are widely used in LECs, including neural networks for forecasts [63] and predictions of deep learning models for optimal control [4,64]. A more in-depth discussion on deep learning topics has been reported in [65].

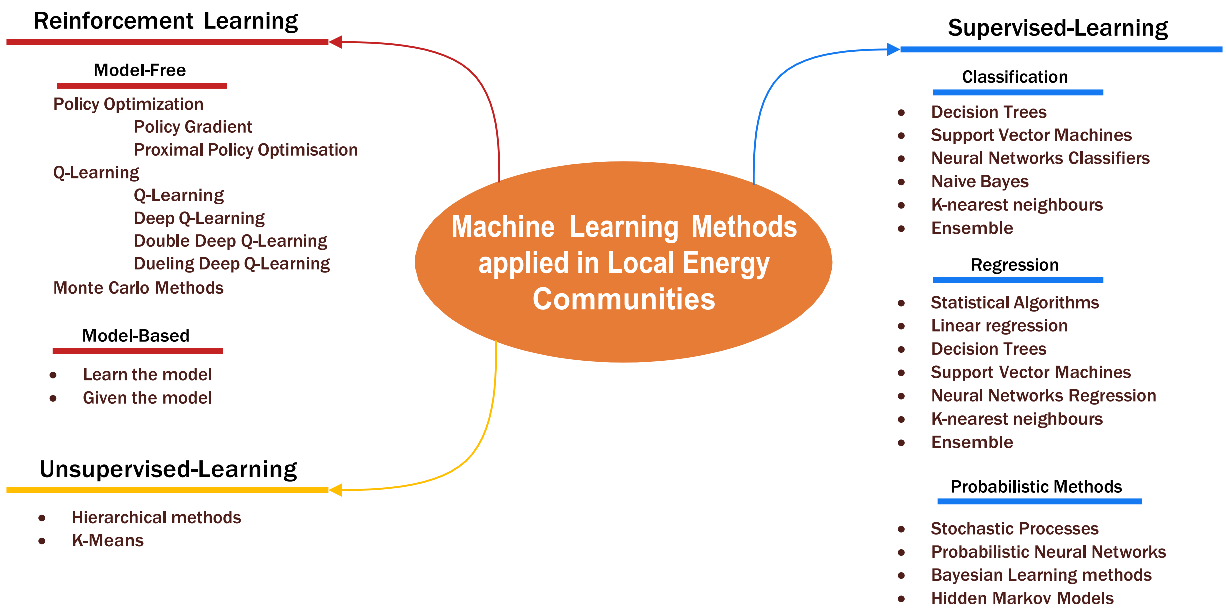

Fig. 2. Machine learning methods and algorithms.

In contrast to supervised learning, unsupervised learning aims to describe associations and patterns between unlabelled input data [59]. Clustering techniques aim to find commonalities in data sets and classify the closest data points as clusters. In the context of LECs, clustering methods are primarily found in applications for load profiling and segmentation.

The last category, reinforcement learning (RL), from the other two categories. It not only passively observes and labels the data but also exerts active control on a given system. A common textbook source for RL algorithm is provided [66]. However, in the traditional literature on electrical engineering, these RL algorithms have also been referred to in the context of optimal control under the name of 'approximate dynamic programming'. Further background information on this topic is currently available [67].

5. Applications in the operation of local energy communities

The literature review presented in Table 4 demonstrates the range of potential applications of machine learning within microgrids, smart grids and other energy communities. However, considering the criteria in the definition of an LEC, as depicted in Section 2, applications such as forecasting, energy management system, power system protection, stability, quality, and optimisation and energy transactions have been selected as a result of a categorisation of the discovered literature associated with the aforementioned topics. The following section presents the analyses and further classification of the studies and models targeted specifically at the aforementioned applications related to LECs.

5.1. Forecasting

Forecasting is the process of predicting a variable in the future by analysing historical data trends. Demand and generation forecasting are of great importance to the system operators of electrical grids. The frequency of occurrence of the algorithms that were used in the reviewed studies for each forecast application is illustrated in Fig. 3.

Forecasting studies are commonly classified to their time horizon prediction: short-term, medium-term, and long-term [57]. However, certain studies approach the problem on a very short-term horizon [61, 68]. The forecasting interval depends on the purpose on the forecast. For daily operation tasks, very short-term and short-term are the required time horizon, whereas for grid planning and investment evaluation, a long-term horizon is preferred [40]. Table 6 shows the machine learning algorithms in the literature review for different forecast tasks classified according to time horizons listed in Table 5.

Table 5
Forecast time horizons.

Forecast horizon	Time interval
Very short-term	1 s to less than 1 h
Short-term	Few minutes to few days
Medium-term	Few days to few months
Long-term	Months, quarters, years

5.1.1. Demand forecasting

The literature on demand forecasting represents the largest share of the recent literature on energy forecasting. This is because of the increased uncertainty in the operation owing to the addition of new actors to the energy system, such as prosumers or new assets, which can act as flexible loads and shift or reduce their consumption during specific periods [48]. An accurate prediction of demand helps to improve the operation of an LEC [97,98]. For LECs with controllable loads, several control strategies rely on an accurate forecasting model [99].

Demand forecasting can be performed at individual, community, or asset level facilitated by the data gathering ability of smart meters and ICT infrastructure. In terms of the asset level, machine learning regression models such as K-nearest neighbours (KNN), decision trees and neural networks (NNs) have been explored to accurately predict the consumption of two machine tools in a factory in a very short-term horizon [68]. A combination of an autoregressive integrated moving average (ARIMA) model with a nonlinear support vector machine (SVM) has been used to predict the electrical consumption of an air conditioner by employing the data retrieved from smart meters [81]. Similarly, [80] compared linear models, linear and nonlinear SVMs, and NNs to predict annual heating and cooling loads in residential spaces in a long-term prediction task; the optimal results were obtained using nonlinear SVMs.

At individual level, researches [73] approached the short-term forecast of the energy consumption of three households in a nanogrid via smart meter data by reviewing several supervised learning algorithms. Refs. [74,76] have discussed on the high volatility and uncertainty of residential load profiles; Long short-term memory neural networks

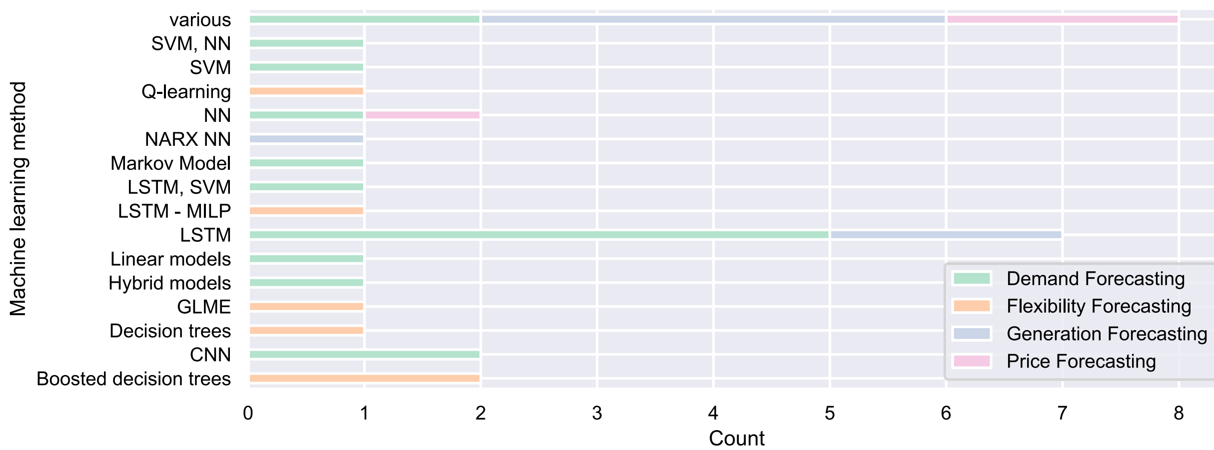

Fig. 3. Machine learning techniques used for forecasting in literature.

Table 6
Machine learning (ML) techniques for forecasting.

Forecast topic	Task	ML Algorithm	Forecast horizon	Year	Source
Demand forecasting	Load curve	SVM	Short term, medium term	2021	[69]
		Hybrid models	Short term, long term	2020	[70]
		CNN	Short term	2019	[71]
		LSTM	Short term	2020	[72]
	Households	Various	Short term	2020	[73]
		Linear models	Short term	2018	[74]
		Various	medium term	2020	[75]
		LSTM, SVM	Short term	2019	[76]
		LSTM	Short term	2018	[77]
	Households and SME	Markov Model	Short term	2019	[78]
	Appliances	LSTM	Short term	2020	[79]
	Residential space heating and cooling loads	CNN	Long term	2020	[80]
	Machine tools	SVM, NN	Very short term	2020	[68]
	Power demand for different facilities	LSTM	Short term, long term	2020	[63]
	AC energy consumption	LSTM	Short term	2019	[81]
	Rural microgrid	NN	Short term	2020	[82]
Renewable energy forecasting	PV generation	LSTM	Short term	2019, 2020	[83,84]
		Various	Short term	2019	[85]
		Various	Various	2019	[61]
	PV generation, wind generation and demand	NARX NN	Short term	2019	[86]
	Wind forecasting	Various	Various	2020	[87]
Flexibility forecasting	Demand side flexibility	LSTM - MILP	Short term	2021	[88]
		Boosted decision trees	Short term, medium term	2020	[89]
		GLME	Medium term	2019	[90]
		Decision trees	–	2021	[91]
	EV charging demand prediction	Boosted decision trees	–	2020	[49]
	EV charging navigation	Q-learning	–	2020	[92]
Price forecasting	Price forecasting Turkish market	Various	Short term	2018	[93]
	Price forecasting Iberian market	NN	Short term	2018	[94]
	Price forecasting EPEX	Various	Short term, long term	2019	[95]
Various	Price, generation, demand	Various	Short term	2021	[96]

(LSTMS) were used to obtain short-term household forecasts, yielding minimal prediction errors.

At community level, load forecasts are usually performed by considering aggregated load. For example, different algorithms have been used to forecast one day-ahead energy consumption in a residential building [77]. The authors first reviewed several single algorithms and subsequently combined these algorithms with an optimisation technique, thereby achieving improved results with the latter technique. Ref. [63] forecasted short-term and long-term energy consumption of different buildings, ranging from a residential to a factory and hospital, and the challenges of each profile have been reported. The authors compare mixed-data sampling method with LSTMs and a combination of both methods, resulting in a more accurate result.

In contrast to deterministic methods, probabilistic methods have been applied in certain studies. These methods extend the capabilities of the deterministic model by quantifying the uncertainty factors in the load forecasting task. As exemplified in [71], the authors trained recurrent neural networks (RNNs) using a probabilistic objective function to forecast the day-ahead load consumption. Probabilistic output prediction provides information on risk and related scenarios for decision making in the operation planning of the energy system [78]. Moreover, a semi-hidden Markov model have been developed to predict short-term consumption of home appliances [79].

5.1.2. Renewable generation forecasting

Most LECs will have renewable energy sources to fulfil their energy needs and sustainability goals. Accordingly, the nature of these energy generation sources results in a significant level of uncertainty in the energy supply [37,100]. An example has been reported [101], wherein multiple methods were reviewed, including nonlinear autoregressive exogenous neural networks (NARX NN), Gaussian process regression, and SVM, to forecast the behaviour of wind generation, PV generation, and demand for households. The authors assessed the inputs needed for each predictive task and highlighted the NARX NN as a robust model for wind and PV generation by conducting a sensitivity analysis. As reported in the literature [96], the results for wind generation forecasts were improved through the incorporation of exogenous information when comparing deterministic and probabilistic methods. Similarly, NARX NNs have been used [102,103] for wind and PV generation.

As mentioned in Section 2.1, PV generation is one of the most popular technologies for the generation of renewable energy in households and communities. Therefore, a number of studies have focused on this particular application. For instance, the statistical and machine learning methods for PV generation forecast have been comparatively analysed [61]. Finally, the authors compared a hybrid combination of two methods and an optimisation theorem, concluding hybrid methods increase the forecasting accuracy by adding benefits of individual methods. The performances of several machine learning algorithms have been analysed to predict the PV generation for a power plant [85]; the importance of input data, such as weather, for the prediction performance has been analysed to predict of PV generation for a power plant. The optimal results were obtained using random forest. RNNs have been extensively explored in the literature for forecast tasks concerning PV generation; for example, LSTMs have been implemented to predict the output power of different PV generation plants for a short-term time horizon [83,84].

5.1.3. Flexibility forecasting

From a prosumer's perspective, flexibility can be defined as the ability to modulate generation/consumption behaviour via an external signal, such as a change in the energy price [104]. Flexibility is a service that can be provided within the LEC at both household and community levels (refer to Fig. 1). Flexibility forecasting is based on load forecasting, considering the available flexibility sources [90]. Accurate flexibility estimation allows the LEC and its participants to generate revenue by selling flexibility to a system operator, such as *Cornwall Local Energy Market* [13]. In accordance with the classification reported in [105], flexible assets can be classified as demand side, supply side, and storage assets. This section focuses on the demand side flexibility and storage.

For flexibility estimation, [88] the economic optimisation of an energy management system has been attempted in an urban microgrid, considering the flexibility of ancillary services. The load consumption forecast was performed using LSTM. Furthermore, mixed integer linear programming (MILP) was used to optimise the energy dispatch in the day-ahead operation of the microgrid with three different types of loads: building, smart homes with and without available PV capacity, and differently clustered loads. In another study [89], the authors forecast the loads' total consumption and flexibility using boosted trees for both day-ahead and week-ahead time horizons in a commercial building. In a study [90], the flexibility was calculated for a single household for one month using generalised linear mixed-effect models (GLMM). The present study also analyses the flexibility at the household asset level.

With the novel vehicle-to-grid (V2G) technology, EV charging stations in the grid serve as a flexible asset. V2G can operate as an available energy storage device, thereby acting as a flexibility source [106]. In addition, they can be considered as a mobile energy storage system [105]. Therefore, they are also subject of study for forecasting flexibility calculations. To this end [49], prediction methods for the EV charging demand during charging sessions have been studied to optimise the management of the electric grid. Models such as linear regression, boosted decision trees, random forest, and SVM were used to predict the charging demand of EVs for flexibility predictions. Ref. [92] proposes a storage optimisation problem for EVs incorporating uncertainty caused by traffic solved by a RL model-free Q-learning algorithm. The use of decision trees has been evaluated for flexibility-based operational planning dispatch in a microgrid system connected to the grid, with storage, renewable generation, critical loads, and an industrial controller [91]. The authors comment on the feasibility of implementing decision tree-based rule programming in a PLC-based controller and highlight its interpretability in the dispatch rules compared to other state-of-the-art alternatives such as NNs.

5.1.4. Electricity price forecasting

Electricity price forecasting is an application for both community and peer-to-peer market-level configurations. A forecast of the energy price at a specific time in the future provides valuable information for handling load consumption and flexibility more efficiently [107]. Moreover, price forecasting helps to create optimised programs to efficiently dispatch the energy within the LEC, by supporting efficient resource scheduling decisions [57]. In this section, although most of the studies focus on centralised energy markets, they are highly relevant for LECs.

Most of the studies on LECs focus on the day-ahead electricity price forecasting. The price forecasting has been analysed in the Turkish day-ahead market using an RNN, and the method was compared with several other NN architectures [93]. The optimal results were obtained using the gated recurrent unit configuration of RNN. The authors highlight the capabilities of this algorithm to capture spikes and volatility. Similarly, scholars [94] implemented a regression technique using NN to predict day-ahead prices in the Iberian electricity market. Additionally, researches [95] approached electricity price forecasting for both day-ahead and a four-week time horizon in EPEX[1] in Germany/Austria. Reportedly, amongst the algorithms tested, the optimal results were achieved using NNs.

5.2. Energy management systems

An optimised energy management system allows efficient energy consumption scheduling through the coordination of the assets in the system, such as PV generation, storage, EVs, and flexible loads via demand response programs. As reported in the existing literature [104,108], an energy management system can be used to process price signals and perform cost-efficient dispatch within a wholesale market framework. Furthermore, the relevant literature indicates that data-driven algorithms support automatic optimisation of energy management systems at both individual and community levels. The distribution of machine learning techniques in the reviewed literature for energy management system is displayed Fig. 4.

5.2.1. Energy management system and control

The majority of the studies focus on the energy management optimisation by data-driven algorithms. As reported in [109], an energy management system has been developed using stochastic processes for an islanded microgrid. Additionally, researches in [110] exposed a method which optimises the power exchanged with the utility through a probabilistic approach using a Gaussian process model and model predictive control for interconnected microgrids. Supervised learning algorithm algorithms were used by researches [111], who presented a multi-agent day-ahead energy management system of a microgrid incorporating various methods from machine learning and operations research. Specifically, it demonstrates the incorporation of forecasting via RNNs and convolutional neural networks (CNNs) into distributed optimisation via the alternate direction method of multipliers. Furthermore, a framework has been introduced to optimise the cost of networked microgrids featuring wind turbine generation, EV charging, and battery storage [112]. The output power of the wind turbines is predicted via SVM and a battery optimisation algorithm is used to find

[1] European Power Exchange SE is an electric power exchange operating in Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Luxembourg, the Netherlands, Norway, Sweden and Switzerland.

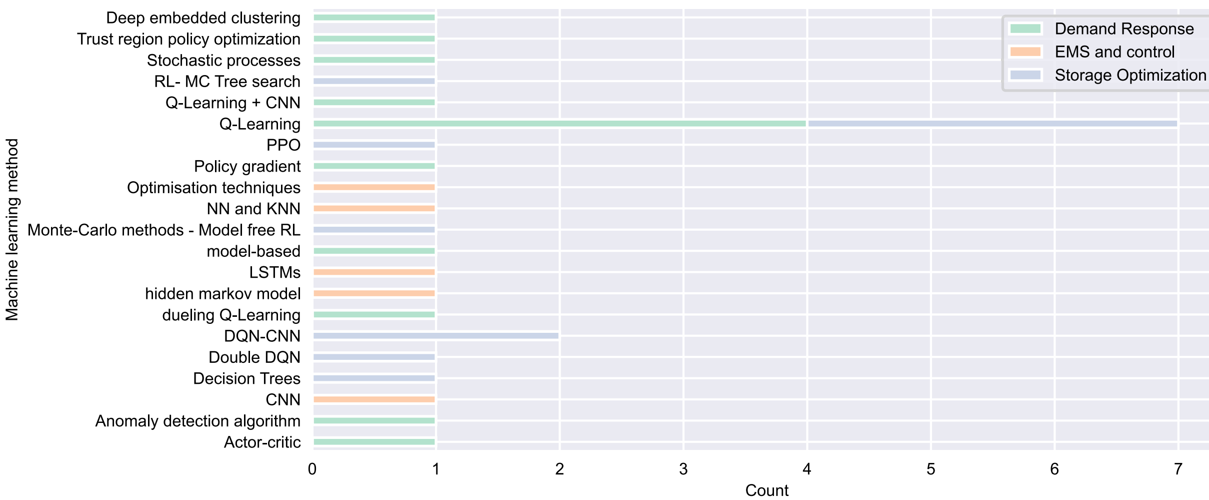

Fig. 4. Machine learning techniques in literature for energy management system.

Table 7
Machine learning (ML) techniques for energy management system and control.

Task	ML Algorithm	Level	Year	Source
Energy management system optimisation	Alternated Method of Multipliers	Microgrid	2019	[111]
	Q-learning	Household	2020	[114]
	MDP, RNN	Microgrid	2019	[115]
	SVM	Microgrid	2021	[112]
	MDP	Microgrid	2021	[116]
	DQN	Microgrid	2020	[117]
	Stochastic processes	Islanded microgrid	2021	[109]
	DQN	Microgrid	2020	[118]
	Linear reward interaction	Islanded microgrid	2020	[119]
Energy management system optimisation —flexible demand	Actor Critic	Microgrid	2020	[120]
Energy management system optimisation —HVACs units	Policy Gradients	Building	2021	[121]
Energy management system optimisation —EVs	Various	Smart grid	2019	[113]
Non-intrusive load monitoring	NN, KNN	Household	2019	[122]
	Hidden Markov model	Household	2019	[123]
	CNN	Household	2019	[124]
Energy share optimisation	DQN	Building	2018	[125]
	Gaussian process	Interconnected microgrids	2021	[110]
Energy data mining	CNN	Household	2019	[126]
	Optimisation techniques	Household	2019	[127]
Topology identification	LSTMs	Household	2020	[128]

the optimal power dispatch for batteries and EVs. Focusing on EVs, researches in [113] reviewed the optimisation of EV charging sessions by considering the vehicle's state of charge with the objective of reducing charging costs. Several machine learning algorithms were tested in this study; the results indicate that deep neural networks provide solutions proximate to the global minimum owing to the complexity of such an algorithm. A literature review of machine learning algorithms for energy management systems and controls for different application levels is presented in Table 7.

For RL approaches, scholars [117,118] used deep Q-learning (DQN) to optimise operation of the elements connected to the EMS. Another model-free approach reported in the literature featured an Actor–critic approach to coordinate flexible demand, generation, and storage in a real-time application [120]. In addition, the utilisation of deterministic policy gradients has been reported for the optimisation of agents comprising heating, ventilation, and air conditioning units [129]. The solution was demonstrated in a case study, suggesting an improvement over classical rule-based policies or discontinuous deep reinforcement learning in the form of Q-learning.

Nonintrusive load monitoring is a technique used to segment the energy consumption into patterns and identify the behind-the-meter loads. In the context of LECs, this method was applied to identify home appliances and consumption patterns. A hidden Markov model approach has been presented to identify individual load sources of various types in a single aggregated load time series, focusing on online (i.e., real-time) applications [123]. Similarly, several machine learning algorithms have been reviewed to perform a non-intrusive load-monitoring task using a home energy management system [122]. As reported in the literature [126,127] sociodemographic information was extrapolated from home energy management systems and smart meter data via clustering techniques, such as KNN, and classifiers, such as SVM.

5.2.2. Energy storage

Energy storage systems are used in LECs to balance energy over multiple periods of operation. These assets provide opportunities for the shifting of loads from peak to baseload periods and the integration of intermittent renewable energy [130]. As [131] storage systems may become essential assets in future LEC projects, such assets are crucial for the day-to-day operation of an LEC, focusing on flexibility and energy sources in islanded microgrids. The principle of optimal dispatching is at the core of these operations. The field of machine learning comprises a range of deep reinforcement learning (DRL) methods, which are the prevalent methods applied to energy storage applications, as indicated

Table 8
Machine learning (ML) techniques for energy storage optimisation.

Task	ML Algorithm	Year	Source
Battery dispatch optimisation w/PV	MC Tree search	2020	[133]
	DQN	2016	[134]
	Q-learning	2016	[135]
	PPO	2020	[60]
Battery dispatch optimisation	Decision trees	2020	[100]
	Double DQN	2020	[136]
	Q-learning	2020	[137]
	DQN	2020	[138]
	MC methods	2020	[129]
Transactional charging	Q-learning	2020	[139]

in recent literature. Such DRL methods can be used to develop a control function, represented via a Q-function that can handle large search spaces for dynamic problems such as optimal storage [132]. The algorithms reported in recent literature to address storage optimisation problems in power systems, which are similar to those in LECs, are listed in Table 8.

Q-learning has become a method of reference for research on most battery storage optimisation, as is the case in [137]. Similarly, [138] applied DQN to an islanded microgrid. The authors used a CNN architecture to predict Q-values, arguing the chosen convolutional architecture for its simplicity and good performance. In contrast, [136] used a double-DQN to address the uncertainty in the microgrid system for both grid-connected and islanded modes. The authors highlighted that the chosen method mitigates the overestimation that a single Q-value estimator can generate in the results. In contrast, [129] approached the DSO's optimisation retail pricing strategy problem with a RL Monte-Carlo method in a simulated multi-microgrid system.

Q-learning has also been used to solve the complexity caused by PV generation in the microgrid [134,135]. Other model-free methods, such as the Monte-Carlo tree search algorithm, have been implemented as solutions to reduce the computational burden involved for solving the stochastic dispatch of battery storage during PV generation [133]. Similarly, as reported in the literature [60], a policy gradient method, namely the proximal policy approximation (PPO) has been established. The PPO agent maximises the accumulated net revenue of the system by successfully adapting to the PV uncertainties and market signals. The PPO agent outperformed the other tested algorithms, such as the deep deterministic policy gradient, Actor–critic, and double-DQN algorithms.

5.2.3. Optimal demand response

Demand response is defined, according to the Federal Energy Regulatory Commission, as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised" [140]. Accordingly, the demand response can be used as a strategy to manage controllable loads when this is beneficial to the user. Data-driven approaches to optimise demand response strategies have been presented in the literature. The machine learning techniques for demand response applications are listed in Table 9. Similarly, for storage problems, RL is generally used to handle the optimal demand response. Most studies have sought a reduction strategy for energy costs. For instance, Q-learning has been applied to determine the optimal hour-ahead consumption of several appliances, such as time-shifting loads, non-controllable loads, and EVs, considering future electricity prices and PV generation trends [114]. Moreover, as reported in [141], DQN has been used for dynamic control of residential loads. A deterministic policy gradient has been employed for the optimal load schedule [142], whereas in another study [143], an Actor–critic approach was used. In contrast to previous model-free algorithms, researchers [144] applied a model-based adjustment to the traditional Q-learning algorithm, thereby improving the performance over traditional model-free learning.

Pricing models have also been explored for the development of efficient demand response programs. A study [146] aimed to approximate the impact of time-of-use pricing on-demand response via the clustering of smart meter usage data into various profiles, whilst considering the uncertainty. With a similar objective, scholars [147] used stochastic processes to incorporate uncertainty in the pricing demand response to maximise the risk-sensitive revenue derived by the DSO. Another algorithm [149] utilised the time-of-use tariffs to control the demand response within a Markov decision process with binary action spaces. This dynamic operation problem was thereafter solved via deep-duelling Q-learning. For a real-time approach, researchers [150] utilised trust region policy optimisation to address the dynamic scheduling problem of batteries and demand response. The authors demonstrated the superiority of the algorithm compared to the traditional DQN and deep deterministic policy gradient within a practical case study, wherein various residential appliances were considered.

5.3. Power system protection, stability, quality and optimisation

Either when operating in islanded mode or when connected to the grid, LECs may experience stability issues owing to weak interconnection points or insufficient capacity of distribution lines to handle the bilateral power flows from renewable sources of energy generation [153]. Hence, the importance of fast location of faults and post-fault decision making can be supported by intelligent computation programs on the basis of machine learning, leveraging the ICT measurements as the input. In the literature, different approaches to assist power system protection, stability, quality, and optimisation for smart grids and microgrids exist, and these approaches are of great interest for the operation of LECs. This section broaches the literature on LEC system adequacy and security applications, including cybersecurity concerns. Fig. 5 illustrates the occurrence of a particular machine-learning technique in the reviewed literature used for power system protection, stability, quality, and optimisation. The machine learning algorithms for each application are summarised in Table 10.

5.3.1. Protection and fault monitoring

The secure operation of the energy service in the presence of a fault is crucial for the security of the LEC [52]. Thus, identifying these faults is an important task for LEC control systems, and historically, the relevant research have focused on faster and more accurate methods to identify fault events in the grid. This is achieved via historical and real-time measurements as input data for the machine learning algorithms, aiming to increase the likelihood of an appropriate response for the grid's protection control system.

Most studies approach the problem of fault event identification as a supervised classification learning problem via training data-driven algorithms and correlating features given by measurements of a prespecified type of fault. Researchers [154,159] have applied different ensemble methods, such as random forest and boosting techniques, to classify faults in a microgrid context. Furthermore, the multi-class classification problem of fault detection in PV arrays has been analysed

Table 9
Machine learning (ML) techniques for demand response.

Task	ML Algorithm	Level	Year	Source
Demand response	Actor critic	Household	2018	[143]
	RL model-based	Microgrid	2016	[144]
	Policy gradient		2021	[142]
	DQN	Household	2018	[141]
	Anomaly detection algorithm		2021	[145]
Demand response pricing models	Deep embedded clustering	Household	2019	[146]
	Stochastic processes	Electric utility	2018	[147]
Demand response energy efficiency	Q-learning	Building	2019	[148]
Demand response control considering tariffs	Duelling Q-learning	Smart grid	2020	[149]
Demand response in real time	Trust region policy optimisation	Household	2020	[150]
Decentralised demand control	Q-learning	Household	2015, 2020	[114,151]
	Q-learning	Buildings	2020	[152]

Table 10
Machine learning (ML) techniques for power system protection, stability, quality and optimisation.

Topic	Task	ML Algorithm	Level	Year	Source
Protection and fault monitoring	Fault detection	Boosted decision trees	Smart grid	2020	[154]
		CNN	Smart grid	2020	[155]
		NNs	energy grid	2020	[156]
		NNs, SVM	Microgrid	2020	[157]
		Boosted decision trees	Microgrid	2021	[158]
		Random forest	Microgrid	2020	[159]
		SVM	Smart grid	2019	[160]
	Line fault detection and location	NNs, SVM	Microgrid	2019	[161]
	Fault detection PV arrays	Random forest	Microgrid	2018	[162]
	Fault detection generators	SVM	Microgrid	2020	[163]
	Line fault detection	NNs	Microgrid	2017	[62]
Stability	Harmonic voltage estimation	LSTM	Unbalanced distribution grid	2020	[164]
	Dynamic event detection	NNs, decision trees, K-NN classifiers	Microgrid	2018	[165]
	Load shedding	Duelling deep Q-learning	Islanded microgrid	2021	[166]
Power quality	Power quality disturbances detection	CNN	Microgrid	2020	[167]
	Power quality disturbances	CNN	Microgrid	2020	[167]
	Volt-var control	Actor–Critic	Smart grid	2020	[168]
Optimal power flow	Simulate uncertain variables	Markov processes	Household	2020	[169]
	Wind power integration uncertainty	Bayesian inference	Microgrid	2020	[170]
	Simulate uncertain variables	Bayesian inference	–	2020	[171]
	Simulate decentralised OPF problem	Linear regression	–	2020	[172]
Cyber security	Cyber attack identification	LSTM-LUBE	Microgrid	2021	[173]
		LUBE-MSOS	Microgrid	2021	[174]
		Markov decision process	Smart grid	2018	[175]
		Bayesian networks	Smart grid	2019	[176]
	Electricity theft identification	RNN-GRU	Distribution grid	2020	[177]
	FDI attack detention	Various	Smart grid	2016	[178]

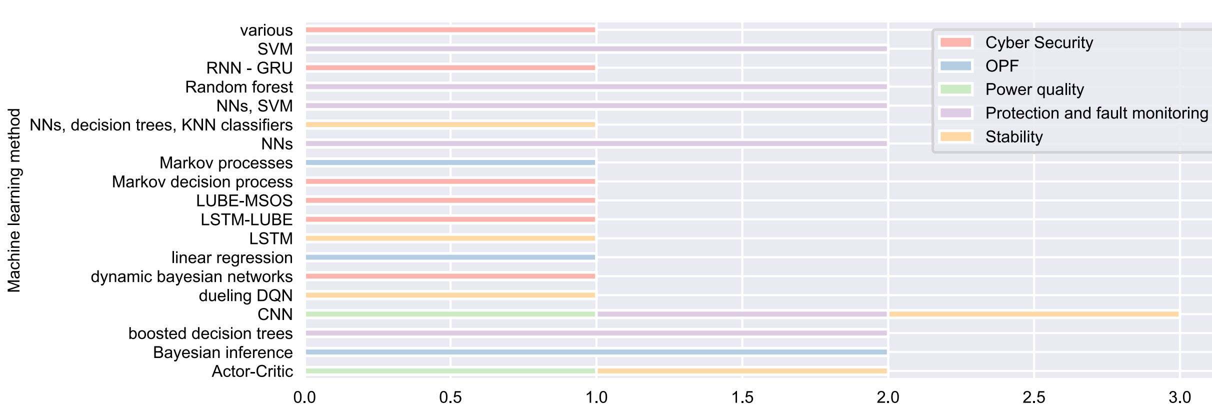

Fig. 5. Machine learning techniques in literature for power system protection, stability, quality, and optimisation.

using a random forest with a majority voting decision on the final ensemble algorithm [162]. Similarly, faults in generators present in a microgrid have been analysed using an SVM [163].

Nonlinear methods have shown the potential to deal with high-complexity classification tasks by determining strong relationships amongst the features extracted from the voltage and current signals.

For instance, a general overview of the fault detection task in microgrids has been provided, whilst focusing on nonlinear classifiers, and a comparative study of NNs and SVMs has been conducted [157]. Scholars [62] proposed a microgrid protection scheme that analyses different classifiers, such as naive Bayes, SVMs, and NNs, highlighting NNs performance over the rest of the classifiers. In a similar context, a microgrid protection scheme has been proposed using line voltage and currents to train the NN to detect faults and an SVM for fault location [161]. In addition, a CNN has been suggested for classifying earth faults and faulty feeders on the basis of signals obtained from smart meters [155]; reportedly, the CNN can detect features in the input dataset and provide accurate results using minimal signal processing techniques.

Researchers [158] have proposed an in-depth analysis of fault current tracing via the decomposition of current signals with wavelet transforms to obtain three-phase line currents and zero-component signals. This paper proposes the utilisation of these signals as the input for optimised decision trees to classify fault types and faulty phases, considering the short detection time and real-time application of the proposed methodology. Moreover, scholars [156] approached fault detection by analysing power signals and proposed applying anomaly detection in the form of NNs classifiers.

5.3.2. Stability

During normal operation of the LEC, grid congestions may arise due to sudden change in generation/consumption and weather events. The ability of the network to maintain voltage magnitudes, voltage angles, and inadequate frequency values is what is referred to as system stability. Therefore, post-fault decision making is another contributing factor in maintaining the grid stability in LECs. The identification of various events has been explored for a microgrid with several sources of energy generation [165]. The explored events include the identification of starting generators, introduction to fault, post-fault stability, operating point, fault clearance, and post-fault transient state. The suggested multi-classifier methods are random forests featuring bagging techniques, NN, and KNN. According to the authors, the further addition of extracted features to the time-series data improved the identification of all events.

Post-fault or preventive measures are required to maintain the grid stability following event detection. In this regard, emergency load shedding under different disturbance scenarios have been addressed as a Markov decision problem, and duelling deep Q-learning has been employed in an islanded microgrid [166].

5.3.3. Power quality

Power quality also refers to the voltage quality. Thus, this parameter is used to analyse the presence of harmonics and the maintenance of operational parameters within the recommended regulations. Power quality issues can interrupt operation, damage equipment, and generate unpredictable behaviour in the controllers. The need for fast methods to detect power-quality issues is increasing because of new energy technologies involving power electronics [51]. Most of the studies associated with LECs present signal analysis of voltage and/or current measurements to classify disturbances in the grid as the main applications of machine learning in this problem.

Accordingly, researchers [167] have proposed a CNN that was trained to identify and classify power quality disturbances from a voltage signal dataset consisting of harmonics, voltage swell, voltage sags, and flicker. In another study, scholars [168] proposed an actor–critic topology to manage the load injections of controllable devices within a microgrid, aiming at decentralised voltage control. Moreover, a method for harmonic state estimation has been reported in the literature [164], which was applied to smart meter data collected within an unbalanced distribution grid. The authors used an LSTM to determine power consumption and finally detected harmonic sources within the grid with a sparse Bayesian learning estimator.

5.3.4. Optimal power flow

To ensure the secure operation of the power system, power flows need to satisfy stability limits, such as voltage limits. The guaranteed optimisation of these power flows ensures the steady-state operation of the system whilst minimising a specific objective function. To this end, the other machine learning applications, which were reported in the literature, focus on the study of the efficient computation of power flows, with data-driven methods serving as an alternative to traditional numerical methods. For example, scholars [172] suggested a mechanism to decentralise the solution of optimal power flows using machine learning by solving several cases under different parameters to build a dataset that allows regression of unsolved optimal points pertaining to the power flow problem.

Similarly, several studies have proposed machine-learning techniques to study probabilistic power flows. In a study [171], variational Bayesian inference was used to approximate probabilistic optimal power flows, thereby addressing wind generation and load uncertainties. Furthermore, the result from a study [170] supports the integration of wind power in a microgrid, considering an AC optimal power flow formulation. This was achieved by incorporating the uncertainty into the balancing equations. The resulting problem was formulated as a stochastic optimisation problem and solved via multi-objective Bayesian learning. In another study [169], the authors utilised Markov processes to simulate uncertain components such as household loads or weather patterns.

5.3.5. Cyber security

Recently, cybersecurity in the context of power systems has become increasingly important owing to the rise of digitalisation and associated risks, such as breaches by third parties. Regardless of the smart infrastructure at both the on-grid and household levels, LECs are not insulated from these risks [179]. In recent studies, data-driven models relying on machine learning have proposed solutions to security challenges on a more local level. Accordingly, the use of power flow equations combined with time-series prediction models has been proposed to identify manipulated meter readings at the distribution grid level [177]. Furthermore, the authors compared traditional models, such as ARIMA, with RNNs. In addition, scholars [173,174] used an LSTM with lower and upper bound estimates (LSTM-LUBE) to detect cyberattacks in microgrids. RL was used in a study [175] to detect cyberattacks in smart grids. The problem was formulated as a model-free partially observable Markov decision problem.

Although the advantages of this method have been demonstrated, the authors remark on the implementation of deep RL as an improvement. Another approach was reported in a study [176], which used dynamic Bayesian networks and a restricted Boltzmann machine to detect unobservable cyberattacks. Furthermore, false data injection detection (FDI) have been formulated as a supervised learning problem [178]. Various classifiers are compared including the KNN, NNs, and SVM algorithms for different grid sizes. AdaBoost and multiple kernel learning were also employed as decision and feature levels; reportedly, these fusion algorithms are less sensitive in terms of grid size.

5.4. Energy transactions

Concerning the transactional activities of energy systems, data-driven algorithms have shown suitability for application in trading programs and as tools to study, analyse, and optimise participant behaviour in local energy markets regardless of the market configuration in the LEC. Emerging blockchain technologies enable trading platforms for LEC participant transactions in peer-to-peer market configurations [104]. The machine learning algorithms reported in the recent literature for energy transaction applications are listed in Table 11.

RL is the architecture chosen for research to generate goal-oriented trading strategies. For example, researchers [180,182] applied

Table 11
Machine learning (ML) techniques for energy transactions.

Task	ML Algorithm	Level	Year	Source
Trading strategies	Q-learning	Microgrid	2017	[180]
	DQN	LEM	2018	[181]
	Q-learning	Distribution grid	2019	[182]
	DQN	Microgrid	2019	[183]
Energy-supply game with economic dispatch and demand response	Q-learning	Smart grid	2017	[184]
Peer-to-peer transactions	Fuzzy Q-learning	Energy community	2019	[185]
Trading strategy, reduce plant schedule	DQN	Microgrid	2019	[186]
Trading strategies real time	DQN	Microgrid	2018	[187]
Blockchain platform	RNN	Smart grid	2021	[188]

Q-learning algorithms to develop efficient trading strategies in local energy markets, aiming to facilitate trading amongst participants and maximising utility for agents in the local energy market. Similarly, scholars [181] sought to model participants' trading behaviour by implementing a DQN algorithm. Furthermore, explored a CNN-DQN incremental RL algorithm has been explored by storing transition samples from training, a so-called experience replay procedure, thereby enabling high data efficiency by reusing the samples [182]. In a study, [186] the authors implemented DRL for energy trading within a microgrid, aiming to optimise the schedule of the virtual power plant, considering the availability of wind power and batteries.

Peer-to-peer market structures are currently being developed using blockchain technology. Blockchain applications for this type of market have been reviewed in detail [104], whilst scholars [188] have explored a blockchain-enabled peer-to-peer energy-trading platform with the integration of machine learning. The development of trading strategies in a peer-to-peer market has been explored in a study [183], which focuses on the development of a trading model for the microgrid market using DQN to overcome the challenges of dealing with uncertain variables, such as renewable generation and load demand, thereby obtaining revenues considering seasonal changes. Furthermore, fuzzy Q-learning has been used to address continuous space-state problems [185], considering a large number of scenarios in an energy trading process.

Researchers [187] generated a bidding strategy to maximise revenues in a microgrid featuring flexible and non-flexible consumption, storage, and solar generation for a real-time trading horizon. The strategy was developed using a DQN algorithm that considers a tractable state-action set.

6. Conclusions

6.1. Summary of findings

In this study, a definition of local energy communities was derived on the basis of European legislation and practical examples of community-based energy projects. The proposed definition identified the traits of locality, energy sustainability, community engagement, information and communication technology, and transactions as the key traits for such an energy community. Based on this, related literature reviews and recent publications on machine learning methods were identified, specifically in the key areas of energy management systems, asset forecasting, power quality, stability, security, and optimal control of storage and demand response. Furthermore, the present study presented an overview of the three main categories of machine learning. Specifically, for reinforcement learning, supervised learning, and unsupervised learning, the specific methods applied to each of the identified application areas were detailed in this study. Accordingly, an analysis of the state-of-the-art techniques of each application was at the core of this study. Fig. 6 maps the literature on machine learning areas and techniques presented in the subsequent sections to the previously introduced components of LECs by classifying each source according to the four dimensions of technique, category, application, and criterion.

This analysis revealed the bulk of the literature on machine learning in local energy communities provided by recurrent neural networks that were applied to forecasting problems. In addition, demand response and storage control problems were solved via reinforcement learning, specifically pure value function approximation techniques in the form of Q-learning. Similarly, reinforcement learning was prevalent in the transaction tasks.

In general, several nonlinear methods, ranging from tree-based to deep learning-based methods, can be observed in recent publications, independent of the application. In contrast, this review revealed a lack of literature on probabilistic tasks and reinforcement learning methods that considered policy function approximations with or without the value function approximations. This finding will inform the future research direction.

6.2. Proposal for future work

The goals and implementation of local energy communities appear to revolve around the uncertainty created by the individualistic community participants and a high share of renewable energy. One result is the increasing uncertainty. Whereas most of the machine learning methods identified in this study do not consider such uncertainty as a core aspect, such uncertainty is considered for the applications of local energy communities. Consequently, a gap in the literature can be observed, which treats uncertainty as a central aspect, especially from a systems perspective in related control algorithms, energy management systems, and forecasting methods.

Another consequence of an individualistic community participation and the transition of the traditional market to a more decentralised market is the need for a faster response from individual participants and their assets. Large, centrally controlled systems might be too slow to operate in real-time, and thus require resource-intensive and in-depth scheduling and optimisation activities to optimally schedule and dispatch whilst still maintaining the system between the operational bounds. In contrast, a decentralised system can provide flexibility proximate to real-time and offer a more granular resolution than discrete decision frameworks such as Q-learning. This can be achieved using the aforementioned policy of approximation methods.

The findings from the literature review suggest that nonlinear methods outperform linear methods in terms of both solution time and quality. This discovery suggests a trend towards neural-network-based methods combined with modern, state-of-the-art hardware. Presumably, these nonlinear methods will gradually be introduced into other traditional power-system applications. A nonlinear method that is yet under-represented in local energy communities is the deep Markov model, i.e., neural network-based formulations of traditional hidden Markov models. Another example of such a method is the traditional nonlinear auto-regression. Because most forecasting tasks are conducted via recurrent neural networks or convolutional neural networks, both these representative nonlinear methods require iterative approaches and thus do not scale as effectively as non-iterative autoregressive processes.

Finally, a fundamental component that is yet to be applied to local energy communities is the analysis of interactions and social aspects

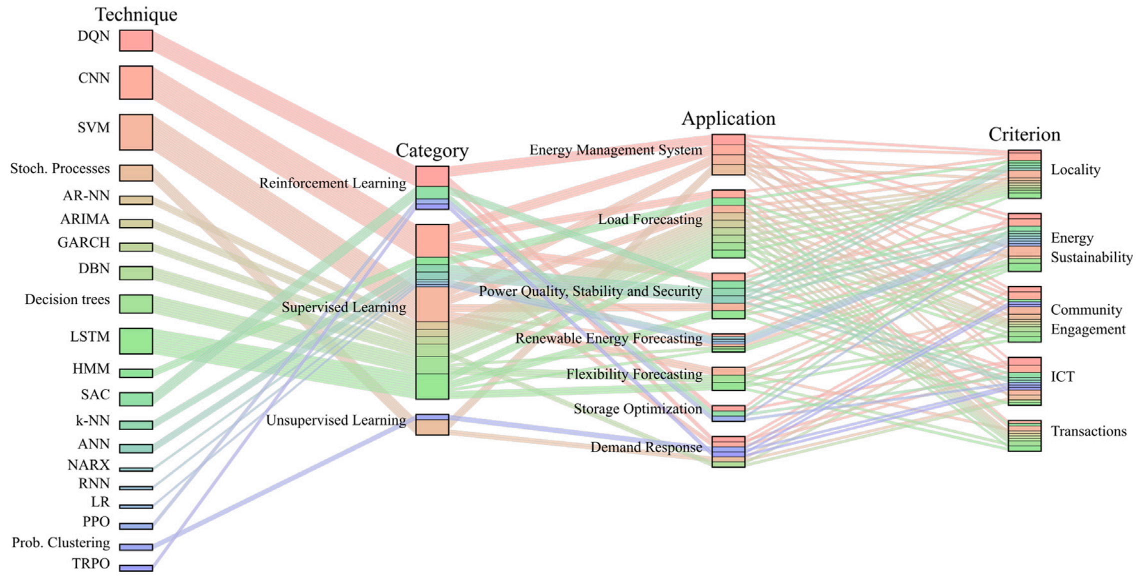

Fig. 6. LEC criteria and corresponding machine learning techniques.

using nonlinear methods. In particular, game-theoretic models and system analysis are not well-represented in the literature; however, they appear to rely on traditional methods and provide opportunities to build on the state-of-the-art methods of other applications, as presented in this paper.

CRediT authorship contribution statement

Alejandro Hernandez-Matheus: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Markus Löschenbrand:** Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Kjersti Berg:** Investigation, Writing – original draft, Writing – review & editing, Visualization. **Ida Fuchs:** Investigation, Writing – original draft, Writing – review & editing, Visualization. **Mònica Aragüés-Peñalba:** Methodology, Supervision. **Eduard Bullich-Massagué:** Methodology, Supervision. **Andreas Sumper:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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