Cities 152 (2024) 105198

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Decentralized AIoT based intelligence for sustainable energy prosumption in local energy communities: A citizen-centric prosumer approach

Bokolo Anthony Jnr

Department of Applied Data Science, Institute for Energy Technology, Os Alle 5, Halden 1777, Norway
Department of Computer Science and Communication, Østfold University College, BRA Veien 4, 1757, Halden, Norway

ARTICLE INFO

Keywords:
Energy prosumption
Artificial intelligence of things
Decentralized energy systems
Distributed ledger technologies
Local energy communities
Architectural model

ABSTRACT

The role of prosumers who are consumers who produce, store, and consume energy is vital to the uptake of renewable energies in Local Energy Communities (LEC). However, the integration of prosumers in the smart grid to facilitate bidirectional flows of energy and information depends on intelligent operations of energy systems and flexible structures of the existing energy markets. But existing energy trading mechanisms are faced with issues of trust, privacy, security, and energy pricing determination. Also, there are fewer studies based on a citizen-centric prosumer approach. Thus, there is need to provide reliable solutions that addresses the aforementioned challenges faced by prosumers in LEC. Advancements in disruptive technologies, such as Distributed Ledger Technologies (DLT), Artificial Intelligence (AI), and the Internet of Things (IoT) have transformed a broad spectrum of intelligent systems in smart cities. Therefore, this study examines the integration of AI and IoT as AIoT and DLT towards a citizen-centric prosumer approach for decentralized energy markets trading. Additionally, this article develops an architectural model for energy prosumption in LEC using design science approach based on a user-centred design method that shows a possible implementation concept to support energy sharing and trading in LEC. The architectural model supports trust, data privacy, security, and energy pricing determination using AI and smart contracts to provides real-time energy trading monitoring, easy access, control, and immutable logs to unearth underlying energy demand and supply patterns thereby supporting citizen-centric prosumer approach. Finally, a use case scenario of DLT and AIoT for prosumption operations is presented.

1. Introduction

Governments around the world aims at achieving a net zero emission by increasing the production and consumption of renewable energy sources in addition to changing the behaviors of citizens to foster the cost-effective balancing of energy supply and demand (Hoppe et al., 2015; Parag & Sovacool, 2016). These goals can be achieved with the advancement of information and control infrastructures of the smart grids which supports interoperability among different stakeholders in Local Energy Communities (LEC) such as prosumers (Bhat et al., 2022; Hua et al., 2022). Nowadays, the use of Information and Communication Technologies (ICT) to foster the production and consumption of Renewable Energy Sources (RESs) is transforming the energy industry across the world (Zhang et al., 2021). Moreover, energy prosumption is becoming popular because electricity is produced from RESs from the consumers' side (referred to as prosumers) (Anthony et al., 2019). However, due to the irregular nature of RESs, some prosumers are incapable of satisfying their energy demands while some have surplus energy. Energy prosumption enables small-scale energy producers to generate, store, share energy via a decentralized approach using an energy trading mechanism (Anthony et al., 2019; Samuel et al., 2022). A typical energy prosumption and trading mechanism offers a platform where supply and demand of energy are possible by decreasing high production costs of prosumers and organizations. Presently, decentralized approach such as peer-to-peer (P2P) energy sharing is being adopted to share energy among peers residing in the same neighborhood (Kyriakou & Kanellos, 2023).

But existing energy prosumption and trading mechanisms are faced with issues of trust, privacy, security, and energy pricing determination. Therefore, there is need to provide efficient and effective solutions that addresses data security, privacy, resource management and price determination challenges faced by prosumers in LEC (Parag & Sovacool, 2016; Samuel et al., 2022). Nowadays disruptive technologies such as DLT, AI and IoT are being adopted in the energy sector. In the energy

E-mail addresses: anthony.bokolo@ife.no, anthony.j.bokolo@hiof.no.

https://doi.org/10.1016/j.cities.2024.105198
Received 15 March 2024; Received in revised form 4 May 2024; Accepted 7 June 2024

sector the convergence of these technologies can drive the advancement of autonomous business models to foster energy sharing and trading in local energy communities. For example, DLT can extract information from volumes of data generated by IoT devices such as energy meters and smart sensors. Presently, the interconnectedness between these technologies is often overlooked, and these technologies are separately adopted (Burkhardt et al., 2019). However, the convergence of AI, IoT, and DLT can improve future energy systems in LEC. For instance, by using IoT devices such as smart sensors and energy meters deployed by citizens data can be produced and collected, whereas DLT sets up the rules and provides peer-to-peer infrastructure needed to support energy trading and of engagement, while AI optimizes energy demand and supply by predicting the production and consumption of flexibilities (Sandner et al., 2020). Moreover, DLT supports a trustful, governed asset exchange between trustless entities, whereas AI enables decision making in an autonomous, yet artificial manner DLT employs smart contracts to communicate with smart IoT devices and sensors without having any central authority. These technologies can be exploited to achieve their full potential when combined (Ahmed et al., 2022).

The integration of AI with IoT is termed as AIoT (Gulati et al., 2020). The convergence of AIoT and DLT can improve energy prosumption services in LEC. As DLT makes AIoT more autonomous and trustworthy, and AIoT can guide DLT towards intelligence (Hua et al., 2022). Integrating DLT and AI synergistically improves the potentials of both technologies to create innovative solutions to promote sustainable energy systems in LEC. AIoT and DLT are one of the key technologies enabling the next wave of the digitalization in the society (Sandner et al., 2020). While prior studies have examined different use cases for integrating DLT, AI, and IoT, the convergence of these technologies to support intelligent energy management in LEC has only been addressed in the conceptual level. It's still unclear how the integration of these technologies could be deployed in a robust way for citizen-centric prosumer approach. Thus, this article aims to examine the following research questions.

- What is the significance of integrating AI, IoT and DLT to improve prosumption services in local energy communities?
- How can the convergence of AIoT and DLT support trust, data security, privacy, and price determination in local energy communities?
- How to support a citizen-centric prosumption operations in local energy communities?

Accordingly, the objective of this article is to investigate how to incorporate AIoT and DLT in LEC for supporting prosumers to participate in decentralized power markets. This study aims to explore how the deployment of AIoT and DLT in energy prosumption can help in managing complexity, enabling automation, and scalability, by leveraging data produced from distributed energy infrastructure in real time. Additionally, this article develops an architectural model for energy prosumption in LEC to support optimal energy management, and control of energy systems in LEC thereby supporting citizen-centric presumption grounded on design science approach based on a user-centred design method. The architectural model was developed based on the smart grid reference architecture developed by CEN-CENELEC-ETSI (2012) and the architecture for interoperability context setting framework (GWAC, 2008). The architecture utilizes AI to analyze, process, and generate insights from data generated from smart IoT devices and sensors. It also uses DLT to support the monitoring and tracking of the devices connected to the internet via different communication protocols. More importantly, the architectural model uses AIoT to unearth underlying energy demand and supply patterns thereby providing useful information for effective decision making for prosumers in LEC. Evidence from this study depicts how the combination of AIoT and DLT can improves the explainability and certifiability needed for commercial realization of energy trading in LEC. Further findings also present a use case scenario of prosumers that intents to securely share, and trade renewable energy enabled by AIoT and DLT technology. The rest of this article is organized as follows: Section 2 introduces the literature review; Section 3 is the research methodology employed. Section 4 is the findings. Section 5 draws the discussion and research and practical implication, and lastly Section 6 is the conclusion of this article.

2. Literature review

This section reviews related works of local energy communities in Norway and other regions. Until now, significant work has been done related to LEC in Norway and across other regions in the world. One of these works is the study conducted by Lindberg and Inderberg (2023) explored the existence of energy injustices within the Norwegian solar policy mix from the lens of collective prosuming. The authors studied the policy mix for rooftop PV solar energy producers in Norway from an energy justice lens, based on housing cooperatives and multi-apartment buildings likened as citizen energy communities and renewable energy communities. Another study by Wethal (2023) investigated power outages or blackouts in rural Norwegian households. The study aimed to use the perspectives of households to identify the consequences of power blackouts, and show how disruption affects relations between practices, infrastructures, providers, and customers. Berg and Löschenbrand (2022) presented a data set of an energy community based on a Norwegian context which includes residential energy consumption, data produced from smart meter measurements categorized into consumer groups, appliance consumption data, wholesale electricity prices, EV data on charging patterns, and simulated photovoltaic energy generation based on irradiance and temperature.

Additionally, Bhat et al. (2022) explored energy autarky and self-consumption in energy communities. The study carried out an evaluation and simulation of scalable 'energy cells' in Norway, Austria, and Belgium. Also, suggestions for the development of local and renewable energy cell infrastructure were provided. Eikeland et al. (2022) examined contributing factors that leads to interruptions within the energy grid based on a case from Northern Norway. The authors collected data on the topography of the area, grid topology, the historical energy consumption/production data, and the historical meteorological data. After which they employed statistical and machine-learning techniques to forecast the occurrence of failures. Heilmann et al. (2022) presented a trading algorithm to represent bidding conditions in the competitive wholesale market of energy communities in Norway and England. The study provided a concrete understanding of how energy sharing in local electricity markets should be consolidated within a local wholesale market or via a centralized sharing. McElhinney et al. (2022) carried out a comparative study to fully understand how effectiveness of existing models deployed in energy communities and further to identify how they operate in Norway and France. The authors aimed to enable energy consumers to be empowered by contributing individually or communally in the energy transition.

Likewise, Anthony Jnr et al. (2020b) employed Application Programming Interface (API) to a design a layered architecture to help smart cities achieve a sustainable energy prosumption services. Evidence from the study revealed that developed approach helps for district energy management in presenting support decision-making and energy information intelligence on energy sustainability in enabling prosumption operations. Backe et al. (2021) carried out a case study to examine sector coupling between the central power system and LEC in Norway based on heat usage in buildings and charging of Electric Vehicles (EV) within the European power system. The study further designed a framework to assess the long-term investments in relation to uncertain short-term operations of nation-wide aggregated assets. Anthony et al. (2019) designed a big data-driven architecture to accelerate energy prosumption service within smart community districts. Also, the architecture designed can be employed as a guide to help policy makers and municipalities in initiating approach for energy data analytics in smart community districts in making decisions for energy prosumption planning. Walnum et al. (2019) identified potential gaps between practice and vision and further designed a scenario calculator for assessing smart energy communities in Norway with link that provides detailed measures associated to the overall climate goals. Baer and Nielsen (2018) identified the challenges and best practices needed for stakeholders' collaboration and planning the actualization of a smart energy communities as well as zero emission neighborhoods based on evidence from seven Norwegian municipalities.

Furthermore, considering other regions Bielig et al. (2022) investigated the social impact of energy communities across Europe. The study analyzed the theoretical background of the social impact connected to energy communities and identified the underlying concepts of energy democracy, social capital, community empowerment, and energy justice. Lode et al. (2022) provided a transition multi-level perspective on energy communities and identified the factors for the emergence of energy communities. Findings from the study highlighted existing research gap and recommended potential pathways for future research to accelerate the diffusion of energy communities. Magnusson (2022) investigated the development of citizen involvement within community energy towards the Swedish energy transition. The author assessed understanding stakeholder engagement and community acceptance in community energy programs to support policy regarding national energy systems. Cunha et al. (2021) studied the society transitioning to a low carbon economy through energy communities based on evidence from Brazil and Italy. The study further explored the process required for reforming of the legal framework for the electric sector mainly focused on energy communities.

Moreover, Dóci (2017) conducted a comprehensive study of local energy initiatives within Germany and the Netherlands towards contributing to renewable energy communities. The analysis considered communities in terms of their size, locations, institutional background, renewable energy technology used and organizational structure. Hoppe et al. (2015) investigated how local governments are supporting local energy initiatives based on best practices evidence from Germany and The Netherlands. Findings from the study suggested three main factors from the strategic niche management which comprises of managing expectations, building networks, and facilitation of learning as vital in local communities. Williams et al. (2015) explored how to support private sector investment within microgrid-based rural electrification. The authors reviewed and identified barriers to impede private sector participation during decentralized electrification initiatives and also proposed strategies that have been previously deployed to overcome the identified barriers. Evidence from the reviewed studies in this section describes works that have been done to promote LEC in Norway and similarly across other regions. Irrespective of these contributions there are fewer studies that converged disruptive technologies, such as DLT, AI, and IoT to improve presumption services in local energy communities in Norway and also in other regions. This shows a gap in knowledge which is explored in this current study.

3. Research methodology

A Design Science Research (DSR) based on a user-centred design method is employed in this study. A DSR is referred to as a research paradigm in which the researcher answers questions relevant to societal problems through the creation of novel artifacts, thus contributing new knowledge to the field of study. This methodology employs an iterative method, facilitating the freedom to adapt the structure and the evaluation of the designed artifact, until a much valuable solution is developed. The DSR approach revolves with the aim of bundling several process, sociotechnical artifacts, computer algorithms, spanning software, and systems with the goal to enhance and/or solve the challenge being investigated (Hevner et al., 2004). A DSR method was employed in this study in order to address the practical problem specified within the research question 2 and 3 of this paper which includes how the convergence of AIoT and DLT can support trust, data security, privacy, and price determination in LEC and overall, and how to support a citizen-centric prosumption operations in LEC. The DSR method ensures that the solution to the challenge accomplishes all requirements and needs of researchers, while interpreting new knowledge both for the practitioners and the scientific community (Hevner et al., 2004).

Additionally, DSR was adopted in this study as it is in line with the engineering model of research intending at developing an artifact (Hevner et al., 2004; Markus et al., 2002; Peffers et al., 2007). The DSR involves the development of artifacts which may comprise of constructs, models, methods, and instantiations. The designed constructs may comprise of symbols and vocabulary, whereas the models can vary from representations and abstractions. The methods can be best practices and algorithms, and the instantiations can be various types of implementations and possible prototypes (Burkhardt et al., 2019). In this article the *DSR is employed based on a user-centred design (UCD) methods* to ensure the citizen-centric prosumer approach proposed is designed and developed in a user centric manner. *The user-centred design* is employed as it aims to capture and improve the whole end-user experience with a definite understanding of the end-users, environments, and tasks. Accordingly, the DSR and UCD process which comprises of an iterative process are shown in Fig. 1.

Fig. 1 depicts the adopted methodology which is a DSR approach based on a user-centred design method. The DSR comprises of five phases (problem identification, solution suggestion and objective, design development, demonstration and evaluation, and conclusion and communication), whereas the user-centred design method comprises of four steps (understand context of user, specify user requirements, design solutions, and evaluate design against requirements), as shown in Fig. 1. In the DSR approach the artifact (architectural model), being designed and the evaluation phase forms the two connected and iterative phases carried out by the researchers to gain relevant knowledge of the domain being examined (energy prosumption in local energy communities). Accordingly, the design comprises of a sequence of review of literature on best practices regarding decentralized AI based energy prosumption options in LEC and document review, whereas the evaluation phase mainly provides information useful for improving the applicability of the architectural model.

As this article aims to develop an architectural model describing the benefits of integrating AI, IoT and DLT to improve prosumption services in LEC. Literature inquiry and qualitative data were used as secondary data source to provide input for the design of the architectural model creation as previously stated. The data collection involves identifying sources and evaluating their suitability to answer the research question (s) being explored in the study. The sources journal article, conference proceedings, technical reports, books, and book chapters published between the years 2000 and 2024 published in English language. After which the collected qualitative data was categorized based on the research questions been examined in the study and descriptive analysis was employed to present the findings from the analyzed data.

Overall, the DSR based UCD cycle structure (as shown in Fig. 1), is adapted to design, develop, and evaluate the architectural model for energy prosumption in LEC with the citizen in mind, while also emphasizing on the role of prosumers and other actors involved in the energy market, which allows for user-centred development process to occur. By incorporating both DSR and UCD perspective, specifically in the convergence of AIoT and DLT, the adapted DSR based UCD cycle structure allows for an accurate capturing of citizens and prosumers needs grounded on a decentralized architecture. Furthermore, the DSR based UCD cycle structure ensures that the implemented features of the proposed architectural model to be developed (as seen in Fig. 3), is fit for the purpose of developing a decentralized AIoT based intelligence for sustainable energy prosumption in local energy communities (as seen in Fig. 4). Thus, the prosumers and consumers energy needs will be assessed during the evaluation stage of the development and due to the iterative nature of DSR based UCD, the architectural model will be

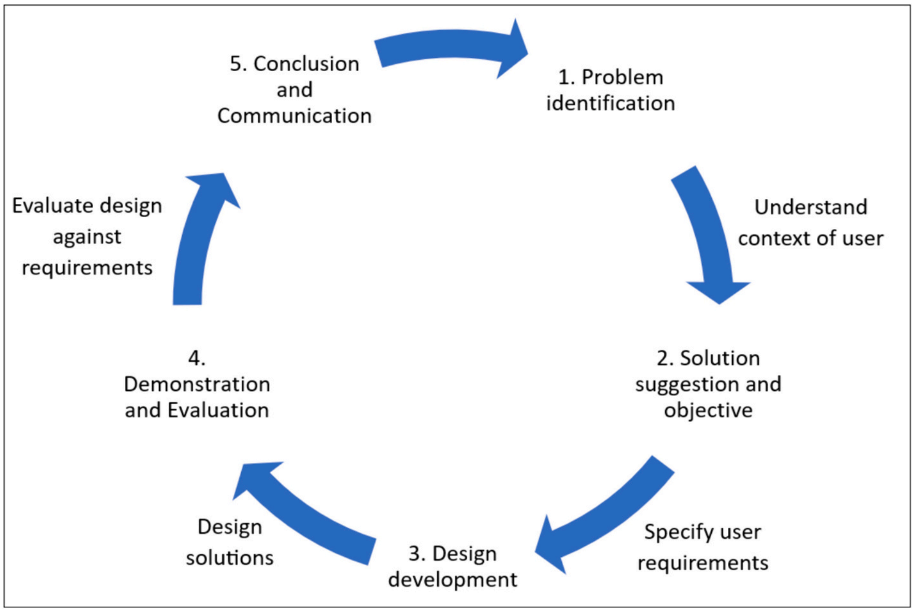

Fig. 1. DSR based on a user-centred design cycle structure.

modified based on feedback from qualitative data until the prosumers/consumers requirements are met. According to Peffers et al. (2007), the DSR process shown in Fig. 1 is summarized as seen in Table 1.

Table 1 provides the activities carried out in the phase elaborated in DSR method as presented in Fig. 1. The main focus lies in providing the design, development, and evaluation of the architectural model. For the evaluation due to the complexity associated with dynamically converging AIoT and DLT to support energy prosumption operations in LEC, a descriptive evaluation is utilized to present the architectural model's usefulness, value, and its correctness to illustrate how the convergence of AIoT and DLT support trust, data security, privacy, and price determination in local energy communities and how to support a citizen-centric prosumption operations in LEC. Therefore, as suggested in prior studies this study used literature inquiry and qualitative research approach to collect data based on a use case for the design of the architectural model and ArchiMate modelling language was employed for evaluation of the architectural model to provide evidence for theory and practice (as seen in Fig. 4).

Table 1
DSR research process being carried out.

#	DSR Process	Research description
1	Problem identification	• Issues related to trust, data security, privacy, and price determination in LEC. • Significance of integrating AI, IoT, and DLT to improve energy prosumption. • Definition, requirements, and functionalities of AIoT and DLT. • Challenges of achieving a citizen-centric prosumption operations in LEC.
2	Solution suggestion and objective	• Deployment of AIoT and DLT as relevant components to support energy prosumption options in LEC. • Identification of relevant capability, functionalities, and limitations of converging AIoT and DLT in energy in LEC. • Definition of how DLT based smart contracts and AI based Machine Learning (ML) algorithms can synergically improve a citizen-centric prosumption operations in LEC.
3	Design development	• An architectural model for energy prosumption in LEC that shows a possible implementation concept to support energy sharing and trading in LEC. • A model visualizing the integration of AI, IoT, and DLT with relevant interfaces and functionalities to promote energy prosumption services.
4	Demonstration and evaluation	• Demonstration of the architectural model to relevant stakeholders. • Modelling of a case study scenarios to show how the developed architectural model (artifact) address the problems defined in step 1.
5	Conclusion and communication	• Summary and publication of results in a scientific peer reviewed journal (cities), to show the architectural model's usefulness, value, and its correctness to support a citizen-centric prosumption operations in LEC.

4. Findings

4.1. Significance of DLT, AI, and IoT in Local Energy Communities

4.1.1. Importance of distributed ledger technologies in local energy communities

DLT started initially with Bitcoin proposed by Satoshi Nakamoto in 2008 (Nakamoto, 2008). A DLT is simply a distributed digital record of data or transactions (Alruwaili, 2020). A DLT, or generally a distributed ledger can store different types of assets analogous to a register. Mostly, these data or transactions can be related to funds and identities (Bokolo, 2022; Sandner et al., 2020). DLT use a decentralized consensus mechanism where different node users participate to process transactions and data without the involvement of a third trusted party (Anthony Jr, 2023; Bosri et al., 2020), in an untrusted distributed system, building trust at a reduced cost (Zhang et al., 2021). DLT uses cryptography to ensure data credibility and security and also employs a distributed node consensus algorithm to verify data transaction which are further synchronize across the entire network (Zhang et al., 2021). To guarantee the legality of business agreements DLT employs the capabilities of peer-to-peer networks and cryptographic algorithms without any involvement of any third party or a regulatory authority which increases data security. The exclusion of intermediaries makes the processing of data and transactions much faster (Anthony Jnr, 2023; Gulati et al., 2020).

There has been a widespread adoption of DLT in the energy sector due to its unique features, such as immutability, privacy, append-only, open, and transparent, anonymity, organized, accountability, etc. (Bosri et al., 2020; Jnr et al., 2023; Sandner et al., 2020). DLT provide provenance histories, enables predictive planning, fraud detection, and regulatory compliance. DLT can provide easy-to-use configurable dashboards, predictive models for energy production, provenance histories of generation and consumption of energy, and compliance checking such as GDPR, privacy and data security (Burkhardt et al., 2019). Prior studies employed DLTs such as blockchain for the management and monitoring of IoT devices as well as for energy distribution and trading in addition to improving the reliability and security of smart grid communications (Anthony Jnr, 2024; Khan et al., 2020). Using DLT, two parties in LEC can exchange renewable energy without fully knowing each other and not involve any third party.

DLT offer *techno-social implications* for local energy communities. From the *techno point of view* DLT offers transparency, simplicity, fairness, and helps in regulation of rules while executing transactions (Jnr et al., 2023). The data stored or transaction recorded in the distributed ledger is immutable, thus improving data integrity, reliable, and consistent. From the *social perspective,* all prosumers get fair incentives and are equally treated. Additionally, all energy trading transactions are automatically managed by smart contracts to reduce disputes between end users (Anthony Jnr et al., 2020b). Every authorized and legitimate energy prosumer or consumer has the autonomy of performing energy sharing, transactions, and trading with other residents without any prejudice. Likewise, the trustless nature of DLT makes it hassle-free and suitable for the citizens in LEC. DLT also supports detailed tracing and tracking of transactions (Gulati et al., 2020) which is useful for achieving energy provenance especially in local energy communities to track the source of renewable energy from solar, wind, hydropower, etc. DLT is an immutable technology which guarantees data integrity; nonetheless, if an incorrect transaction or data is added and the node users want to undo their transactions, the executed transactions are mostly irreversible. Moreover, DLT is quite complex to be implement for some prosumers. Thus, its adaptability is moreover limited. Another limitation of DLT relates to how prosumers and consumers can resolve dispute between different parties (Samuel et al., 2022).

4.1.2. Usefulness of artificial intelligence in local energy communities

AI which is the intelligence of machines has been applied in different sectors such as in finance, retail, education, medicine, transportation, energy, etc. (Zhang et al., 2021). The concept of AI technology started from the Dartmouth Society within 1956. As a branch of computer science dedicated to research and development involved with the mechanization of intelligent behavior, used to simulate, expand, and extend human intelligence. AI is also the ability of machine to carryout task and make decisions autonomously without the involvement of humans (Gulati et al., 2020). Generally, AI is employed to achieve intelligence involving the ability to learn, understand, and make choices or have opinions that are based on reasoning (Burkhardt et al., 2019). AI enable machines to think much more like humans in order to carryout various tasks. Algorithms are written and pre-defined to describe how the AI based system will work under different circumstances and how what action it should take. The benefits of deploying AI based Machine Learning (ML) in energy prosumption operations in LEC is summarized in Fig. 2.

AI is simply a computerized machines executing tasks that are normally linked with cognitive functions of the human mind. Examples of such tasks include knowledge representation, expert systems, robotic, translations, computational vision, speech interpretation, reasoning technology, problem solving, intelligent adaptive learning, and natural language processing (Burkhardt et al., 2019; Ragot et al., 2020; Zhang et al., 2021). AI is employed to support autonomous behavior of assets. Presently, AI is gaining prominence in businesses and the society at large (Ragot et al., 2020). AI improves processes by identifying patterns and also optimizing outcomes of industrial processes (Sandner et al., 2020). AI can organize complex data to make precise predictions and has had prominent successes in facial, voice, and image recognition, in scientific fields and diverse industrial (Krittanawong et al., 2020), and is now being applied in the energy sector. AI offers the prospect to achieve a high level of automation required for optimization of energy system performance and managing of the complexity associated with energy trading and sharing operations in LEC (Ericsson, 2022).

Furthermore, AI based ML can be applied to offer new insights to enable intelligent operations, control, and to optimize decision making leading to decentralized peer-to-peer business models for local energy communities (Samuel et al., 2022). The advanced metering infrastructures deployed in smart grids generates a substantial volume of valuable data (Anthony Jnr et al., 2020a). This data could be used by AI based ML models to improve the operability of energy systems and situational awareness for prosumers (Heilmann et al., 2022; Lode et al., 2022). This is specifically useful when small or medium sized prosumers contribute to the operations of energy systems and make decisions for energy management systems (Hua et al., 2022). Table 2 depicts the phase of applicability of how AI can improve prosumer operations in

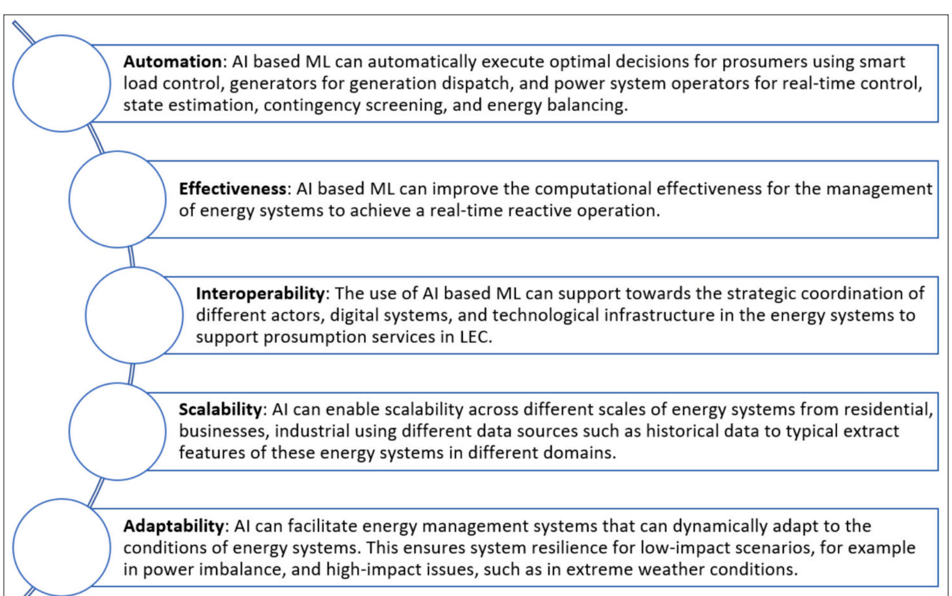

Fig. 2. Benefits of deploying AI for energy prosumption adapted from (Hua et al., 2022).

Table 2
Applicability of AI to improve prosumer operations in local energy communities.

Phase of applicability	Description
Automated phase	This phase involved the complete automation AI to support prosumer operations in LEC with less or no human intervention. Energy related services such as self-health in the energy grid, network optimization, wide area control can be carried out by AI (Hua et al., 2022; Williams et al., 2015). Moreover, this phase entails conventional operations of the energy systems in which AI can assists for situational awareness across the smart grid, fault detection, and restoration of electricity after receiving a procedure call of blackouts or outages (Cunha et al., 2021; Hua et al., 2022; Wethal, 2023).
Prescriptive phase	The digitalization of the smart grid and the energy systems has enabled the LEC transition towards this phase (Dorahaki et al., 2023; Hua et al., 2022). This phase involves the use of AI for partial automated within the energy system to minimize disturbances and outages (Wethal, 2023), using ML based optimization models (Hua et al., 2022).
Predictive phase	In this phase AI based decision support modules are deployed to forecast real-time renewable energy generation, demand, and possible uncertainties (Eikeland et al., 2022; Hua et al., 2022). This helps to improve energy system performances for resilience, stability, and capacity margin in LEC. Similar to the automated and prescriptive phases this phase can be automatically executed with the support of AI based ML algorithms that can systematically help to minimize the disturbances and outages in LEC (Hua et al., 2022).
Responsive phase	This level involves the reaction or response of the energy system expected after receiving a notification of an unexpected occurrence such as blackouts or outages in LEC (Hua et al., 2022). In futuristic energy prosumption services operated within LEC it is expected that full automation would be sustainably attained where the smart grid control, decisions, and network optimization could be smartly managed by an AI system without the involvement of any system operators, thus enabling the entire energy system to maintain situational awareness, fault detection self-healing and restoration (Hua et al., 2022; Mehta & Tiefenbeck, 2022).

LEC.

Overall, the application of AI in energy systems for management, scheduling, predicting, etc. has been well documented in the literature (Anthony Jnr, 2021; Samuel et al., 2022). However, the application of AI in LEC is faced with some issues such as scenarios when historical data needed by ML algorithms are too few to train an accurate ML algorithm, how do the system guarantee the models` accuracy. Also, it is still unclear in the literature how prosumers and other actors participating within LEC can ensures that AI based ML decisions align well with the existing physical constraints of the energy power systems (Hua et al., 2022). Additionally, there are fewer studies that have explored how AI based ML has been applied for data-driven operations exploiting historical data to improve the role of actors in the operation of energy systems, and also improving the computational efficiency and scalability using optimization approaches (Heilmann et al., 2022; Hua et al., 2022).

4.1.3. *Applicability of internet of things in local energy communities*

Internet of Things (IoT) is simply a network of things such as actuators, intelligent devices, smart meters, sensors, wearables etc. that share information across the internet (Kumar et al., 2021; Mohanta et al., 2020). In the last decade IoT devices are connected via wireless or wired communication to process, compute, and monitor different scenarios in real-time (Jamil et al., 2021; Sandner et al., 2020). IoT is recognized as one of the newest technologies due to its practical application in different industries (Sharma et al., 2021). As such, the IoT has also drawn great attention from academics, practitioners, and businesses due to its innovative capabilities and services across various smart social applications (Ahmed et al., 2022). The IoT provides communication between device-to-device, human-to-device, and human-to-human. IoT enables everything to be connected to the internet allowing the sharing of data between electronic devices and humans in an intelligent way (Imran et al., 2021). IoT fosters the automatization of industries and has evolved as one of the widely deployed technologies in various domains (Sandner et al., 2020). IoT has previously been deployed in across the society such as in the smart grid system (Mohanta et al., 2020). IoT is one of the enabling technologies for actualization of LEC. Thus, IoT can be deployed in a different environment such as local energy communities to capture information, and even trigger some events during certain conditions. IoT has changed the way that prosumers interact with the energy market.

With the availability of low-cost electronic circuits and the improvement in sensor technology, IoT is developing as a promising technology for actualization of communities becoming local energy communities. IoT can be applied in real-time applications such as in prosumption operations. As it connects intelligent sensors, smart metering devices, Radiofrequency Identification (RFID) across the Internet to active an intelligent energy management system. The applications of IoT have made a huge impact in local energy communities like energy meters and sensors deployed in residential buildings, organizational and in industrial facilities to measure energy consumption, monitoring energy generation, tracking provenance of renewable energy sources from the Transmission System Operator (TSO) and Distribution System Operator (DSO). The energy meters and sensors are deployed in LEC using IoT infrastructure connected through wirelessly or wired across heterogeneous networks (Mohanta et al., 2020). Besides, IoT can seamlessly connects heterogeneous energy systems and devices or sensors to establish an energy as a service network that enables communication, sensing, data generation, processing, and storage automatedly and systematically managed, monitored, and regulated with less human intervention (Ahmed et al., 2022).

4.2. *Background of decentralized artificial intelligence of things*

AI and DLT have their own benefits as well as corresponding drawbacks. AI is faces with issues related to explainability, effectiveness and interpretability (Zhang et al., 2021). DLT can empowers AI for reliable and transparent data sources, privacy protection, efficient autonomy, better fairness guarantee, and distributed computing power (Zhang et al., 2021). Furthermore, AI depends on three main foundations: data, algorithms, and computing power, and DLT can enable interoperable access to data and support the running of algorithms, data resources, and computing power grounded on its intrinsic features such as immutability, decentralization, and anonymization. DLT can guarantee the provenance (origin), and credibility to confirm the originality of the data as well as the traceability and audit credibility of AI algorithms. Moreover, DLT can record the decision-making of AI, which supports to analyze and understand the behavior of AI and ultimately promotes the explainability of AI, making it more trustworthy and transparent (Zhang et al., 2021). DLT design and operation involves several parameters as well as trade-off of throughput, security, and other parameters.

DLT has problems regarding energy consumption, efficiency, scalability, privacy, security. Therefore, AI can optimize DLT to achieve better governance and performance. Also, AI can also improve the intelligence of DLT applications and limit errors possibly caused by human influence. AI can optimize the construction of DLT to make it more efficient, secure, and energy-saving (Zhang et al., 2021). AI systems are typically based on two architectures which comprises of centralized AI and decentralized AI. Currently most AI systems are based on the centralized AI architecture which typically requires third party involvement to carry out a task. This necessitates that the AI systems are under the supervision of human intelligence. Thus, humans will be expected to pre-define what the AI system can do at a specific situation or event. In such centralized architecture the data can be easily tempered with and also there is limited authenticity. Thus, decentralized AI is needed as no party is required to govern, take, or make decisions occasionally for the AI systems. Overall, the combination of AI and DLT together is referred to as decentralized AI. By deploying DLT, AI can perform tasks without the involvement of any party. Thus, all the data analysis and decision making can be executed on a private and secured platform as data tampering is much difficult in a decentralized AI based platform (Gulati et al., 2020).

Decentralized AIoT can also support prosumption services as DLT allows safe and secure storage and distribution of data generated from IoT devices. While AI can help in detecting patterns, optimize, analyze, and generate insights from the data to provide interpretation and visualization that improves renewable energy generation, consumption, and storage for prosumers. Since DLT is based on a distributed and tamper-proof nature it can handle privacy issues security and protection in IoT based applications (Ahmed et al., 2022). Additionally, in a decentralized AIoT based energy prosumption environment DLT will store and transfer energy related data, and AI can autonomously make decision based on the stored data. Also, the stored data can be shared across to different actors within the LEC via a reliable and secured DLT infrastructure. By converging AIoT with DLT energy data will easily be made available for prosumers, and they will be able to see energy related data of the LEC (Gulati et al., 2020). Decentralized AIoT can improve the security of DLT applications, by adjusting the dynamic parameters to provide effective personalization for scalability, and improved governance mechanisms. Decentralized AIoT can provide customized data driven services to prosumers without violating their personal information by enabling prosumers to have control over their personal information (Jeon et al., 2022).

4.2.1. Feasibility analysis of integrating AIoT and DLT in local energy communities

As mentioned in the literature AI and IoT have been integrated to form a new specification termed as Artificial Intelligence of Things (AIoT) (Gulati et al., 2020; Imran et al., 2021) which aims to enhance data management, improve human–machine interactions, and implement complex data analysis (Imran et al., 2021). The integration of AI and IoT brings new possibilities, even though the concept of AIoT is new (Imran et al., 2021). The use of AI based machine learning techniques can discover patterns in data generated from IoT infrastructure deployed by prosumers in local energy communities (Imran et al., 2021). With the use of intelligent sensors, smart meters, protocols, and network devices prosumers transmit energy related information to different stakeholders who collaborate in local energy communities. To date studies that technologically converge DLT and AIoT simultaneously are limited. Though, the true potential of these disruptive technologies can only be unlocked if these technologies are combined (Sandner et al., 2020).

Previously, DLT was mostly discussed in the perspective of payments, i.e., in the area of Bitcoin and Ether. Over the years, more non-financial use cases such as digital identity management, decentralized electric mobility sharing, and supply chain management has emerged highlighting the potentials of DLT (Jnr, 2024; Sandner et al., 2020). While AI can help to limit human errors and lessen repetitive tasks carried out by prosumers in LEC. DLT can offer a digital asset to ensure reliable, trustworthy, safe, and secured energy trading transaction via decentralization (Jeon et al., 2022). Recently, along with AI and IoT, DLT has also been identified as a technology that has the potential to enhance modern energy systems and generate new business models to provide citizen energy communities (Ahmed et al., 2022). DLT, for example, can enhance trust, transparency, safety, security, and privacy of energy processes by providing a decentralized and distributed energy eco-system (Anthony Jnr, 2021). DLT helps to improve interoperability among different platforms and systems and limits centralized control over prosumers data thereby providing access to prosumers based upon request. DLT can support the storage and management of energy related data and further improves information management among energy community stakeholders.

As prosumers in LEC require reliable, secure, and decentralized IoT devices that support energy trading and sharing between multiple peers. DLT can be integrated as a viable alternative to support IoT-enabled prosumption operation in LEC (Kumar et al., 2021). Although, findings from the literature highlighted the value of combining DLT such as blockchain with other technologies such as IoT and/or AI (Khan et al., 2020; Sandner et al., 2020). The convergence of DLT applications with AI is a still rather new and has just started to get more attention in recent years (Brune, 2020). Although prior studies examined prosumption services there is a lack of a comprehensive and concrete study on integrating AIoT and DLT for energy prosumption services grounded on a citizen-centric prosumer approach in LEC. Moreover, only few studies have exploited the deployment of AIoT and DLT to examine how to support energy trading, control, and setting policies for energy in LEC. Also, studies that provides empirical evidence as related to security, privacy, resource management, and price determination are limited and the direct applications in LEC is still early in development (Krittanawong et al., 2022).

4.3. Use of DLT to accelerate energy prosumption services within smart grids

The energy sector represents almost 40 % of global carbon emissions generated from the combustion of fossil fuels (D'Adamo et al., 2024). In an effort to achieve net zero energy systems, policy makers are formulating sustainable measures for enabling the integration of RES and fostering behavioral change in the consumption of energy in residential areas (Hua et al., 2022). The smart grid is one of the important infrastructures needed to actualize a LEC. A smart grid is an intelligent energy network which cost-efficiently integrates information and control infrastructures to improve the efficiency and reliability of energy systems operations. From the *viewpoint of information system infrastructures*, the smart grid facilitates bidirectional communications between stakeholders across the energy systems such as the consumers, prosumers, TSO and DSO, generators, and system operator which enables the active engagement of consumers and the optimal operation of generators (Hua et al., 2022; Ringholm, 2022). *From the control viewpoint*, the interoperability of the smart grid fosters the optimal harmonization of several entities such as the generation units or loads to cooperatively accomplish the overall benefits of the energy systems. The smart grid offers regulatory supports that enable energy to actively produce, consume, sell, and store clean energy using storage devices, distributed RESs, and smart metering infrastructures (Hua et al., 2022; Talandier, 2018).

Presently, the energy markets are currently transitioning to acknowledge and promote the role of energy. Thus, a shift of the energy markets towards decentralized generation and consumption is necessary for the integration of the emergent role of energy (Parag & Sovacool, 2016). The current energy market structures that operate within the smart grid as mentioned in the literature comprises of peer-to-peer trading markets, intermediary-based trading markets, and microgrid-based trading markets. These aforementioned energy market structures are based on the information and control infrastructures of the smart grids, and they are categorized based on associated information exchange and the functions of control units (Hua et al., 2022). In LEC energy can contribute to the energy supply to consumers. Overall, energy can be small or medium sized energy users, such as residents, companies, or industries who also produce renewable energy on-site, and seamlessly exchange this energy with other prosumers or the smart grid to meet their own demand or make earnings from the energy arbitrage. Where the term "energy arbitrage" is a process where energy is purchased during off-peak hours (when grid electricity prices are cheapest). The purchased energy is then stored and utilized during peak hours (when grid energy prices are highest). The emerging role of energy is projected to support the Demand Side Management (DSM) and consequently decrease the reliance on the fossil-fuel based production with the long-distance transmission (Hua et al., 2022). Nonetheless, researchers such as Hua et al. (2022) argued that the participation of energy from the perspectives of energy systems and energy markets in LEC also some challenges. For example, the current structures of energy markets are not mostly appropriate to accommodate the role of energy, since energy balancing mechanisms and pricing schemes are independent of the state of electricity exchange among energy.

Moreover, the information infrastructures of existing energy systems may not be able to handle the increasing information flows initiated by the energy related transactions of huge amounts of distributed energy (Addae et al., 2019). Also, given the inadequate budgets for residential energy' control systems, it may be difficult for them to utilize historical data for optimally scheduling the production and consumption according to their individual energy patterns. Lastly, it is difficult to precisely forecast energy prosumption behaviors given uncertainties triggered by the intermittency of flexible demand and distributed RESs (Schrage, 2023). Therefore, to promote energy, there is need for decentralized approach that inform the policy design and further supports energy prosumption operations in LEC. Research related to decentralized energy trading have been subject of active research and practical over the years. Also, DLT and smart contracts have been previously applied in power systems control and (Hua et al., 2022). DLT can prevent the double spending attack and replay attack within the energy markets, i.e., where the same digital currency is spent twice or the same energy is traded twice, using smart contracts for accounting, and managing the ownership of energy as an asset. The decentralized feature of DLT enables a distributed ledger to be accessed and verified by all participants of the energy market.

Besides, DLT employs smart contract to reduce the operational and maintenance costs of energy to improve and encourage community energy participation of market players (Zhang et al., 2021). By deploying DLT the trading system is open and accessible for all energy, market operators, and system operators. The disintermediating nature of DLT changes the role of energy aggregators or suppliers to a neutral facilitator for supporting energy' participation. DLT employs encryption that protects energy' personal information such as transactions, addresses, and energy profiles. The computational complexity of data mining and shared validation for achieving consensus guarantees the security of distributed trading networks (Hua et al., 2022). The deployment of a DLT based energy prosumption environment can enable distributed energy trading and sharing in LEC, which is limited in the traditional centralized energy grid systems which cannot facilitate distributed energy sharing and trading. Thus, the decentralized feature of DLT can effectively help LEC, realize the transformation from centralization to distribution. The decentralization of DLT can help to breaks data silos and information barriers to realize a secure data sharing among multiple participants.

Thus, the use of DLT based smart contracts for energy trading which may involve the supply of energy or other related services such as the demand side management, which is monitored and maintained by smart meters installed in the residence of energy (Anthony Jnr, 2020). The payment of energy is executed by the smart contracts in a self-enforcing method, thereby ensuring trustworthiness of the energy trading ecosystem which is reliant on the trustworthiness of smart meters and the smart contracts (Samuel et al., 2022). However, the interoperability between the smart meters or controllers and smart contracts requires the initiation of interfacing and communication protocols (Hua et al., 2022). In addition, DLT can be employed to enhance intelligent operations of energy systems and flexible structures of the energy markets which are two critical factors in the smart grid. From an *energy market perspective* DLT provides the decentralized trading application and technical supports for peer-to-peer energy markets which are open and accessible to individual energy with the better data privacy, security, and enhanced automation (Hua et al., 2022). Also, considering the *operational perspective* the deployment of DLT can supports the control systems in strategic decisions towards optimizing system operations to achieve societal, economic, and environmental goals. These goals include increasing the generation of profits, saving electricity bills, reducing carbon emissions, and predicting uncertainties such as power outages or shortages in LEC (Hua et al., 2022; McElhinney et al., 2022), and support decision making by employing intelligent controlling techniques, such as the optimization using historical data from the energy systems (Hua et al., 2022).

Even though DLT can support decentralized energy trading towards the integration of prosumers, this transition of energy markets raises a series of challenges. For example, when energy feed their distributed generation into the smart grid, this results to issues for market operations, such as negative grid operations and energy prices, harmonic distortion, spike in the voltage, and power imbalance definitely challenges the protocols and control infrastructures of the current energy systems (Hua et al., 2022). Furthermore, the operation of the decentralized energy markets without any central authorities results to issues related to how to maintain the overall value of the power systems as regards to resilience mitigation. This will require the setting of pricing schemes, incentive measures, and sophisticated rulesets to align individual energy' behaviors with systems' benefits. Also, the transactional costs of most DLTs such as blockchain applications are mostly high in comparison to conventional IT based trading platforms. These high transaction cost can be a barrier for prosumers who wants to participate in the distributed peer-to-peer energy trading (Hua et al., 2022).

4.4. Developed architectural model for sustainable energy prosumption in LEC

The energy system is presently experiencing a paradigm change, that has been influenced by a change from the conventional centralistic and top-down electricity production chain. The existing generation to transmission and then to distribution and lastly consumption is now being changed towards a more sustainable and decentralized system, in which different actors such as energy dynamically change their roles and interact in an energy cooperative manger as seen in LEC. The framework proposed by CEN-CENELEC-ETSI (2012), and its components aimed to capture the design of several smart grid use cases such as energy in local energy communities within an architectural model to achieve a generic and neutral reference architecture. The framework supports the evaluation of different smart grid use cases enabling standardization and interoperability.

Overall, the framework consists of five distinct layers capturing business objectives and processes, information exchange and models, functions, communication protocols and related components. These five layers denote an abstract and integrated version of the interoperability classifications introduced in the GWAC Stack methodology (GWAC, 2008), where three main layer and-layer were presented which comprises of Technical *(basic connectivity, network interoperability, syntactic interoperability)*, Informational *(business context, semantic understanding)*, Organizational *(business procedures, business objectives, economic/regulatory policy)*. Each *architectural layers* proposed covers the smart grid level, which is covered by *electrical domains* and connected *information management zones* as seen in Fig. 3. The objective of the developed architectural model as mentioned in the literature (CEN-CENELEC-ETSI, 2012) is to depict on which zones of information management connections is carried out between domains where local energy communities evolve.

This enables the presentation of the current state of implementations in the smart grid, but also depict the evolution of future smart grid scenarios that supports the principles of interoperability, localization, universality, flexibility, and consistency. As suggested in the literature (CEN-CENELEC-ETSI, 2012; GWAC, 2008) the developed architectural model comprises of the architecture layers, domains and zones as seen in Fig. 3. In this study an architectural model is developed to show how the convergence of AIoT and DLT can support trust, data security, privacy, resource management, and price determination in local energy communities grounded on the smart grid reference architecture proposed by CEN-CENELEC-ETSI (2012) and the architecture for interoperability

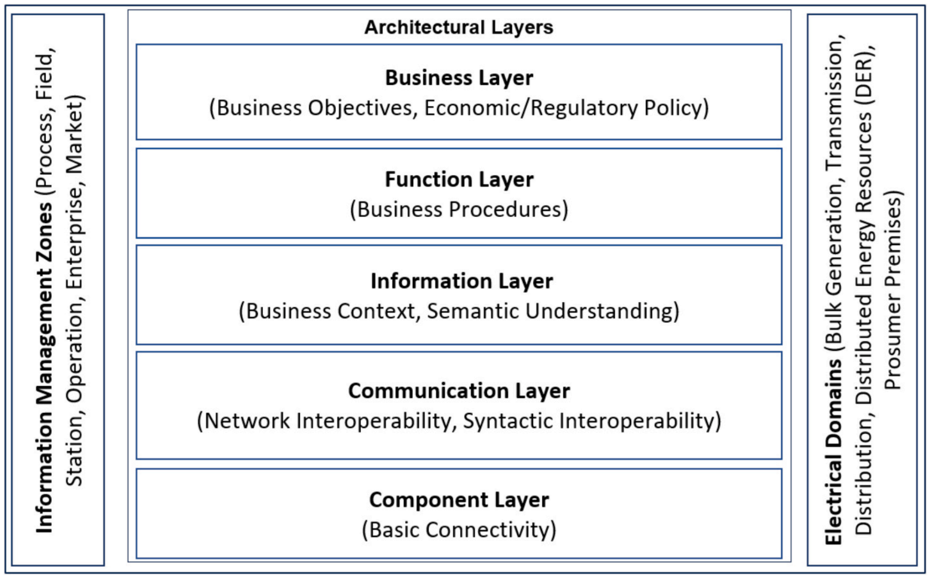

Fig. 3. Developed architectural model for sustainable energy prosumption in LEC.

context setting framework (GWAC, 2008) as seen in Fig. 3. Accordingly, Fig. 3 depicts the developed architectural model which mainly comprises of the architectural layers, information management zones, and electrical domains. Each of these components are discussed in the subsequent section based on the work by GWAC (2008); CEN-CENELEC-ETSI (2012).

4.4.1. Architectural layers

a. Business layer

This layer comprises of the business view on available information exchange within the LEC and the smart grids. As recommended in the literature this layer can be employed to map economic (market), regulatory structures and policies, energy business models, incentivization schemes for prosumers, pricing mechanisms for energy trading, and business portfolios of products and services for all market parties involved in energy prosumption services in LEC. Also, the energy business processes, and business capabilities can be represented within this layer. Accordingly, this layer supports business managers in decision making associated with the use of disruptive technologies such as AI, DLT, IoT, etc. to create innovative business models as well as specific business use case scenarios in addition to regulators required in defining novel market models.

b. Function layer

This layer describes energy related services, functions and business procedures including capturing the relationships from an architectural perspective. The functions are independently characterized from actors or stakeholders and physical deployment needed in systems, applications/digital platforms, and components. Within the architectural model the functions are derived by accessing the functionality needed to achieve energy prosumption operations in LEC.

c. Information layer

This layer mainly describes the data and information needed to improve the current business context for better semantic understanding. It also involves data that is being utilized and exchanged between different components, systems, applications, services, and functions. It comprises of information objects and the related canonical data models. Where a canonical data model enables an organization to create and distribute a common description of its whole data unit. These canonical data models and information objects represent the common semantics for components, systems, applications, services, and functions to enable an interoperable information exchange which is achieved through communication.

d. Communication layer

The communication layer describes the protocols and mechanisms required to achieve seamless interoperable exchange of data between different actors, digital systems, physical infrastructure, and electrical components for prosumption operations in LEC. The communications are needed to achieve network interoperability and syntactic interoperability towards have a connected services and functions as related to data models or information objects.

e. Component layer

The component layer comprises of the physical distribution and basic connectivity required for all deployed physical soft and hard components involved in running of LEC and within the smart grid context. This includes applications, system actors, energy system equipment (usually located at field and process domains), protection equipment and telecontrol devices, network infrastructure (wired and wireless communication connections, switches, routers, servers) and different types of computer systems.

4.4.2. Electrical domains

a. Bulk generation

In the context of this study this domain represents the production of electrical energy in bulk quantities, from renewable energy sources such as large-scale solar power plant (i.e. Photovoltaics (PV), Concentrated Solar Power (CSP)), hydro power plants, off-shore wind farms within or close to LEC which is typically connected to the transmission system connected to the smart grid.

b. Transmission

Mainly represents the organization needed and infrastructure deployed to transports clean electricity over short and long distances across LEC controlled and managed by the Transmission System Operator (TSO).

c. Distribution

Primarily represents the required infrastructure and organization which are involved in the distribution of clean electricity to energy customers.

d. Distributed Energy Resources (DER)

Mainly represents the distributed electrical resources which are directly linked to the public distribution grid. The DER also involves applying small-scale energy generation technologies normally in the range of 3 kW to 10.000 kW. These distributed electrical resources at times are directly controlled and managed by Distribution System Operator (DSO).

e. Prosumer premises

Comprises of the consumers who are the end users of energy, as well as the also producers of clean energy. This domain may range from commercial, industrial, and home/residential facilities. Also, the prosumer premises comprises of energy generation from PV generation, EV storage, stationary batteries, micro turbines, etc.

4.4.3. Information management zones

a. Process

This includes the chemical, physical, or spatial transformations of energy (solar, electricity, heat, water, wind, etc.) and the physical infrastructure or equipment directly involved. (such as the generators, overhead lines, circuit breakers, transformers, cables, electrical loads of sensors and actuators which are directly or partly connected to energy prosumption operations in LEC.

b. Field

Involves physical equipment installed to protect, control, and monitor the process of the energy system. It includes the bay controller, protection relays, any type of intelligent electronic devices which gets and utilize process data from the energy system.

c. Station

Mainly represents the spatial aggregation level within the field level. The station comprises of data concentration, substation automation, functional aggregation, plant supervision, local Supervisory Control and Data Acquisition (SCADA) systems, etc.

d. Operation

This involves hosting energy system control operation within LEC. In the context of prosumption services operation comprise of virtual power plant management systems (aggregating several DER), Energy Management Systems (EMS), microgrid management systems, Distribution Management Systems (DMS) in generation and transmission systems, charging management systems for EV fleet.

e. Enterprise

Includes organizational and commercial processes, infrastructures, and services needed for prosumption services on LEC. With organizational process in LEC comprises of service providers, utilities, energy traders and the commercial processes comprises of logistics, staff training, asset management, work force management, billing, customer relation management, procurement, etc.

f. Market

Mostly reflects existing market operations which are possible across the energy conversion chain, such as energy trading, retail market, mass market, etc.

4.4.4. Use case of DLT and AIoT for prosumption operations

In order to depict how the convergence of AIoT and DLT support trust, data security, privacy, and price determination in local energy communities. ArchiMate modelling language is employed to present a use case scenario showing the applicability for evaluation of the developed architectural model to support prosumption services in LEC as seen in Fig. 4. The description of the notations and components used in modelling in the ArchiMate tool is out of the scope of this paper and is well described in The Open Group (2022). Accordingly, the modelling of the application of AIoT and DLT for as enablers for sustainable energy prosumption in local energy communities is depicted in Fig. 4. Findings from the literature suggest that the convergence of AIoT and DLT can unlock new business models for the incentivization of energy (Sandner et al., 2020).

Fig. 4 illustrates a use case scenario of a LEC use case comprises of an energy prosumer in a residential area with its own RES generating energy from solar (or wind, hydropower), who also have its own digital identity stored in the DLT system such as Hyperledger Fabric or Ethereum which is one of the employed since it is based on a public permission network enabling an open and accessible energy sharing. Moreover, Hyperledger Fabric and Ethereum supports smart contracts, which can be used to write contract for energy trading and sharing in the Solidity language. Also, the proof of authority consensus mechanisms is proposed, which will enable prosumers who sell renewable energy to approved transactions. In this use case the DLT based system and smart contracts are integrated with the AIoT module via a REST Application Programming Interface (APIs) which connects to smart meters, sensors, solar panels, and other physical infrastructures deployed in LEC to record in kilowatts the amount of energy produced, stored, and traded within LEC.

Therefore, using the unique identity the energy prosumer can share and trade energy tokenized as assets using a digital wallet which converts cryptocurrency to local currency such as Euros, US dollars, etc. (Anthony Jnr, 2024; Bokolo, 2022). Also, within the distributed ledger network orchestrated by the DLT based DApps the energy prosumer gets the status of an independent business actor operating autonomously on its own. By utilizing smart contracts, micropayments can be directly made to the energy prosumer, triggering the sharing and trading of energy across the LEC to other consumers. A consumer who needs energy then access the DLT system and request for energy for a specific period of time. An energy consumer can also request to purchase energy due to power outages or blackouts. Smart contracts calculate the fee for the kilowatt of energy required based on the current spot price from the local energy market operator (e.g. Nord pool, European Energy Exchange, etc.), for a kilowatt and prompts the consumer for payment. Once payment is made by the consumer who request for energy the prosumer is notified and the energy supplied to the local community grid is shared with the consumer.

As suggested in the literature (Sandner et al., 2020), a pay-per-use payment or incentivization schemes could be deployed. Since the energy prosumer owns a digital wallet, where payment is transferred to by the consumer. The digital wallet is managed by smart contracts connected to the DLT based DApps which stores energy related data. Additionally, AI can be employed on the data collected from IoT devices (smart meters, sensors, solar panels, and other physical infrastructures) to optimize and forecast energy production and consumption within LEC

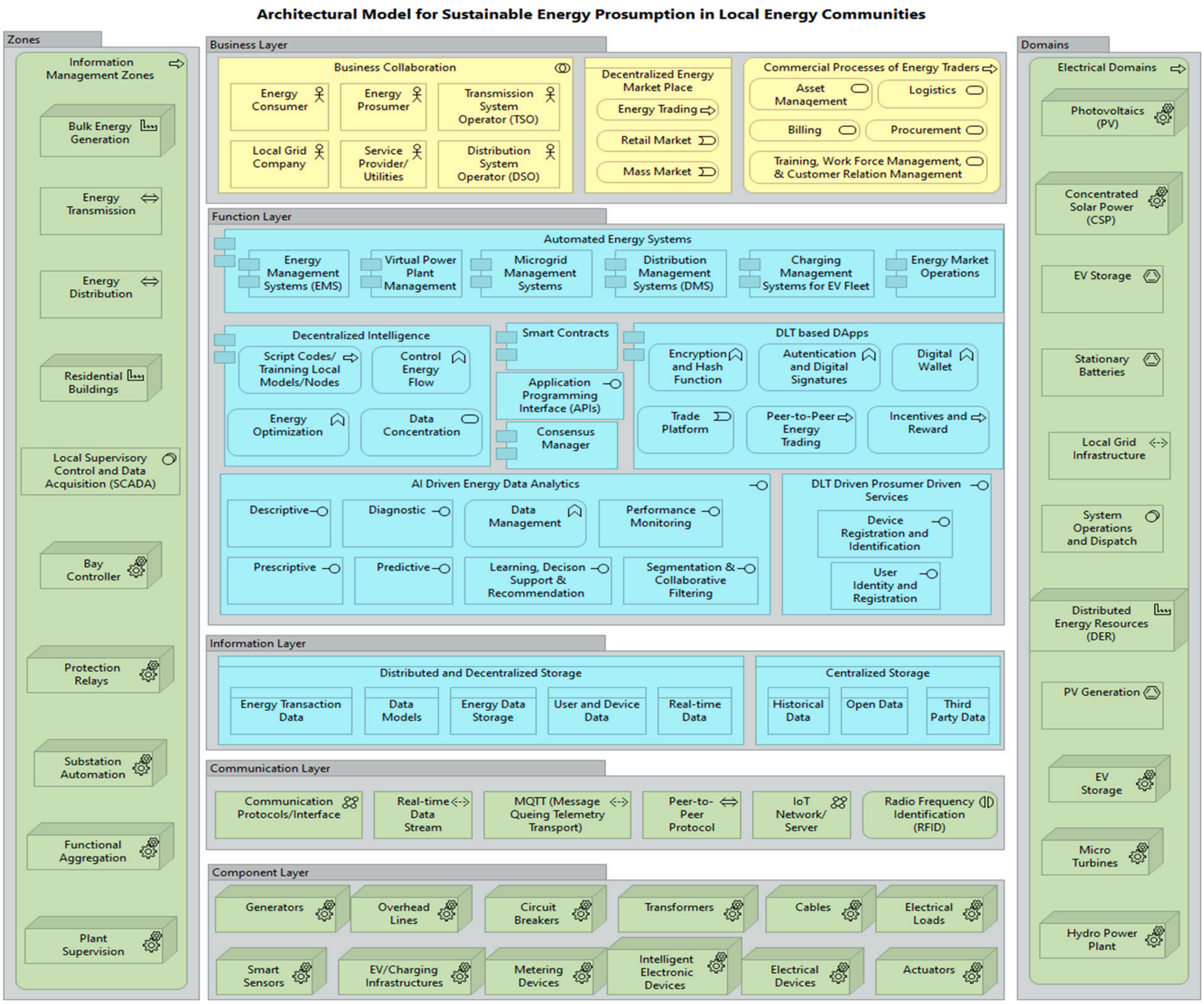

Fig. 4. Architectural modelling in ArchiMate to support prosumption services in local energy communities.

for efficient operation of the prosumption services. The analyzed data from AI can be used for predictive and conditional maintenance based on the "AI Driven Energy Data Analytics" module to suggest a more regular maintenance of physical infrastructures resulting in less downtime of the electricity network across LEC (Sandner et al., 2020).

4.4.5. Implementation, simulation, and experiment

The implementation of the developed architectural model comprises of different components, such as a front-end, the AI based data analytics models, IoT devices, IoT server/gateway, and smart contract. Also, a decentralized application referred to as (DApp) which is a type of distributed, open-source software platform that is based on a peer-to-peer distributed ledger network rather than the conventional centralized single computer. A flow diagram for the implementation, simulation, and experiment plan is shown in Fig. 5.

DApp is implemented either as Hyperledger Fabric or Ethereum employed as the DLT platform to support optimal energy management, and control of energy systems in LEC thereby supporting citizen-centric presumption. The implementation modelling and experiments of the developed architectural model will be deployed on a minimum eighth-generation machine equipped with Intel core i-7 processor with 16 GB memory and Ubuntu Linux operating system. Minimum eighth-generation machine equipped with Intel core i-7 processor with 16 GB memory and Ubuntu Linux operating system For DLT development, the docker engine and docker composer will be used which will provide the development environment to set up the docker image and container on the virtual machine.

Furthermore, Hyperledger Fabric, an open-source framework that is hosted by the Linux Foundation, will be used for client software toolkit. Hyperledger Fabric is used as compared to Ethereum as it enables the implementation of smart contracts, and also supports existing programming languages such as Java, Javascript, Go, and service-based architecture (Mohanta et al., 2020). In addition, Hyperledger Fabric was chosen due to its ability to execute calls to external endpoints from smart contract (Mohanta et al., 2020). Using Hyperledger Fabric AI based models can be implemented with oracle services which can be integrated into smart contracts to support energy sharing and trading. Accordingly, smart contract will be programming in solidity programming language which will be exposed to front-end Graphical User Interface (GUI) using different RESTful API. The Message Queuing Telemetry Transport (MQTT) communication protocol will be used to communicate between the Metering Devices, smart sensors, etc. and the IoT server, whereas Hypertext Transfer Protocol (HTTP) is used as one of the communication protocols between DLT and IoT server. For the front-end of the DApp HyperText Markup Language (HTML), Cascading Style Sheet (CSS), and JavaScript can be used.

Additionally, open-source web development toolkits, such as Bootstrap and jQuery will be used as suggested in the literature (Jamil et al., 2021). Also, to implement the AI based data analytic model, PyCharm Professional 2020 will be used as an Integrated Development

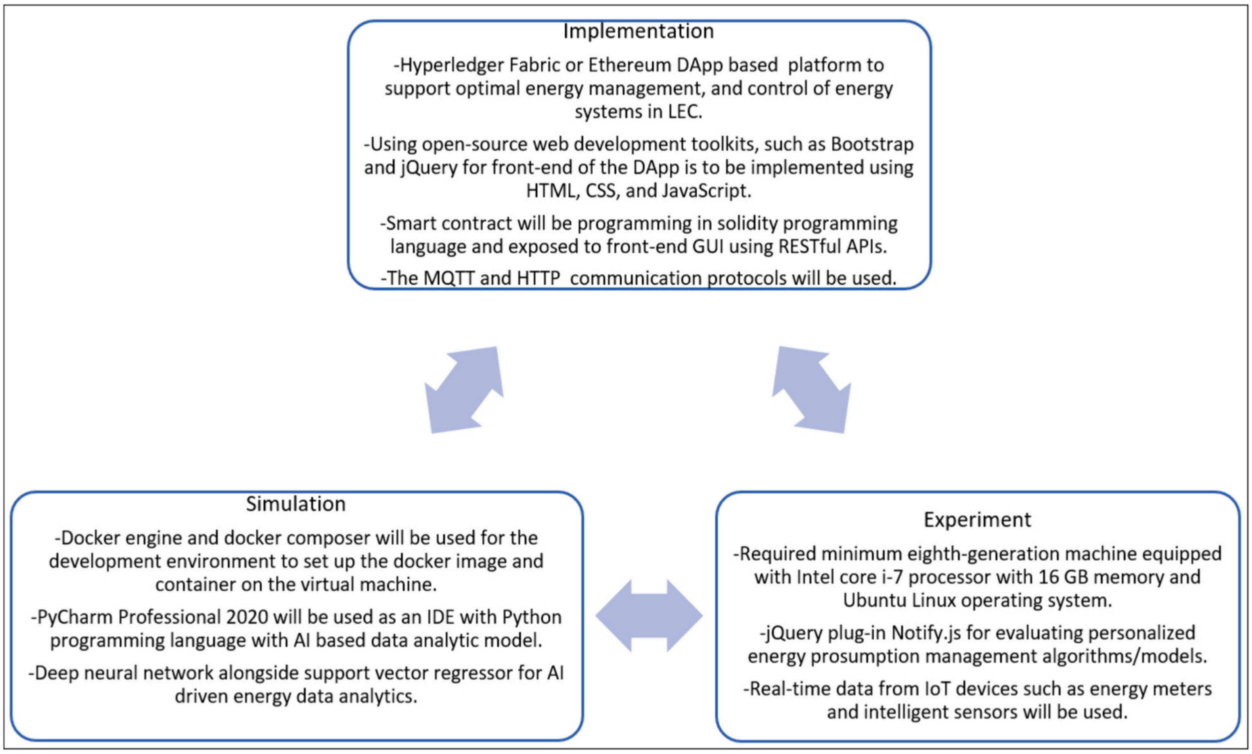

Fig. 5. Flow diagram for implementation, simulation, and experimental plan.

Environment (IDE) with Python programming language. Real-time data from IoT devices such as energy meters and intelligent sensors will be used. Deep neural network alongside support vector regressor are suggested to be used to implement the "AI Driven Energy Data Analytics" as seen in Fig. 4. Besides, jQuery plug-in Notify.js will be used for generating a personalized energy prosumption management models and algorithms for providing notification to the prosumers, energy consumers, and other actors. That subscribe the decentralized energy trading solution which is to be submitted as a transaction via a REST API deployed using the HTTP communication protocol (Jamil et al., 2021). The data are stored with the distributed ledger as asset which can represent any digital or physical object. The energy provenance is queries on Hyperledger Fabric employing Fabric which keeps track of all energy trading transactions executed as well as the associated transition details (Dillenberger et al., 2019).

5. Discussion and implications

5.1. Discussion

The use of disruptive technologies in businesses fundamentally changes how enterprise operations are implemented and also how value-added services are delivered to the customers. Digital twins, cloud computing, virtual and augmented reality, data analysis, AI, IoT, and DLT are some of the disruptive technologies driving transformation across the society (Shaker et al., 2021). AI when deployed with IoT is referred to as AIoT, which is denoted as the Artificial Intelligence of Things (Gulati et al., 2020). Accordingly, this study argued that AI, IoT, and DLT are technologies that can be integrated to develop novel business models, services products to improve energy prosumption services in LEC. The technological convergence of AIoT and DLT will drive the development of existing business models and the digitalization of the energy sectors to achieve immense efficiency gains. This study examines the significance of integrating AI, IoT and DLT to improve prosumption services in local energy communities. The findings further demonstrated how the convergence of AIoT and DLT support trust, data security, privacy, and price determination in local energy communities. Secondly, this study discusses on the potential of adopting DLT to improve the structures of energy markets and further explores the deployment of AIoT for enhancing the optimization, prediction, decision making and state monitoring during the operations of prosumption services in LEC.

In this article, an architectural model for energy prosumption in local energy communities is developed to shows a possible implementation concept to support energy sharing and trading. The architectural model also employs AIoT and DLT to support a citizen-centric prosumption operations in local energy communities. Findings from this study examines energy policies as related to architectural design of citizen-centric prosumption services so as to facilitate the integration of energy with renewable energy sources within LEC. Findings from this study discusses issues related to how the applications of decentralized AIoT in smart grids could facilitate the integration of energy to decarbonize the power systems. Furthermore, this study suggests that the operation of energy in LEC is influenced by *regulatory perspective, market perspective, and operational perspective* as reported in the literature (Hua et al., 2022). The *regulatory viewpoint* involves the main issues needed to facilitate the engagement of energy which is mainly associated with the lack of decentralized and dynamic policy measures. Overcoming this challenge necessitate future practical and research based regulatory design to identify key assets, responsibilities models, and roles for energy (Hua et al., 2022). Similarly, from the *market viewpoint* the main challenge involves accommodating the new role of energy by designing suitable local market structures that align system benefits with individual profits, which necessitates the setting up of pricing mechanisms, rulesets, transactions provenance, decentralized trading platforms, and automated auction schemes (Hua et al., 2022).

Additionally, considering the *operational perspective*, issues related to the use of AI based machine learning models fitted with physical operations and constraints associated with the energy systems (Hua et al., 2022). This demands the transition towards a more digitalized, connected, and interoperable energy systems which provides seamless interactions between digital systems and physical infrastructure deployed in LEC. Evidence from this study explores how to exploit the potential of

AIoT and DLT to support the emerging role of energy in local energy communities to be integrated with the smart grids towards the decarbonizing of the energy systems. This study provides a comprehensive review of the literature from the aspects of the existing energy prosumption operations and local energy communities in Norway and other regions. This study specifically focuses on the state-of-the-art research and applications of the AIoT and DLT in terms of supporting the decentralized intelligence for energy sharing, trading, and decision-making support during the energy prosumption operations.

Therefore, findings from this study concludes that the incorporating of AIoT and DLT can support the integration of energy with the functions of governance, trading, policy, and control. However, this is attainable only if the critical challenges related the regulation, operation, and market are overcome (Hua et al., 2022). In this study, the developed architectural model enables the securely sharing of information among energy prosumer, consumers, and other actors within the LEC. The deployment of DLT based DApps, smart contracts, and decentralized intelligence enables the architectural model to provide a different level of data integrity, data access, privacy, data visibility, authenticity and security support to all stakeholders while sharing energy related data via a distributed method. Moreover, the architectural model ensures price determination to enable the traceability of energy source, energy sharing and trading in LEC based on a distributed peer-to-peer framework that provide an efficient and stable data storage. Also, it can foster trust between different stakeholders such as the energy consumer, energy prosumer, local grid company, service provider/utilities, TSO, and DSO involved in the decentralized energy marketplace.

5.2. Research implications

In the current age of technological advancement, the energy sector is implementing disruptive technologies such as AI, IoT, and DLT providing automated and autonomous capabilities within LEC. Disruptive technologies such as AI, IoT, and DLT which are showing tremendous development and potential in their respective fields can be utilized to support energy prosumption operations towards a modularized and flexible energy sharing and trading operations. The use of these disruptive technologies opens up a wide range of possibilities such as enabling intelligent communication among energy systems with limited human involvement by reducing associated complexity faced in LEC. Accordingly, findings from this study present an architectural model developed based on the smart grid reference architecture developed by CEN-CENELEC-ETSI (2012) and the architecture for interoperability context setting framework (GWAC, 2008). More importantly, findings from this article present a use case scenario of prosumers that intents to securely share, and trade renewable energy enabled by AIoT and DLT technology.

The prosumer is connected to the community grid via the DLT based platform which ensures that fair pricing via smart contract and data security and privacy concerns are re-enforced for safe energy trading transaction and incentivization of multiple stakeholders (enabled by smart contracts) in LEC. The developed architectural model demonstrates a novel decentralized network framework that leverages advanced technologies to improve energy prosumption service towards a citizen-centric prosumer approach. The overall goal of this study is to provide a holistic and systematic approach of how to integrate AI and IoT as AIoT and DLT to accelerate sustainable energy prosumption in LEC. Furthermore, this study contributes to sustainable energy prosumption to enable a reliable, low-cost, and effective energy production, consumption, storage, and trading framework. The approach proposed in this paper allows energy and consumers to control their usage of electricity as well as production based on decision support. This can contribute to reducing energy wastage, advancing the effectiveness of clean or green energy, and decreasing the consumption of fossil fuels.

5.3. Practical implications

In recent years, the convergence of AI and IoT as well as DLT has become a promising solution to improve data driven services in energy sector. An integration of the key features of these technologies can aid to achieve a fault-resilience and tolerant energy system. This is because the trustworthy and decentralized nature of DLT makes this technology ideal for integration with technologies such as AIoT to revolutionize the challenges in energy prosumption operations. The adoption of DLT in the energy sector can also help to address interoperability issues faced in LEC. The capabilities of decentralized intelligence can lead to smart and futuristic energy solutions. Synchronized AIoT and DLT tools can improve interoperability between different energy systems (e.g., Energy Management Systems (EMS), virtual power plant management systems, microgrid management systems, Distribution Management Systems (DMS), charging management systems for EV fleet, energy market operations, etc.), incorporating multidimensional data from multiple sources (such as Historical Data, Open Data, Third Party Data, etc.).

To the best of the authors` knowledge there are few research that has provided a decentralized citizen-centric prosumer approach that emphasizes on the potential implications using converging AIoT and DLT to improve the overall sustainable energy prosumption in LEC. The learning abilities of AI based ML can be integrated with DLT based DApps and smart contracts in order to improve "energy as a service business model" capability smarter and more autonomous and resilient to systematically help to minimize the disturbances and outages in LEC. In addition to this DLT can help to preserve data security, privacy, and maintain trust and transparency within the energy sharing network. Also, towards enabling the entire energy system to maintain situational awareness across the smart grid, fault detection, and restoration of electricity after receiving a procedure call of blackouts or outages. Whereas AI can create new insights based on the data produced from IoT devices for AI driven energy data analytics such as descriptive, diagnostic, data management, performance monitoring, prescriptive, predictive, learning, decision support and recommendation, and segmentation & collaborative filtering of information.

6. Conclusion

Disruptive technologies such as AI, IoT, and DLT can utterly revolutionize future energy systems (Zhang et al., 2021). DLT and AIoT opens up new paradigms for energy as a service ecosystem especially in local energy communities. DLT enables the creation of a secured distributed ledger of data, where citizens are in control, govern and own their data, thereby monitoring access and sovereignty of their data. Most importantly, DLT and smart contract allows for the implementation of a distributed data-driven energy marketplace, where citizens as prosumers can earn tangible rewards or be incentivized for sharing and trading renewable energy in LEC. Therefore, this article provides a comprehensive discussion of the significance of integrating AI, IoT and DLT to improve prosumption services in LEC In addition, this study develops an architectural model for energy prosumption in LEC that shows a possible implementation concept to support energy sharing and trading in LEC across Norway and beyond using design science approach based on a user-centred design method. The architectural model supports trust, data privacy, security, and energy pricing determination using AI and DLT based smart contracts to provides real-time energy trading monitoring, easy access, control, and immutable logs to unearth underlying energy demand and supply patterns thereby supporting citizen-centric prosumer approach. Finally, this study employs ArchiMate modelling language to present findings from a use case scenario to support a citizen-centric prosumption operations in LEC.

One of the limitations of this study is that only secondary data was used in this research to present the use case scenario. Likewise, primary data from case study, survey, interview, etc. was not used. Also, no tool was implemented and validated to support sustainable energy prosumption in local energy communities. Further work will involve the implementation of a DApp either as Hyperledger Fabric or Ethereum employed as the DLT platform to support optimal energy management, and control of energy systems in LEC in Norway. For simulation, and experimentation of the architectural model, including details on the testbed setup, datasets, and evaluation metrics a minimum eighth-generation machine equipped with Intel core i-7 processor with 16 GB memory and Ubuntu Linux operating system. Real-time data from IoT devices such as energy meters and intelligent sensors will be used. A docker engine and docker composer will be used which will provide the development environment to set up the docker image and container on the virtual machine. For implementation of the AI based data analytic model, PyCharm Professional 2020 will be used as an IDE with Python programming language. The performance measures or evaluation metrics will include R^2 score, mean square error, mean absolute error, and the root mean square error.

CRediT authorship contribution statement

Bokolo Anthony: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization.

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.

Data availability

Data will be made available on request.

Acknowledgements

Open access funding provided by Institute for Energy Technology (IFE), Norway.

References

Addae, B. A., Zhang, L., Zhou, P., & Wang, F. (2019). Analyzing barriers of smart Energy City in Accra with two-step fuzzy DEMATEL. *Cities, 89*, 218–227.

Ahmed, I., Zhang, Y., Jeon, G., Lin, W., Khosravi, M. R., & Qi, L. (2022). A blockchain- and artificial intelligence-enabled smart IoT framework for sustainable city. *International Journal of Intelligent Systems, 37*(9), 6493–6507.

Alruwaili, F. F. (2020). Artificial intelligence and multi agent based distributed ledger system for better privacy and security of electronic healthcare records. *PeerJ Computer Science, 6*, Article e323.

Anthony, B., Petersen, S. A., Ahlers, D., Krogstie, J., & Livik, K. (2019). Big data-oriented energy prosumption service in smart community districts: A multi-case study perspective. *Energy Informatics, 2*, 1–26.

Anthony Jnr, B. (2020). Smart city data architecture for energy prosumption in municipalities: Concepts, requirements, and future directions. *International Journal of Green Energy, 17*(13), 827–845.

Anthony Jnr, B. (2021). Integrating electric vehicles to achieve sustainable energy as a service business model in smart cities. *Frontiers in Sustainable Cities, 3*, Article 685716.

Anthony Jnr, B. (2023). A developed distributed ledger technology architectural layer framework for decentralized governance implementation in virtual enterprise. *Information Systems and e-Business Management*, 1–34.

Anthony Jnr, B. (2024). Enabling interoperable distributed ledger technology with legacy platforms for enterprise digitalization. *Enterprise Information Systems, 18*(1), Article 2255979.

Anthony Jnr, B., Abbas Petersen, S., Ahlers, D., & Krogstie, J. (2020a). Big data driven multi-tier architecture for electric mobility as a service in smart cities: A design science approach. *International Journal of Energy Sector Management, 14*(5), 1023–1047.

Anthony Jnr, B., Abbas Petersen, S., Ahlers, D., & Krogstie, J. (2020b). API deployment for big data management towards sustainable energy prosumption in smart cities-a layered architecture perspective. *International Journal of Sustainable Energy, 39*(3), 263–289.

Anthony, B., Jr. (2023). Deployment of distributed ledger and decentralized technology for transition to smart industries. *Environment Systems and Decisions, 43*(2), 298–319.

Backe, S., Korpås, M., & Tomasgard, A. (2021). Heat and electric vehicle flexibility in the European power system: A case study of Norwegian energy communities. *International Journal of Electrical Power & Energy Systems, 125*, Article 106479.

Baer, D., & Nielsen, B. F. (2018). Challenges and best practices for the planning of zero emission neighborhoods and smart energy communities–the case of seven Norwegian cities. In *proceedings of the 54th ISOCARP congress, Bodø, Norway* (pp. 1-5).

Berg, K., & Löschenbrand, M. (2022). A data set of a Norwegian energy community. *Data in Brief, 40*, Article 107683.

Bhat, K. S., Ganglbauer, J., & Tragner, M. (2022). Self-consumption and energy autarky in energy communities–simulation and evaluation of scalable 'energy cells'. In *Austria, Belgium and Norway. In 2022 AEIT international annual conference (AEIT)* (pp. 1–6). IEEE.

Bielig, M., Kacperski, C., Kutzner, F., & Klingert, S. (2022). Evidence behind the narrative: Critically reviewing the social impact of energy communities in Europe. *Energy Research & Social Science, 94*, Article 102859.

Bokolo, A. J. (2022). Exploring interoperability of distributed ledger and decentralized technology adoption in virtual enterprises. *Information Systems and e-Business Management, 20*(4), 685–718.

Bosri, R., Rahman, M. S., Bhuiyan, M. Z. A., & Al Omar, A. (2020). Integrating blockchain with artificial intelligence for privacy-preserving recommender systems. *IEEE Transactions on Network Science and Engineering, 8*(2), 1009–1018.

Brune, P. (2020). Towards an Enterprise-ready implementation of artificial intelligence-enabled, Blockchain-based smart contracts. *arXiv preprint arXiv:2003.09744*.

Burkhardt, D., Frey, P., & Lasi, H. (2019). *The Symbiosis of distributed ledger and machine learning as a relevance for autonomy in the internet of things*.

CEN-CENELEC-ETSI, C. C. E. (2012). Smart Grid Coordination Group Smart Grid Reference Architecture. https://energy.ec.europa.eu/system/files/2014-11/xpert_group1_reference_architecture_0.pdf Accessed: 21 February 2024.

Cunha, F. B. F., Carani, C., Nucci, C. A., Castro, C., Silva, M. S., & Torres, E. A. (2021). Transitioning to a low carbon society through energy communities: Lessons learned from Brazil and Italy. *Energy Research & Social Science, 75*, Article 101994.

D'Adamo, I., Gastaldi, M., Koh, S. L., & Vigiano, A. (2024). Lighting the future of sustainable cities with energy communities: An economic analysis for incentive policy. *Cities, 147*, Article 104828.

Dillenberger, D. N., Novotny, P., Zhang, Q., Jayachandran, P., Gupta, H., Hans, S., & Sarpatwar, K. (2019). Blockchain analytics and artificial intelligence. *IBM Journal of Research and Development, 63*(2/3), 5–11.

Dóci, G. K. (2017). *Renewable energy communities: A comprehensive study of local energy initiatives in the Netherlands and Germany*.

Dorahaki, S., Rashidinejad, M., MollahassaniPour, M., Kasmaei, M. P., & Afzali, P. (2023). A sharing economy model for a sustainable community energy storage considering end-user comfort. *Sustainable Cities and Society, 97*, Article 104786.

Eikeland, O. F., Maria Bianchi, F., Holmstrand, I. S., Bakkejord, S., Santos, S., & Chiesa, M. (2022). Uncovering contributing factors to interruptions in the power grid: An Arctic case. *Energies, 15*(1), 305.

Ericsson (2022). Artificial intelligence in next-generation connected systems. https://www.ericsson.com/en/reports-and-papers/white-papers/artificial-intelligence-in-next-generation-connected-systems accessed on 27 November 2022.

Gulati, P., Sharma, A., Bhasin, K., & Azad, C. (2020). Approaches of blockchain with AI: Challenges & future direction. In *proceedings of the international conference on innovative Computing & Communications (ICICC)*.

GWAC. (2008). The GridWise Architecture Council-GridWise® Interoperability ContextSetting Framework. https://gridwiseac.org/pdfs/GridWise_Interoperability_Context_Setting_Framework.pdf Accessed: 22 February 2024.

Heilmann, J., Wensaas, M., del Granado, P. C., & Hashemipour, N. (2022). Trading algorithms to represent the wholesale market of energy communities in Norway and England. *Renewable Energy, 200*, 1426–1437.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, 75–105.

Hoppe, T., Graf, A., Warbroek, B., Lammers, I., & Lepping, I. (2015). Local governments supporting local energy initiatives: Lessons from the best practices of Saerbeck (Germany) and Lochem (the Netherlands). *Sustainability, 7*(2), 1900–1931.

Hua, W., Chen, Y., Qadrdan, M., Jiang, J., Sun, H., & Wu, J. (2022). Applications of blockchain and artificial intelligence technologies for enabling prosumers in smart grids: A review. *Renewable and Sustainable Energy Reviews, 161*, Article 112308.

Imran, M., Zaman, U., Imtiaz, J., Fayaz, M., & Gwak, J. (2021). Comprehensive survey of iot, machine learning, and blockchain for health care applications: A topical assessment for pandemic preparedness, challenges, and solutions. *Electronics, 10*(20), 2501.

Jamil, F., Kahng, H. K., Kim, S., & Kim, D. H. (2021). Towards secure fitness framework based on IoT-enabled blockchain network integrated with machine learning algorithms. *Sensors, 21*(5), 1640.

Jeon, H. J., Youn, H. C., Ko, S. M., & Kim, T. H. (2022). Blockchain and AI meet in the Metaverse. *Advances in the convergence of Blockchain and artificial. Intelligence, 73*.

Jnr, B. A. (2024). Developing a decentralized community of practice-based model for on-demand electric car-pooling towards sustainable shared mobility. *Case Studies on Transport Policy, 15*, Article 101136.

Jnr, B. A., Sylva, W., Watat, J. K., & Misra, S. (2023). A framework for standardization of distributed ledger Technologies for Interoperable Data Integration and Alignment in sustainable smart cities. *Journal of the Knowledge Economy*, 1–44.

Khan, A. S., Zhang, X., Lambotharan, S., Zheng, G., AsSadhan, B., & Hanzo, L. (2020). Machine learning aided blockchain assisted framework for wireless networks. *IEEE Network, 34*(5), 262–268.

Krittanawong, C., Aydar, M., Virk, H. U. H., Kumar, A., Kaplin, S., Guimaraes, L., … Halperin, J. L. (2022). Artificial intelligence-powered blockchains for cardiovascular medicine. *Canadian Journal of Cardiology, 38*(2), 185–195.

Krittanawong, C., Rogers, A. J., Aydar, M., Choi, E., Johnson, K. W., Wang, Z., & Narayan, S. M. (2020). Integrating blockchain technology with artificial intelligence for cardiovascular medicine. *Nature Reviews Cardiology, 17*(1), 1–3.

Kumar, P., Gupta, G. P., & Tripathi, R. (2021). TP2SF: A trustworthy privacy-preserving secured framework for sustainable smart cities by leveraging blockchain and machine learning. *Journal of Systems Architecture, 115*, Article 101954.

Kyriakou, D. G., & Kanellos, F. D. (2023). Optimal frequency support method for urban microgrids of building prosumers. *Sustainable Cities and Society, 98*, Article 104776.

Lindberg, M. B., & Inderberg, T. H. J. (2023). Just sharing? Energy injustices in the Norwegian solar policy mix for collective prosuming. *Energy Research & Social Science, 103*, Article 103219.

Lode, M. L., Te Boveldt, G., Coosemans, T., & Camargo, L. R. (2022). A transition perspective on energy communities: A systematic literature review and research agenda. *Renewable and Sustainable Energy Reviews, 163*, Article 112479.

Magnusson, D. (2022). *5 better off alone? The development of citizen involvement and community energy in the Swedish energy transition.* Understanding Stakeholder Engagement and Community Acceptance: Energy Transition in the Baltic Sea Region.

Markus, M. L., Majchrzak, A., & Gasser, L. (2002). A design theory for systems that support emergent knowledge processes. *MIS Quarterly*, 179–212.

McElhinney, M. T., Strindö, J. E. S., Turco, E. L., & Chicharo, L. (2022). *Energy communities in France & Norway*.

Mehta, P., & Tiefenbeck, V. (2022). Solar PV sharing in urban energy communities: Impact of community configurations on profitability, autonomy and the electric grid. *Sustainable Cities and Society, 87*, Article 104178.

Mohanta, B. K., Jena, D., Satapathy, U., & Patnaik, S. (2020). Survey on IoT security: Challenges and solution using machine learning, artificial intelligence and blockchain technology. *Internet of Things, 11*, Article 100227.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, Article 21260. https://assets.pubpub.org/d8wct41f/31611263538139.pdf.

Parag, Y., & Sovacool, B. K. (2016). Electricity market design for the prosumer era. *Nature Energy, 1*(4), 1–6.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems, 24*(3), 45–77.

Ragot, S., Rey, A., & Shafai, R. (2020). IP lifecycle management using blockchain and machine learning: Application to 3D printing datafiles. *World Patent Information, 62*, Article 101966.

Ringholm, T. (2022). Energy citizens–conveyors of changing democratic institutions? *Cities, 126*, Article 103678.

Samuel, O., Javaid, N., Alghamdi, T. A., & Kumar, N. (2022). Towards sustainable smart cities: A secure and scalable trading system for residential homes using blockchain and artificial intelligence. *Sustainable Cities and Society, 76*, Article 103371.

Sandner, P., Gross, J., & Richter, R. (2020). Convergence of blockchain, IoT, and AI. *Frontiers in Blockchain, 3*, Article 522600.

Schrage, J. (2023). Three tensions in governing energy demand: A social practice perspective on Nordic urban interventions. *Cities, 141*, Article 104497.

Shaker, M., Shams Aliee, F., & Fotohi, R. (2021). Online rating system development using blockchain-based distributed ledger technology. *Wireless Networks, 27*(3), 1715–1737.

Sharma, A., Podoplelova, E., Shapovalov, G., Tselykh, A., & Tselykh, A. (2021). Sustainable smart cities: Convergence of artificial intelligence and blockchain. *Sustainability, 13*(23), 13076.

Talandier, M. (2018). Are there urban contexts that are favourable to decentralised energy management? *Cities, 82*, 45–57.

The Open Group (2022) ArchiMate® 3.2 Specification-The Open Group. https://pubs.opengroup.org/architecture/archimate3-doc/_archimate_3_2_specification.html. Accessed 23 February 2014.

Walnum, H. T., Hauge, Å. L., Lindberg, K. B., Mysen, M., Nielsen, B. F., & Sørnes, K. (2019). Developing a scenario calculator for smart energy communities in Norway: Identifying gaps between vision and practice. *Sustainable Cities and Society, 46*, Article 101418.

Wethal, U. (2023). Practices, provision and protest: Power outages in rural Norwegian households. In *Consumption, sustainability and everyday life* (pp. 135–170). Cham: Springer International Publishing.

Williams, N. J., Jaramillo, P., Taneja, J., & Ustun, T. S. (2015). Enabling private sector investment in microgrid-based rural electrification in developing countries: A review. *Renewable and Sustainable Energy Reviews, 52*, 1268–1281.

Zhang, Z., Song, X., Liu, L., Yin, J., Wang, Y., & Lan, D. (2021). Recent advances in blockchain and artificial intelligence integration: Feasibility analysis, research issues, applications, challenges, and future work. *Security and Communication Networks, 2021*.