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AI-Driven Approaches for Optimizing the Energy Efficiency of Integrated Energy System

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ABSTRACT:

To decarbonize the global energy system and replace the unidirectional architecture of existing grid networks, integrated and electrified energy systems are becoming more demanding. Energy integration is critical for renewable energy sources like wind, solar, and hydropower. However, there are still specific challenges to overcome, such as their high reliance on the weather and the complexity of their integrated operation. As a result, this research goes through the study of a new approach to energy service that has arisen in the shape of data-driven AI technologies, which hold tremendous promise for system improvement while maximizing energy efficiency and reducing carbon emissions.

This research aims to evaluate the use of data-driven AI techniques in electrical integrated energy systems, focusing on energy integration, operation, and planning of multiple energy supplies and demand. Based on the formation point, the main research question is: "*To what extent do AI algorithms contribute to attaining greater efficiency of integrated grid systems?".* It also included a discussion on four key research areas of AI application: Energy and load prediction, fault prediction, AI-based technologies IoT used for smart monitoring grid system optimization such as energy storage, demand response, grid flexibility, and Business value creation. The study adopted a two-way approach that includes empirical research on energy industry expert interviews and a Likert scale survey among energy sector representatives from Finland, Norway, and Nepal. On the other hand, the theoretical part was from current energy industry optimization models and a review of publications linked to a given research issue.

The research's key findings were AI's significant potential in electrically integrated energy systems, which concluded AI's implication as a better understanding of energy consumption patterns, highly effective and precise energy load and fault prediction, automated energy management, enhanced energy storage system, more excellent business value, a smart control center, smooth monitoring, tracking, and communication of energy networks. In addition, further research directions are prospects towards its technical characteristics on energy conversion.

KEYWORDS: Artificial Intelligences, Integrated Electrical System, Virtual Power Plant

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Networks
AR	Auto Regression
BC	Bloack Chain
CHP	Combined Heat and Power
CNN	Convolutional Neural Network
DEM	Decentralized Energy Management
DER	Distributed Energy Resources
DL	Deep Learning
ESS	Energy Management System
EV	Electric Vehicle
FL	Fuzzy Logic
GA	Genetic Algorithm
HVAC	Heating Ventilation and Air Conditioning
IEC	International Electrotechnical Comission
IED	Intelligent Electronic Device
IES	Integrated Energy System
IoT	Internet of Thing
ML	Machine Learning
PSO	Particles Swarm Optimization
PV	Photo Voltaic
SVM	Support Vector Machine

1 Introduction

This chapter summarizes the thesis, including the background, research gap, question and objectives, study definition and limitations, thesis scope, and report structure with a description of the task.

1.1 Background

Energy integration is increasingly used to decarbonize energy systems and reduce CO2 emissions to fight against climate degradation. According to an energy solution company (Danfoss, 2021), the most pressing concern in decarbonizing the energy industry is not how much renewable energy can be generated. However, it is how it can be integrated into the energy system. The increasing worldwide demand for energy has prompted the rapid development of sophisticated energy generation and distribution networks based on integrated energy solutions and data-driven systems.

Energy integration is a concept that applies to any system that allows for real-time supply and demand optimization, and that may provide or consume energy from another industry (Business Finland, 2021). Energy integration is significant when it comes to distributed energy resources like wind, solar, and battery storage system. Energy integration enables the electrification of new industries while also providing much-needed flexibility. However, there are still a few issues to overcome, such as their strong dependency on weather and the complexity of their integrated operation. Therefore, a new approach to energy service has emerged data-driven AI technologies that offer enormous promise for system improvement and maximizes energy efficiency along with minimizing carbon emissions.

Nowadays energy world is moving toward digitalization as there are many possibilities for data interfacing and interaction. Digitalization enables flexibility in all parts of the energy system since it lowers barriers across energy sectors and enhances interconnectivity, making it a critical clean energy revolutionizer. Digitalization and data-driven system allow for more effective use of available energy resources and better identification of system inefficiencies. (Business Finland, 2021.) They provide successful integration through the real-time process and energy measurement and advanced data analytics technologies, such as Artificial Intelligence (AI), Machine Learning (ML), and Internet of Thing (IoT) (Ahmad et.al, 2021). Data-driven AI techniques have much potential in electrical and industrial engineering for system optimization.

The energy industry is implementing energy efficiency solutions, with a particular focus on artificial intelligence and analytics approaches. The most essential initiatives for lowering environmental footprints, improving efficiency, energy management, and transparency is the integration of AI approaches to renewable energy systems (solar, wind, and battery storage system), and power plants (Ahmad et al., 2022). The emphasis is on data-driven AI approaches that integrate basic statistical ideas, exhibit algorithm applicability, compare improvement over traditional methods as well as provide commercial value (Ning, 2021).

The conventional power grid infrastructures are typically obsolete and unable to adapt to ever-changing and expanding energy demand due to their unidirectional nature. The characteristics of distributed energy resources (wind, solar, and batteries) are evolving and offering significant challenges in meeting the power grid's varying demands. As a result, new AI advancements such as machine learning, deep learning, the Internet of Things, big data analytics, are transforming the energy industry. (Ahmad et al., 2022.) Using multiple artificial intelligence technologies, an integrated energy system is created that functions as a bi-directional power network that changes traditional grids into intuitive, auto-mated, and responsive power networks (Azad et al., 2019).

The application of AI technology in integrated energy systems has not been researched as thoroughly as it might be. However, new research on their integration is released regularly. With this research, the interrelation between AI-driven techniques and integrated energy systems may become more specific and broader. This thesis looks at how AI algorithms may be used to the growing amount of data from integrated energy resources to improve and boost energy efficiency. It also delves into the unique technology, emphasizing its differences from typical traditional approaches.

1.2 Research gap, question, and objectives

The research work goes through a series of process and follow demanding criteria for reviewing published papers and uncovering current research trends to determine the research gap. The study used a well-defined, rigorous, and trustworthy technique to produce objective and reproducible data, eliminating the risk of bias. Most of the journal articles will be found by searching Google Scholar, the Tritonia-Finna database at the University of Vaasa Library, IEEE, Springer, Science Direct, and Scopus. The thesis will use just the most recent publications as sources of information. The following are the study criteria: I) paper published entirely in English during timeframe between 2017 to 2022; ii) articles devoted only to examining or investigating application of AI driven approaches in Integrated energy system. The criteria and techniques used to select the literature for inclusion in the research are depicts in **Figure 1**.

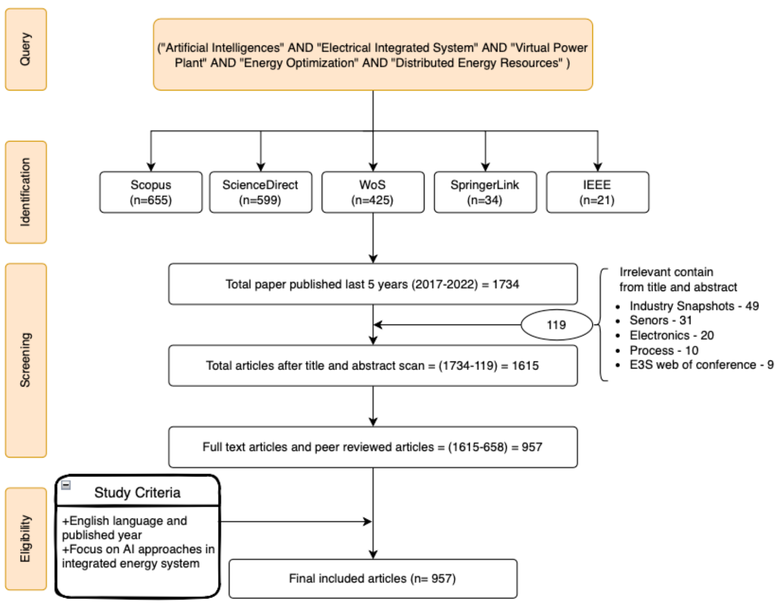


Figure 1. Step for the research gap analysis.

The first database search engine turned up 1734 articles, authored in English and published between 2017 and 2022. In addition, 655 were found in Scopus, 599 in ScienceDirect, 425 in Web of Science, 34 in Springer Link, and 21 in IEEE Explore. By keeping search criteria narrower, the articles were sorted by the order they were published and their relevancy. 119 journals that appeared in all five databases were eliminated because their titles and abstracts were irrelevant. The remaining articles were studied in further depth, with 658 being eliminated as not fitting the required requirements. In the end, 957 publications were found related to the current research.

Table 1. Research gaps in our subject

Title	Keywords	Timeline (2017-2022)	Database	Hits	Journal title & author
AI-driven approaches for optimizing the energy efficiency of integrated energy system	• Artificial Intelligences • Electrical Integrated Energy system • Virtual Power Plant	2021	Scopus	6	Smart contract for distributed energy trading in virtual power plants based on blockchain (Lu et al., 2021).
		2020	SpringLink	154	Computational Intelligence based optimization of hierarchical virtual power

					plants (Rädle et al., 2020)
		2019	IEE	12	An Integrated Approach for Value-Oriented Energy Forecasting and Data-Driven Decision-Making Application to Renewable Energy Trading (Carriere et.al, 2019).
		2020	WoS	23	Distributed energy resources and the application of ai, iot, and blockchain in smart grids (Kumar et.al, 2020)
		2019	ScienceDirect	40	Deep reinforcement learning–based approach for optimizing energy

					conversion in integrated electrical and heating system with renewable energy (Zhang et.al, 2019))
		2022	Scopus	1	Integrating artificial intelligence and analytics in smart grids (Khosrojerdi et.al, 2022)
		2021	ScienceDirect	5	A data-driven approach to anomaly detection and vulnerability dynamic analysis for large-scale integrated energy systems (Zhang et.al, 2021).

AI-driven technology and integrated energy systems are two independent areas. However, there has been progressively studied on their subsector. According to (Zhang et al., 2021), fluctuation of the energy generated by the industrial subsystem has an impact on the functioning of an Integrated Energy System (IES). Therefore, to detect and assess possible threats and vulnerabilities in response to changes in its operational condition and each subsystem, further understanding of the system operating state needs to be identified for more added value, considering the high volatility of complex systems operations.

Khosrojerdi et al. (2022) stated in their research that AI technology and data analytics initiatives introduce a new approach to designing intelligent grid networks in the integrated energy system. This type of grid requires the identification of attributes that identify a distinct identity. However, future research is yet to explain this fast-developing power grid's technical characteristics and definitions. (Rädle et al., 2020) provide an abstract control approach for a virtual power plant that uses computational intelligence to develop control configurations for various power plant types in varied compositions that are neutrally optimum. However, to maximize the methodology's optimization potential, a second abstract interface will be added in the future, allowing for the neutral assessment of various energy storage systems (e.g., battery storage, hydrogen storage).

Exploring distributed energy resources utilizing AI, IoT, and blockchain in smart grid, the researcher recognizes no comparative analysis of all the protocols specified in a scenario spanning a more prominent architectural paradigm that encompasses IoT systems, the cloud transition zone, and cloud computing has been made. Therefore, interoperability and related interaction models may become an essential new study subject. (Kumar et.al, 2020.)

In a technical sense, this thesis' major goal is to investigate the use of technologies that apply AI algorithms to the expanding quantity of data from integrated energy resources to optimize and increase energy efficiency. Discuss on what are the existing technical challenges, benefits that focuses on four key research areas of AI application: (a) Energy and load prediction, (b) Fault prediction, (c) AI based technologies IoT used for smart monitoring grid system optimization such as energy storage, demand response and grid flexibility, (d) Business value creation. The research will also evaluate and synthesize data to define methods/concepts for adding communication capabilities, monitoring, analysis, and control to the electrical delivery system to increase system throughput while lowering energy usage. Base on the formation points research question is set as:

- *Rc1: To what extent AI algorithms contribute to attaining greater efficiency of integrated grid system?*

1.3 Defination and Limitation

Artificial intelligence does not yet have an accurate description since the concept of what components form human intelligence is unclear (Simmons & Chappell, 1988). Different researchers have varied ideologies concerning its definition, and it has yet to be thoroughly investigated. AI is a vast branch of research that includes computer science and psychology, philosophy, linguistics, and other disciplines. Artificial intelligence aims to get computers to do activities that would typically need human intelligence. There are several perspectives on AI, as well as numerous definitions. However, some crucial qualities are highlighted in the definitions below. (Duin & Bakhshi, 2017.)

- According to John McCarthy (1956), the pioneer of artificial intelligence, "*AI is the science and engineering of making intelligent machines, especially intelligent computer programs"*
- *"AI is the replication of human analytical and/or decision-making capabilities"* (Finlay, 2018).
- *"Artificial intelligence denotes behavior of a machine which, if a human behaves in the same way, is considered intelligent"* (Simmons & Chappell, 1988).

As a limitation to AI this thesis covers only study related to machine learning and deep learning algorithms such as support vector machine, artificial neural network, regression model. It also includes IoT technology as a subchapter describing its application and role in energy integration.

An *electrical integrated energy system* is a bidirectional energy flow system that shares interconnectivity among various electricity-producing resources such as hydropower plants, solar, wind, and electric vehicles (Zhang et.al, 2019). As a limitation to electrical integrated system this thesis only includes essence of the electricity generating technology such as conventional, hydro, distributed energy resources, smart grid network, and energy storage technology.

Virtual Power Plant (VPP) is a new approach technology that brings together all the energy networks that have controlled distributed energy sources to collaborate, bringing together their disparate capabilities to meet specific energy integration demands (Feng & Liao, 2020). This study's limitations include uses of advanced control system, integration concepts, and communication technologies to mix many different types of DERs, such as distributed power sources, energy storage systems, and regulated loads in VPP components.

1.4 Scope of study

Artificial intelligence (AI) has proliferated over the decade, becoming a critical element for optimizing energy industries. This study aims to assess the use of data-driven AI techniques in electrical integrated energy systems, with a focus on energy integration, operation, and planning of multiple energy supplies and demand, to optimize energy efficiency, reliability, security, and flexibility and ultimately to facilitate the transition to a decarbonized energy system. The study is exploratory and based on qualitative data and a literature review. The research approaches used in this study will be a literature review, an empirical survey, or a case study focusing on specific electrical power sectors and their technical characteristics rather than functioning in a socio-political vacuum. The creation of analyses and syntheses will be guided by critical thinking, simplicity, and articulation.

The integrated energy system shares multiple domains of energy integration system such as Heating, Ventilation, and Air Conditioning (HVAC), Combined Heat and Power (CHP), Nuclear energy, Building materials, and Insulation systems. However, this research is more confined to electrical integrated systems and power generation resources. Manufacturers or load operators can access the user facility through artificial intelligence and energy-integrated systems, allowing them to investigate and optimize the performance of electrically powered systems while conforming to IEC and IED certification criteria.

1.5 Report structure

This thesis is divided into five chapters, each with its own set of characteristics. It contains the following list of tasks completed in the thesis. The report's structure provides a summary of each chapter for easy access. Each chapter contains its own topic description, introductions, model characteristics, tasks discussion , analysis, and comments, all with appropriate references.

- Chapter 1: Introduction

  This chapter primarily covers the research's background, research gap, question, aim, definition, limitation, and importance of study. It also includes a generic development methodology for examining AI-driven techniques in integrated energy systems.

- Chapter 2: Literature review

  This section contains earlier studies on AI approaches for energy efficiency optimization in the integrated energy system. It also highlights the fundamental requirement for energy integration and helps develop knowledge of artificial intelligence concepts and integrated grid systems to assess the environmental impact.

- Chapter 3: Methodology

  This chapter covered the study's methodology. It contains details on the review process and approach used to design a better-integrated energy system. The technological challenges of an integrated system will also be assessed by an empirical survey based on a preliminary article review, focusing on the four key research areas of AI application.

- Chapter 4: Result and discussion

  This section is more constructive and goes through the answers to the research questions and the outcomes of the study will be discussed in this chapter.

- Chapter: Conclusion and future recommendation

  The research conclusion is presented in the last portion of this chapter. The research findings will be acknowledged in the written synthesis, along with a review of the study for future development.

2 Literature review

This part will discuss the literature relevant to the study topic and fits within the parameters established in the definition and limitation section. In addition, it explains the various subjects' concepts, features, and uses.

2.1 Description and types of electrical integrated energy system

An electrical integrated energy system is a regional electrical supply network that is becoming an inevitable trend for traditional energy systems since it is driven by a clean, cost-effective, efficient, and ecologically friendly energy source at the current time (Shuangrui et al., 2018). In electrically integrated energy systems, multi-energy complementarity, synergistic optimization, and energy cascade consumption have considerably increased system energy efficiency and reduced carbon footprint. Concurrently, by balancing regional energy demand inequalities, the multi-source integrated energy connection minimizes peak loads, fills troughs, and increases energy supply dependability. However, the complexity of the energy system, the connectivity of various energy sources, and the meeting of installed capacity have a direct impact on the system's operation and stability. (Bo et.al, 2018.) Therefore, modifying system operations and supervision through AI-driven technology have significant implications for allocating multiple energy resources optimization and helps in better-operating ways in the total energy consumption.

Multiple energy supplies are connected by a standard electrical network and transformed to meet terminal demands by various coupling components. The correlation and complementarity among diverse energy flows carry out energy storage and transformation on different temporal and geographical scales with an acceptable operation approach. (Li et.al, 2021.) Renewable energy resources such as hydropower, wind, solar, and battery storage systems (electric vehicles) are crucial types of electrical integrated energy systems. It is further investigated as Distributed Energy Resources (DERs), and the smart grid energy control system shown in **Figure 2** is used for driving the control and monitoring process.

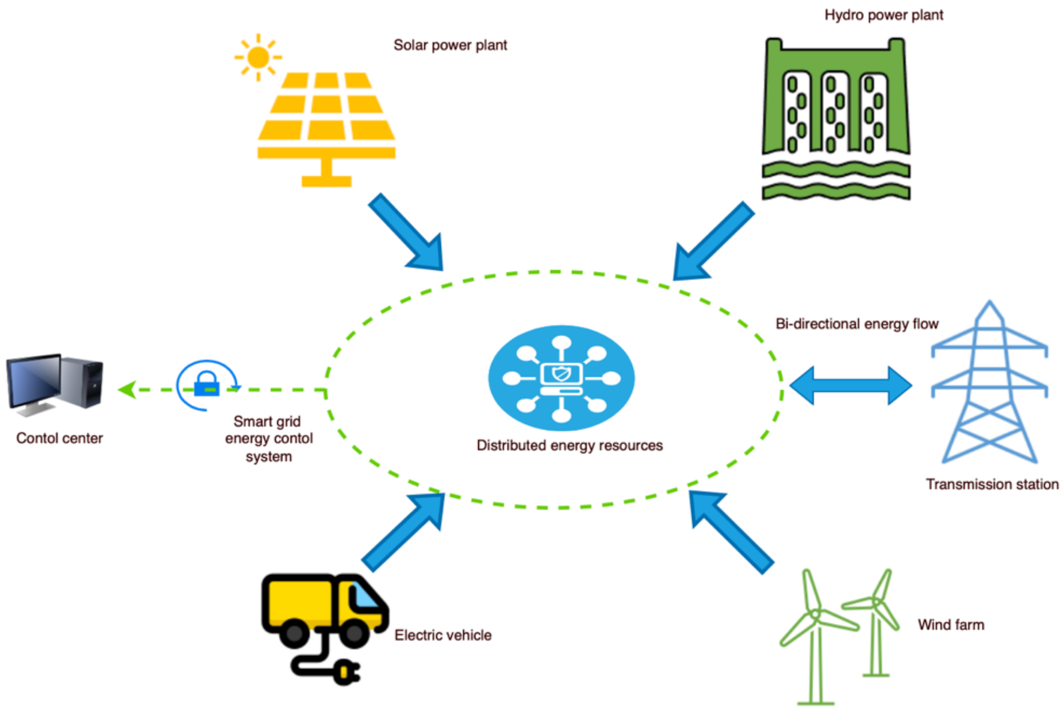


Figure 2. Electrical integrated energy system.

The conventional centralized power generation system consists of a single-way power flow system that focuses on stable, reliable, and affordable power. However, with growing technology advancement, market demand, and environmental policy and regulation, the emerging energy trend shift towards renewable energy resources. Renewable power plant capacity is increasing at a higher rate than total investment capacity in all fossil fuels combined (Erdinc, 2017). Simultaneously, as seen in **Figure 3**, renewable energy resources system is gaining considerable power sources. The tendency is intensified as the need for renewable energy sources develops.

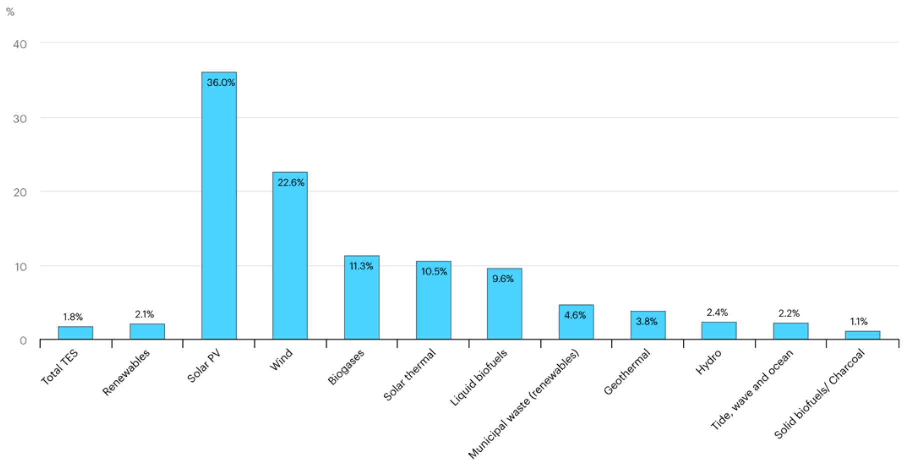


Figure 3. Average annual growth rates of world renewables (1990–2019) (IEA, 2021).

Distributed energy resource systems are small-scale power generation or storage technologies; it means are generated from rooftop solar, moving electric vehicles, small wind farms, micro-hydro, etc., which are well sustainable and efficient in nature. Its goal is to provide an alternative and augmentation to the traditional electricity flow system. Distributed energy resources generate electricity with variable loads linked to a local distribution system and a host facility inside the local distribution system (Ning, 2021).

DERs are a well-diversified energy system that is no longer only reliant on fossil fuels or natural gas for user use. In this situation, the consumer load is no longer merely a passive spectator but also an energy producer. When it comes to bidirectional energy flow, energy balancing is always a significant issue. While controlling a centralized power plant, it is easily accessible in a traditional system; on the other hand, controlling DERs is more complicated. Because DERs are primarily dependent on weather conditions and have grid uncertainty in energy balancing. Therefore, concepts of smart grid network system designs are developed to control each energy asset, accept feedback from the grid operator, and control them all together.

2.2 Virtual power plant

Renewable energy resources are currently in high demand, and they are being integrated into the primary power grid more and more. According to an (IEA, 2021) report, renewable energy sources will meet half of the world's energy needs by 2050. However, a few issues, such as unpredictable power generating characteristics, inflexibility, and unpredictability in the power system, need to be addressed in time (Tang & Yang, 2019). The critical problem with renewable energy sources is their heavy reliance on weather and the complexity of their integrated operations. As the demand for generated energy grows, the energy supply will become more unstable. Therefore, the new energy service concept VPP in **Figure 4** is a solution for maintaining the power supply's stability by accurately predicting electricity demand and power generation. VPP refers to managing disparate energy sources, such as distributed power sources and storage batteries, controlled remotely by AI-based technology IoT and operated as a single power plant.

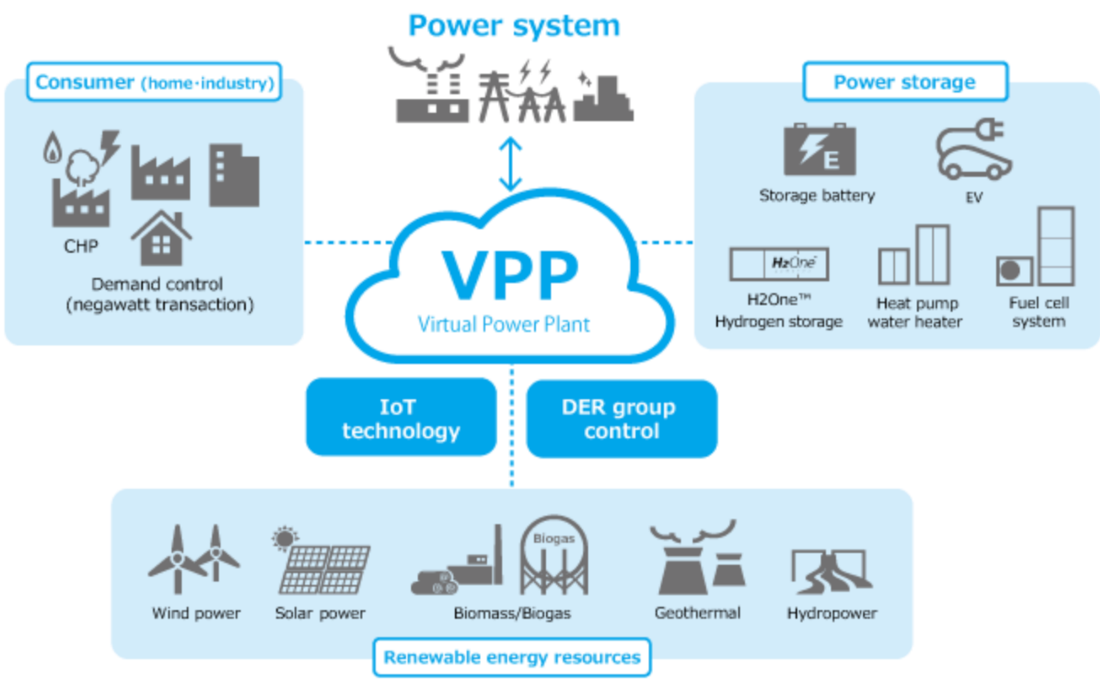


Figure 4. Schematic diagram of virtual power plant (Toshiba, 2020).

VPP is a portfolio of distributed energy resources (DERs) that includes decentralized generators, power storage providers, and sliding-load customers (Zielonka & Becker, 2019). VPP functions as a cloud-based control center that aggregates several dispersed power plants via various distribution routes and demand centers, optimizing and controlling them remotely (Nwauka et al., 2018). VPP model comes with multiple benefits, such as allowing energy production at lower cost, providing load consumers with enhanced flexibility, reduced Co_2 emission, and a smart energy management system. However, DERs' integration from numerous locations while considering essential factors such as demand-side response, networking, technical model proliferation, and current technology dynamics necessitates a greater degree of digitization. VPP employs automated intelligent distributed technologies and control interfaces, data information methodologies, protocols, and cloud platforms to meet these requirements. (Nwauka et al., 2018.)

The integration of AI algorithms contributes significantly to all parts of the VPP mode (forecasting, scheduling, grid flexibility, and optimization) to attain the system's control capabilities (Toshiba, 2020). In addition, the capacity of the VPP controller to self-learn is aided by the availability of massive amounts of IoT data and artificial intelligence algorithms. **Figure 5** shows the VPP system operation architecture configuration model with artificial intelligence algorithms and IoT-enabled modules. According to the design, each module makes intelligent decisions based on IoT data, including improved scheduling, forecasting, and reliability management. (Ning, 2021.)

A digitalized VPP control center retrieves the data from all interconnected system elements. All the information is visualized in the control dashboard: actual data, metered data, power forecast, or the status of the generating unit. Based on the derived data, energy traders, aggregators, or grid operators make better decisions and deliver signals, supplying peak load electricity or load-aware power production in short intervals. VPP dispatches and optimizes generating, demand-side, and storage resources in a single, secure web-connected system remotely and automatically using AI-driven software (Nwauka et al., 2018). In addition, a Decentralized Energy Management System (DEMS) with bidirectional data transmission capabilities is connected to VPP in **Figure 5**. The DEMS enables DERs to operate under multiple operating regimes to fulfill specified regulatory objectives through various applications, including modeling, forecasting, scheduling, and real-time optimization (Nwauka et al., 2018).

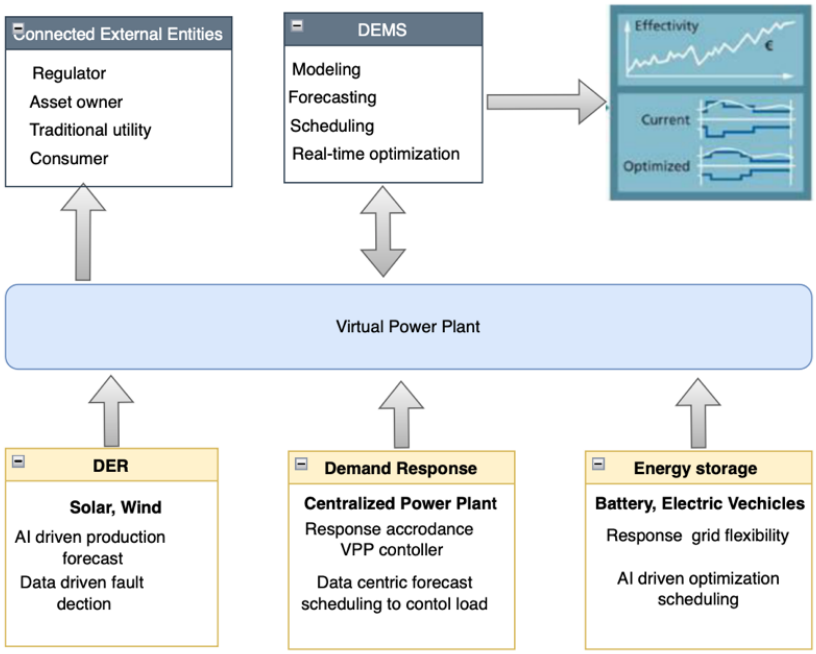


Figure 5. VPP operation system architecture.

2.3 The role of AI for optimizing integrated energy system

Artificial Intelligence (AI) has become one of the most disruptive sciences and technologies, with significant computational, perceptual, and cognitive intellectual processing skills (Zhang et al., 2021). As like previously stated in the introduction section, AI is defined as “the replication of human analytical and/or decision-making capabilities” (Finlay, 2018). According to another definition by (Jakhar & Kaur, 2019), to a field of computer science dedicated to the creation of systems performing tasks that usually require human intelligence”. However, according to (Paschen et al., 2020), the fundamental distinction between these two definitions is that AI incorporates a computational agent in the process rather than as humanlike intelligence. Human intelligence is a mental attribute that includes learning from experience, adapting to new conditions, comprehending, and managing abstract concepts, and influencing one's surroundings using knowledge (Sternberg, 2020). In contrast, computational agents refer to intelligent mediums that sense information from their surroundings and solve issues in practice rather than merely in theory and take preventive activities that increase work accuracy.

AI is gaining traction and finding applications in a variety of fields. Three primary characteristics features are learning (the ability to continuously and automatically increase knowledge and algorithms based on acquired data, also known as machine learning), recognizing (the ability to recognize circumstances and processes based on resemblance to past times), and acting (take autonomous actions). (Serban & Lytras, 2020.) According to the (Netto et al., 2019) AI technology is characterized as application integrates intelligent sensing and physical state, data-driven and simulation models, and auxiliary decision-making and operation control in electrical integrated energy systems. Which successfully enhances the capacity to regulate complex systems, improve security, and improve the business service model, while also altering the conventional energy usage paradigm and supporting renewable energy sources.

Electrically integrated energy systems have data interfaces and create large amounts of high-dimensional, multi-variant data from several energy-producing resources, complicating the electrical power system (Jiao, 2020). As a result, AI is required to assist in the decision-making process. Artificial intelligence is having a significant impact on the global energy infrastructure. However, as renewable energy has risen in importance in integrated energy systems, variability in the wind or solar radiation has been a source of concern for grid operators or aggregators (Das et al., 2018). Therefore, precise weather forecasting (wind and sun) mediator is necessary to figure out how much electricity requires delivering to the power grid. In the same context, AI helps to gather and analyzes vast amounts of data from all the network's intelligent components and employs autonomous algorithms coupled with weather forecasting to fully exploit the potential of renewable energy resources and predict the energy demand and supply provided by interconnected energy systems. Then it offers speedy optimizing decision-making algorithms for the most efficient resource distribution in and out of the system. (Serban & Lytras, 2020.)

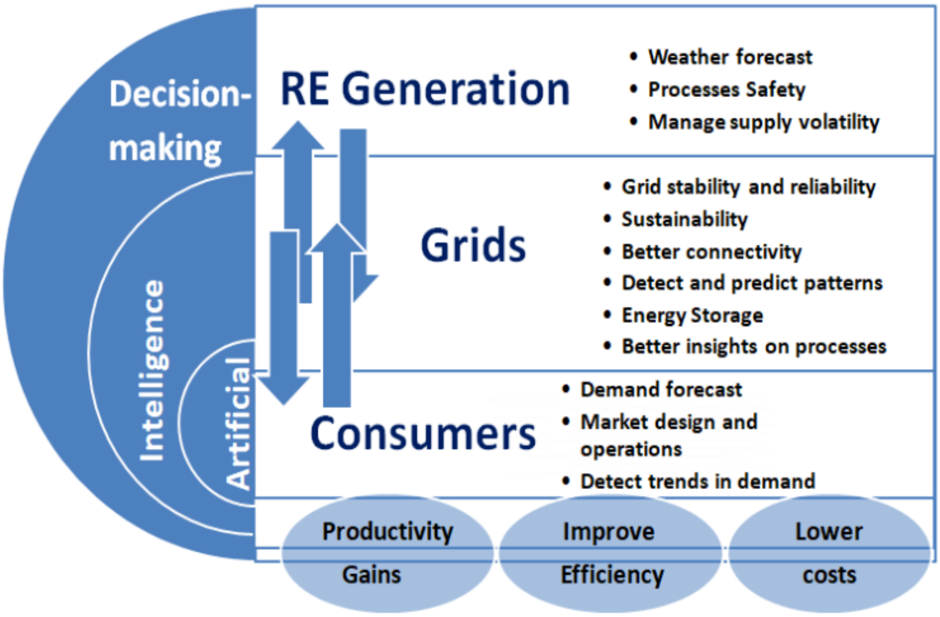


Figure 6. AI application in integrated energy system (Serban & Lytras, 2020).

AI can help the integrated energy system improve monitoring, operation, maintenance, energy storage, and timely system operations and control. The essential applications of AI (Das et al., 2018) depicted in the **Figure 6** are related to integrating renewable energy resources into electrically interconnected systems. Other critical uses of AI in the renewable energy field, according to (Serban & Lytras, 2020) are "*smart supply-demand matching, intelligent storage, centralized control systems, and smart microgrids*".

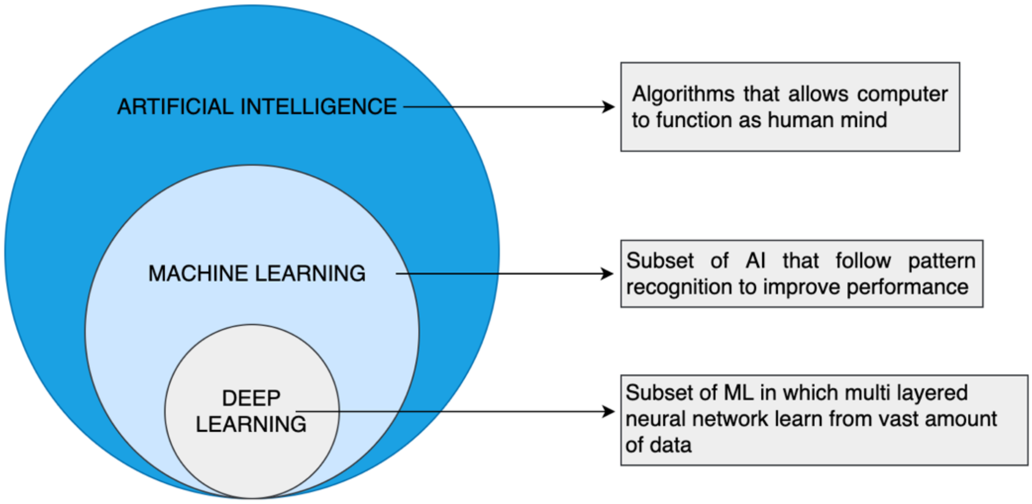


Figure 7. Layers of artificial intelligence approaches.

Artificial intelligence covers multi-layer approaches. They are basically classified according to the techniques they employ. On broader spectrum, if AI is taken as main umbrella, then machine Learning is a branch of artificial intelligence that focuses on extracting patterns from large data sets (Mattab, 2019). Support vector machines, regression models, and artificial neural networks are methods used to achieve machine learning. Artificial Neural Networks (ANNs) are statistical learning models inspired by natural neural networks. Deep learning is a subset of ML techniques that employ sophisticated neural networks. The next subchapters will go deeper into this topic.

2.3.1 Machine learning and deep learning for integrated energy system optimization

Machine learning is a data analytics technique that teaches computers to learn from practice data and experience with little or no human involvement, as people and animals do naturally. Its algorithms employ computational approaches to swiftly "learn" information from data without the aid of a preconceived equation. (Abualigah et al., 2022.) The learning methodology initiated by data observation, or a training dataset; after a trend has been established, the learning algorithm forecasts future events based on data collected in previous instances. The algorithm performs better as more training data is fed into it. The machine learning is divided into two learning algorithms supervised and unsupervised learning shown in **Figure 8**.

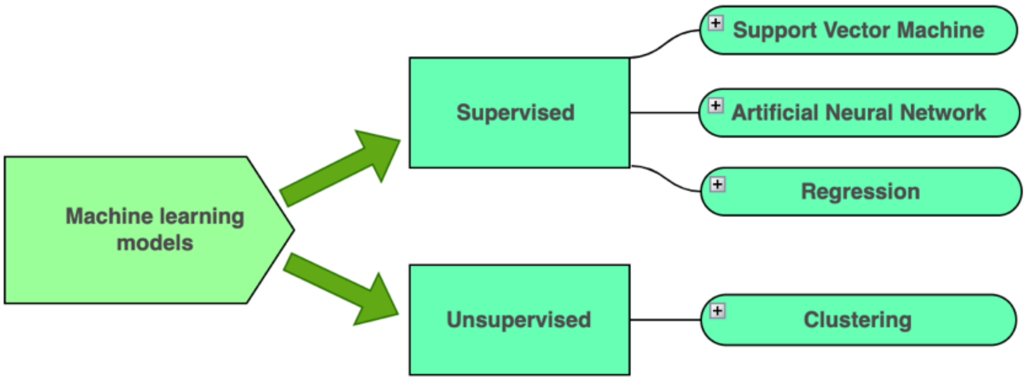


Figure 8. Machine learning algorithms.

The most prevalent machine learning algorithm is supervised learning, which is designed to operate with already taught datasets. It necessitates extensive data pre-processing and the assistance of an expert. Learning algorithms organize the training data set into a mathematical model based on its labels, then anticipate possible outcomes. On the other hand, unsupervised learning is concerned with discovering any underlying structure, similarity, or pattern in unlabeled data (Abualigah et al., 2022). Unsupervised algorithms for learning do not require any input data or supervision. Instead of outputs, it includes a self-learning system that uses raw data to train a network and methods for self-organization for each project (Chen, 2021). Clustering is one of the commonly used methods of the unsupervised learning.

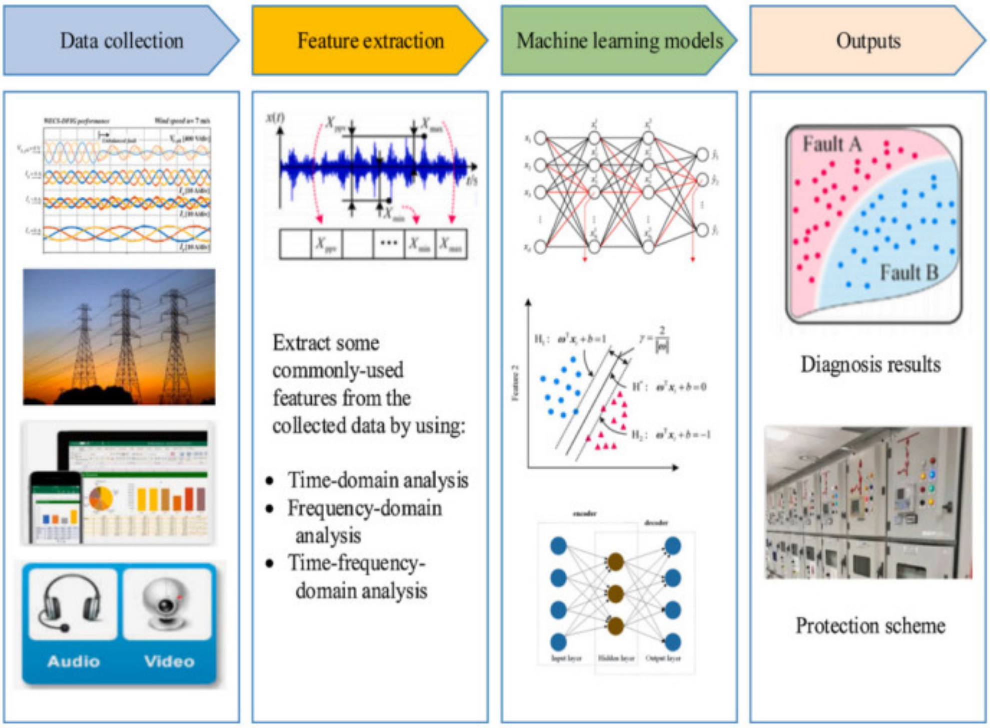


Figure 9. Machine learning algorithms in fault analysis (Yang et al., 2021).

Machine learning presents a unique way for complete energy operation, management, and control system with the emergence of artificial intelligence technologies. Machine learning has sparked research into the electrical sector in fault analysis. However, compared to defect detection techniques based on various machine learning (ML) algorithms, supervised learning has multi-layer nonlinear features that can solve any complicated function by deepening network layers. (Chen, 2021.) In this context, a complete energy operation management and control platform based on supervised machine learning is constructed around the energy service system shown in **Figure 9**, which is integrated with end-user data to enable real-time monitoring and supervision to improve the overall level of energy service.

"The fault diagnosis framework consists of four major processes: data collection, feature extraction, model learning, and diagnosis. In terms of data collection, the power system's monitoring sensors are continually collected various structured or unstructured data in the form of images, text, video, and other media. Then, different machine learning

algorithms extract the information characteristics based on the acquired data and application domains. Time-domain, frequency-domain, and time–frequency-domain analysis of data from multi-source monitoring devices are some of the most often utilized analytic features. The machine learning-based diagnosis models build a link between the selected sensitive characteristics and the outputs that reflect the operational status of devices, which may be regarded as the "learning" process, depending on the sensitive features gathered. The diagnosis models are trained using labeled data stated in supervised learning methods. Finally, based on the predicted outcomes of the fault diagnosis, the associated protective scheme will disconnect defective portions to safeguard the remainder of the electrical network." (Yang et al., 2021.)

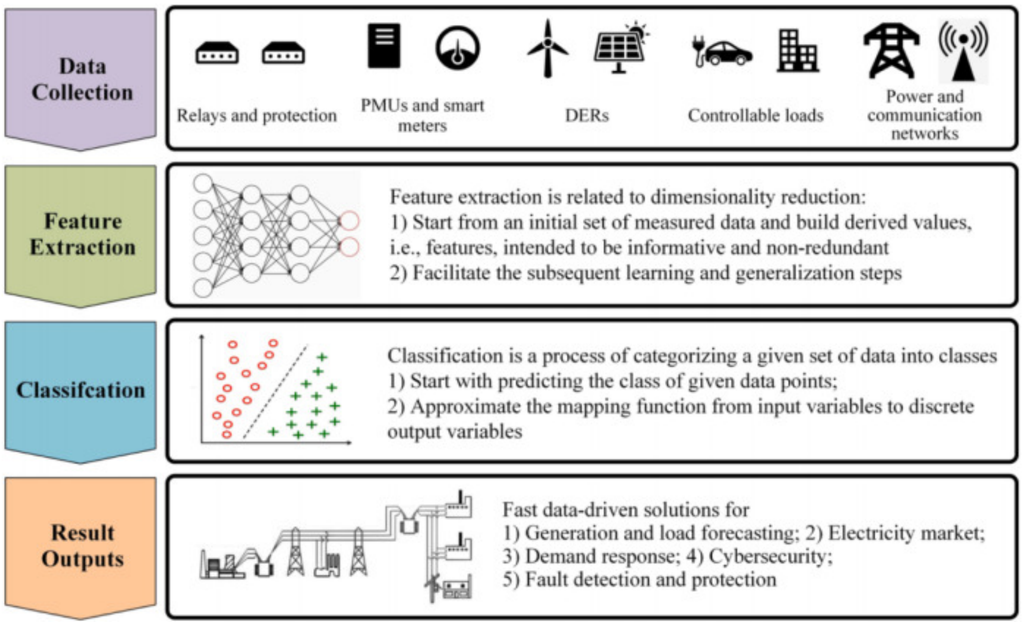


Figure 10. Machine learning framework in electrical power system (Farhoumandi et al., 2021).

Machine learning application in electrical power systems illustrated in **Figure 10** has four central processes, data collection, feature extraction, classification, and results outputs. Machine learning's primary goal in power systems is to achieve model generalization based on large amounts of collected data and to provide fast and accurate data-driven solutions for a wide range of power system applications, including forecasting and control, scheduling and electricity markets, customer participation, and distributed demand responses, fault detection and protection, and cybersecurity. (Farhoumandi et al., 2021.)

Deep learning is a machine learning discipline that works with artificial neural network methods inspired by the structure and function of the brain (S, 2021). The characteristics features of deep learning algorithms in integrated smart grid network is shown in **Figure 11**. The deep learning algorithm includes multiple hidden layers that automatically extract rules from raw data and build deep network models by integrating various nonlinear modules. These modules start with the initial input and improve the qualities of an artificial neural network into higher and more abstract traits. (Chen, 2021.)

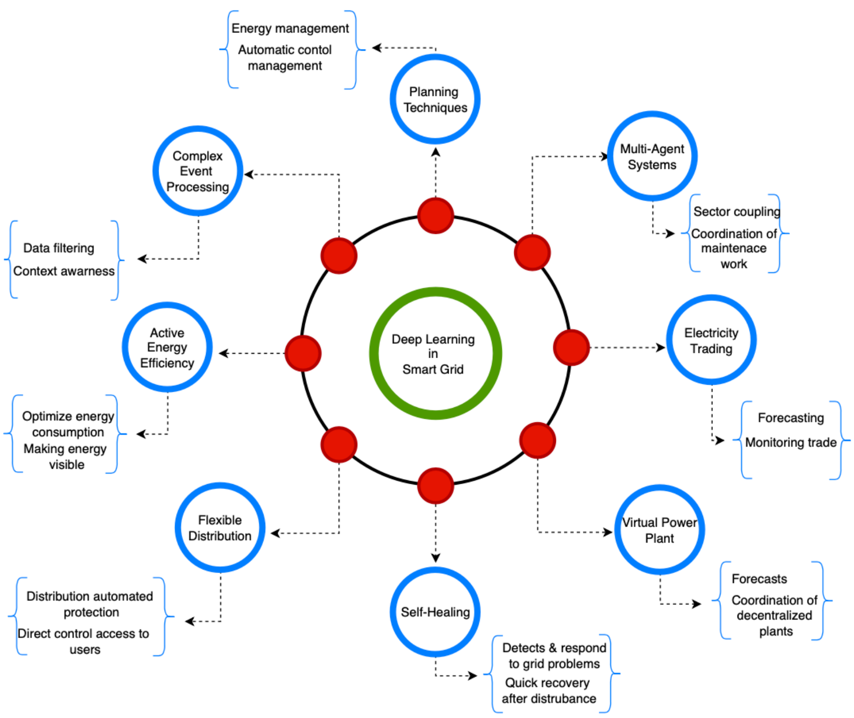


Figure 11. Role of deep learning in smart grid network (Pham et al., 2021).

According to Lu et al., 2017, various learning approaches, such as deep autoencoder, deep belief network convolutional neural network, deep residual network, and recurrent neural network are used to explain the application of deep learning in power equipment monitoring and health management systems. (Yang et al., 2020) proposed a solution based on deep learning to solve uncertainties in wind power generation, involving the preparation of a statistics controller that maps the input findings based on forecasted wind availability and energy pricing, control actions, including a schedule of the functional energy storage unit, and the reserve buying schedule. According to computational results, the proposed technique successfully copes with hazards while also bringing in considerable revenue.

Machine learning and deep learning are two popular approaches for forecasting models in integrated energy systems, i.e., Solar and Wind energy domains (Luo et al., 2021). (Abualigah et al., 2022) reported that machine learning and deep learning are the fundamental, necessary, and powerful learning-based methodologies of Artificial Intelligence. Therefore, future researchers can utilize the approaches to develop better solutions for wind and solar energy vulnerability. To summarize, the development of energy systems may be improved and optimized by combining machine and deep learning approaches with other optimization methods. Due to precise forecasting, machine and deep learning approaches have higher achievements and results when dealing with integrated energy systems for predicting difficulties than a single learning method (Abualigah et al., 2022). As a result, advanced machine, deep learning, and other optimization algorithms approaches are highly suggested for dealing with energy-generating issues.

2.3.2 Support vector machine for integrated energy system optimization

Power load forecasting accuracy is essential for ensuring safe dispatch and stable power system functioning. Therefore, the Support Vector Machine (SVM) is commonly utilized in power load forecasting as an effective forecasting tool (Dai & Zhao, 2020). SVMs have been used in various applications, including feature identification, data categorization, classification, regression analysis, and prediction (Liu et al., 2018). For example, (Qin et al., 2021) used SVM technology to estimate energy consumption on electric bus routes, including bus scheduling and improving charging facility layouts. The suggested study also employed a grey wolf optimization approach based on a support vector machine regression model to find the best parameters of the proposed model. (Yang et al., 2018) introduced an SVM-based typhoon rainfall forecast model, with results indicating that rain prediction appears to be reliable, especially for long lead periods. As SVM handles tiny samples and nonlinear data, thus it has been chosen as the primary model for wind power prediction.

In the working process, SVM reduces the dimensionality of enormous data dividing it into two categories, green dotted and blue dotted surface by hyperplane as indicated in the **Figure 12**. SVM chooses the best hyperplane that maximizes the margin and optimize the model. The point that lies exactly on the margin is support vectors. SVM requires training data to find the hyperplane in the best possible plane. (Javatpoint, 2021.)

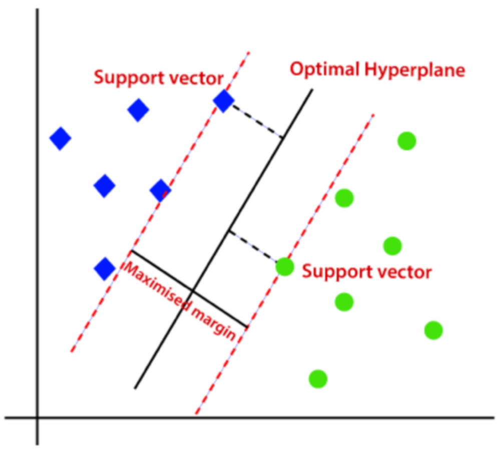


Figure 12. SVM data set classifier (Javatpoint, 2021).

The generated data is gathered from several energy industries, then standardized and separated into three groups: train, assess, and verify. Next, feature selection and extraction go through dimensionality reduction to break data sets into smaller subsets and optimize the model with the most significant characteristics. The involved strategies are decision trees and recursive feature elimination (Nayab et al., 2019). The data is then sent into an SVM classifier for testing, training the network, and verifying it by regularly examining fresh data sets. The relearning and tuning of the network continue until the predicting error is kept to a minimum. Finally, the updated final model is used to predict the energy demand and consumption of an integrated smart grid network, based on the information optimizing decision is made by grid operators.

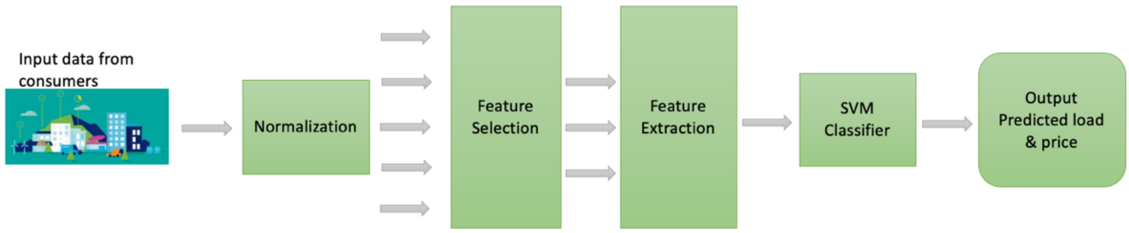


Figure 13. SVM process mechanism for load forecasting in integrated grid system.

Power demand predictions may be determined using statistical and artificial intelligence technologies. Statistical methods are straightforward, but they demand high time-series stability and are no longer precise enough to forecast smart grids. Artificial intelligence technologies, such as the artificial neural network (ANN) and the support vector machine (SVM), on the other hand, do not necessitate excellent stability but produce accurate and stable prediction models using training data. (Dai & Zhao, 2020.) To deal with the difficulty of limited sample learning, they depend on a set of solid theoretical foundation and regression features (Ma, 2018). As a result of the benefit of establishing a worldwide optimal solution, the SVM proved to be very implacable when it came to forecasting building energy consumption (Ma, 2018) and yearly power usage on dairy farms (Shine, 2019).

2.3.3 Role of Artificial neural network for integrated energy system optimization

Energy forecasting is a technique for estimating energy production from various sources (Rahman et al., 2021). Traditional energy forecasting approaches depend mainly on physical model as input such as time-series, Auto regression, integrated moving average, and exponential smoothing, which are all linear form and have been shown to provide less accurate forecasts (Ning, 2021). As a result, the current energy forecasting technique is deviating further toward new modern data-driven algorithms that increase the predictability of all renewable energy sources through improved control and optimization systems (Tina, 2019).

Artificial neural networks (ANNs) are a widely used data-driven optimization technique (Abdolrasol et al., 2021) that researchers have progressively tried to improve the integrated energy system by accurately predicting renewable energy generation (Debnath & Mourshed, 2018). Artificial neural networks have various advantages, such as learning fundamental information patterns in the multi-dimensional information domain. Modeling, performance estimate, forecasting electricity demand, diagnostic of PV, hydro, and wind generator; balancing power systems; the optimal sizing of renewable energy systems; energy management systems for microgrids, and many more. (Tina, 2019.)

Artificial neural networks are data-modeling algorithms, and design is based on the human brain's architecture and seeks to emulate the way humans learn via the organic nervous system. ANNs are framed with several interconnected processing units called neurons. These neuron structures work together harmoniously to solve problems, identify trends, and detect patterns. (Abdolrasol et al., 2021.) The artificial neural network comprises three layers shown in **Figure 14**: input, hidden, and output layers. Input layers receive the input from the environment or the optimized output; the hidden layer performs the computational function required by the network. Finally, output layers are created because of optimization that predicts the final output (Chandrasekaran, 2021).

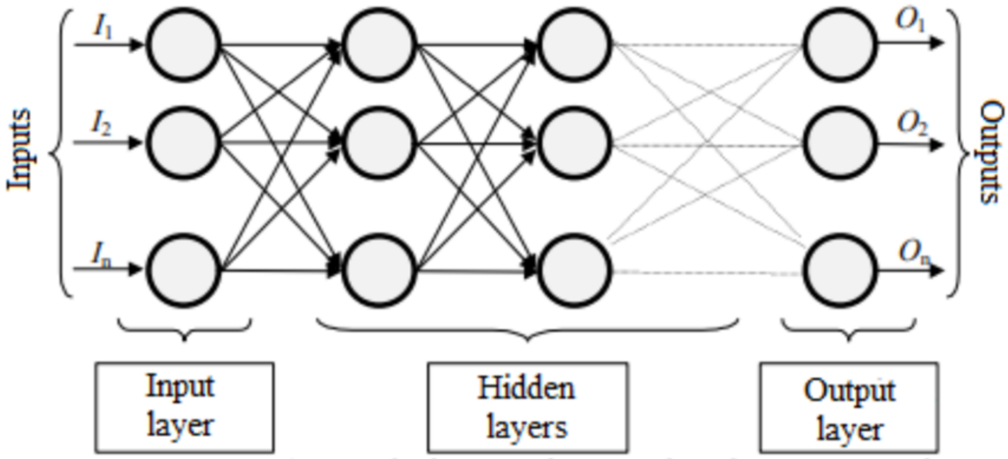


Figure 14. The simple ANN structure (Sanchez-Huertas et al., 2018).

Artificial neural networks are used in a wide range of renewable energy resource applications. For example, (Tayab et al., 2021) suggested a research project based on ANNs that demonstrated the superior performance and long-term durability of artificial neural network algorithms for load demand forecasting and scheduling. In addition, the experimental findings show that the suggested forecasting method and grey wolf optimization (GWO) based scheduling technique provide intelligent guidance for a range of forecasting tasks, including load prediction, storage availability, and supply-demand forecasting. According to (Heo & Lee, 2018), ANN is capable of detecting, diagnosing, and eliminating defects, as well as guaranteeing that process activities meet performance standards. In publications by (Singh & Badge, 2017), an Artificial Neural Network approach with an adequate number of Neurons is utilized to detect internal and exterior fault using

Artificial Neural Network logic. The simulation findings reveal that the proposed method can discriminate between internal and external fault and provides a safe, rapid, effective, and efficient protection technique.

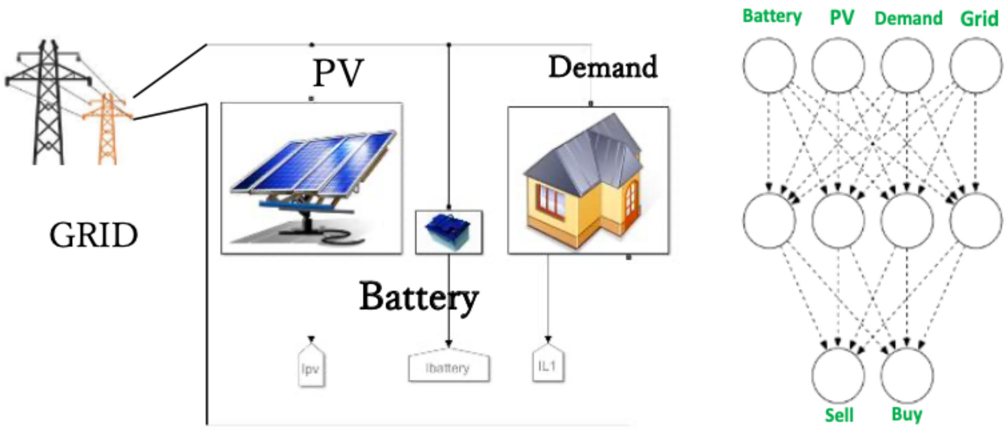


Figure 15. Power balancing model using ANN algorithms (Sogabe et al., 2018).

The basic working principles of artificial neural algorithms to achieve load prediction for energy balancing is shown **in Figure 15**. At initial state, data from the various energy source such as Battery, PV, Demand, Grid is provided as input to each neuron in the first layer. A neuron in the first layer communicates via a channel with a neuron in the second layer. Each channel is given a numerical value called weight, and the input is multiplied by the weight allocated to it before being transferred to the hidden layer. The hidden layer then uses the activation function to do the mathematical computation recursively. The activation function's outcome determines whether a specific neuron is activated. Finally, the signal from the active neuron is sent to the output player. The neuron with the highest probability value is predicted to be the balancing system's likely output.

2.3.4 Role of Internet of thing for improving integrated energy system optimization

The global energy trend is steadily expanding. Renewable and sustainable energy alternatives are introduced to meet rising demand and minimize carbon footprints (Kazmi et al., 2019). However, the addition of clean energy technologies to the existing conventional grid increases complexity and dynamism (Roberts, 2019). Therefore, to deliver on the promise of renewable energy, the power industries started a new initiative called the Internet of Things (IoT), which uses the internet as a mediator to hold communication and control configuration among the interconnected grid system. Due to great advancements in wireless communications and real-time data supervision, the Internet of Things has acquired global attention and acceptance as a unique paradigm in just a few decades (Mao et al., 2021).

Table 2. IoT applications in the energy industry.

Application	Description	Benefits
Integrated grid system	A platform that combines big data analytics and ICT technologies to optimize variable renewable energy resources into the standard electrical power network.	Improving energy efficiency and integrating renewable energy resources allows infrastructure, EVs, and other devices to communicate more efficiently, boosting supply security and decreasing backup supply capacity and costs (Pal et al., 2021).
Integrated Electric Vehicles (EV)	A promising technology for building sustainable future energy because of zero carbon emissions, low	Improves peak-time charging response; evaluates and estimates the impact of electric

	noise, high efficiency, and grid operation and integration flexibility.	vehicles load, and finds sites for new charging stations and distribution system reinforcement (Urooj et al., 2021).
Demand response	Central control (e.g., through shedding, shifting, or leveling; consumers load by assessing load and appliance functioning).	Automatically managing appliances and moving load from peak to off-peak hours manages energy consumption according to supply (Kazmi et al., 2019).
Advanced Metering Infra-structure (AMI)	Use smart meter sensors and devices to collect power data and analyze the load on a consumer side.	Facilitate peak demand reduction by monitoring the power demands over short periods and providing various ratings and effective management based on remote metering data (Cebe & Akkaya, 2019).
Battery Storage system	Battery activation at the most opportune time is aided by intelligent data analytics.	The ideal technique for charging and discharging the battery across various time scales improves energy efficiency while also assisting the grid at peak times and lowering the cost

		of energy consumption (Motlagh et al., 2020).

The Internet of Things (IoT) has a wide range of applications in the integrated energy system, including communication, processing, warning, self-healing, disaster recovery, and dependability in energy supply, transmission, and distribution, as well as demand side (Motlagh et al., 2020). **Table 2** summarize IoT applications in the energy industry, ranging from integrated grids system to energy end-users. With the use of IoT-based technologies, an energy system can be changed from a unidirectional to a bidirectional integrated energy system. The **Figure 16** depicted all the essential elements of an integrated energy system connected through IoT-based technologies. IoT collects and analyzes real-time data using sensors and communication technologies, enabling fast computation and effective decision-making (Tamilselvan & Thangaraj, 2020).

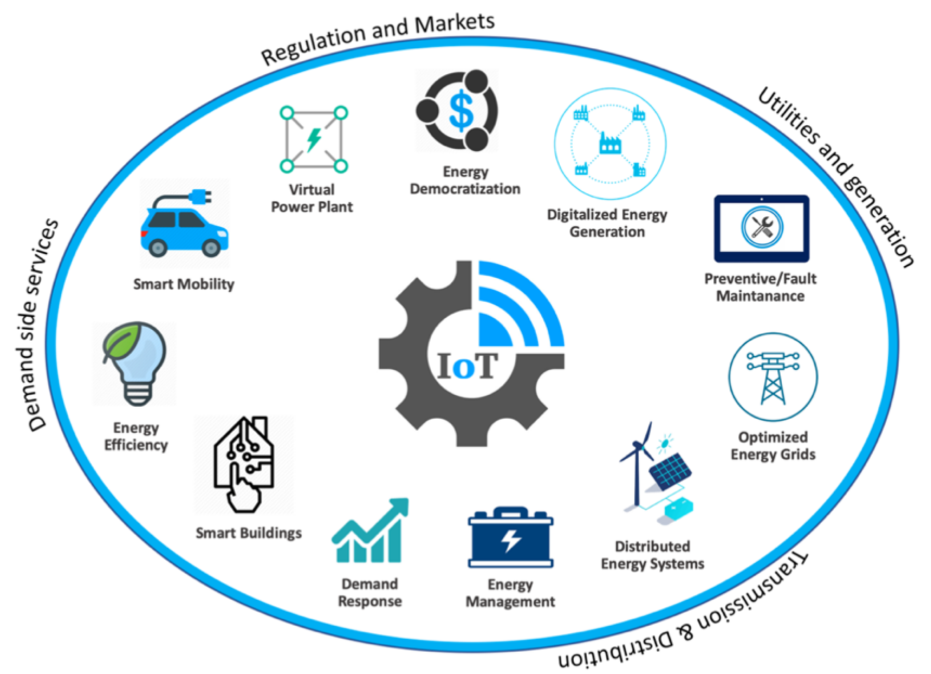


Figure 16. IoT application in an integrated energy system (Motlagh et al., 2020).

Furthermore, its real-time data exchange and control architecture aids in the monitoring and efficient regulation of energy consumption patterns of various users and devices across a various time scale (Motlagh et al., 2018). The IoT plays a critical role in the transition of the energy system from a centralized to a distributed, intelligent, and integrated one. It is a significant component in deploying locally generated energy resources like micro-hydro, wind, and solar energy, transforming numerous small-scale energy end-users into prosumers by aggregating their supply and optimizing their demand whenever beneficial to the grid (Motlagh et al., 2020).

2.4 Summary of theoretical framework

The proposed theoretical advancement in the preceding section is an intelligent framework for optimizing integrated renewable energy sources based on artificial intelligence technology. An electrical integrated energy system combines a variety of processes and systems into a single intelligent model for continuous development, allowing energy companies to meet their objectives. Furthermore, the use of AI-based technologies that integrate with a variety of energy resources aids in achieving a steady state of energy supply and demand. The goal is to maintain regular power generation distribution in the electrical network by precise forecasting, energy balance, and strategic planning.

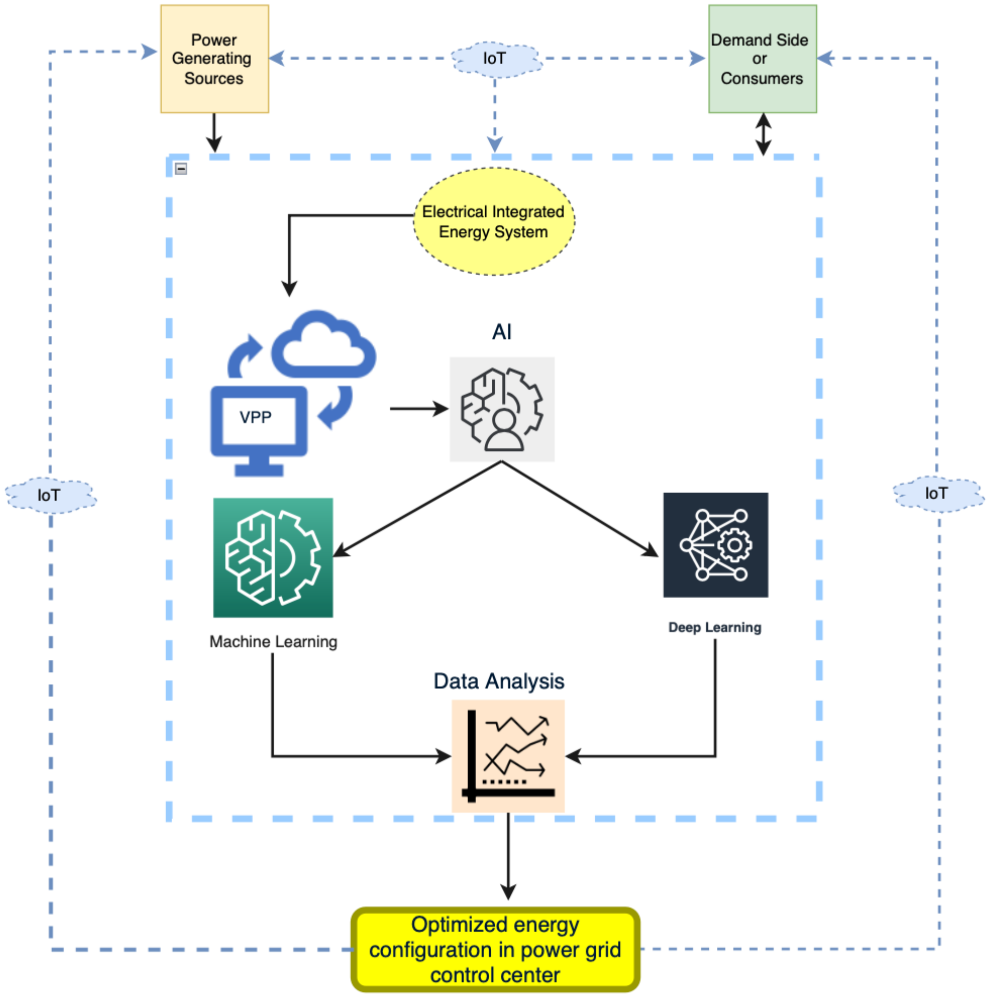


Figure 17. The basic framework of theoretical study.

With research gaps and limitations highlighted, a conceptual framework is designed shown in **Figure 17** to improve overall performance and encourage beneficial interaction between AI-driven technologies and electrically integrated energy systems. The centralized power generation and distribution trend's obsolescence and their poor performance in adapting to ever-changing and expanding energy demand due to their unidirectional nature prompted to investigate the role of AI data-driven techniques in electrically integrated system optimization. Based on the previous research study, the literature on essential aspects to increase performance is identified, and several algorithms required to execute the integrated renewable energy system are suggested. The diagrammatic elaboration of the theoretical framework is depicted in **Figure 18.**

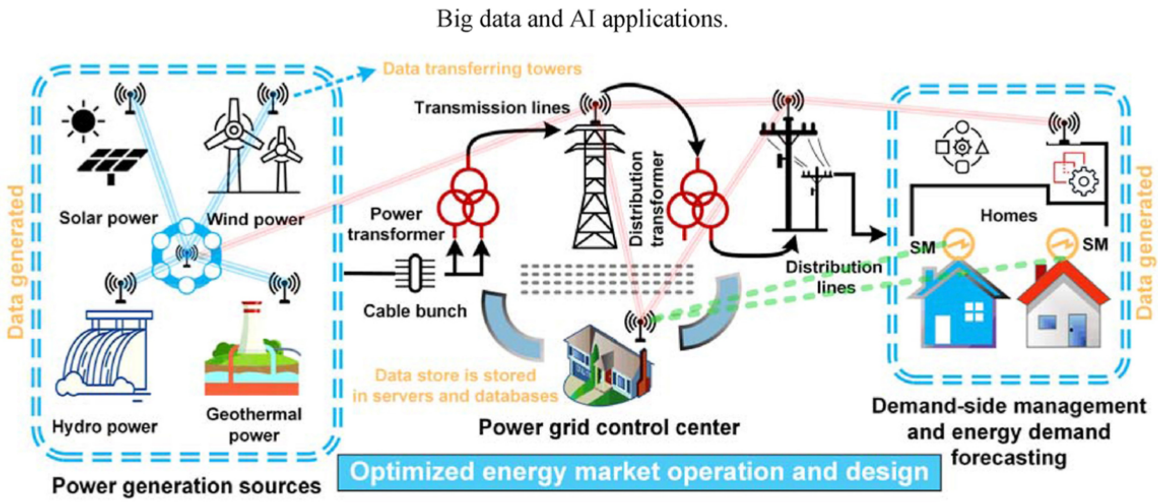


Figure 18. Schematic diagram of theoretical framework (Ahmad et al., 2021).

The literature study covers many subjects relating to artificial intelligence (AI) and data analytics application in integrated renewable energy systems. It delves into themes such as integrating various energy sources, integrated grids for energy supply and consumption, and integrated renewable energy optimization approaches based on software and artificial intelligence algorithms. Artificial intelligence (AI) technology has been utilized to discover the best system configuration for changing the traditional energy use paradigm and supporting renewable energy sources. The most common approaches used to optimize integrated energy systems are machine learning and deep learning algorithms such as Artificial Neural Network (ANN) and Vector Support Machine (VSM).

Different AI algorithms offer various benefits, such as When it comes to choosing the appropriate parameters for a regression model, VSM uses a grey wolf optimization strategy. This scheduling approach can help with various forecasting tasks such as load prediction, storage availability, and supply-demand forecasting. At the same time, Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are two standard ANN algorithm optimizing strategies that accomplish the optimization in less time and with more accuracy.

Artificial neural network optimization techniques change training parameters to acquire the optimal structural network pattern to resolve issues. The neural network output is used to solve energy management issues, including forecasting electricity demand, diagnostics of PV, hydro, and wind generators, balancing power systems, the optimal size of renewable energy systems, energy management systems for microgrids, or virtual power plants.

3 Methodology

This chapter lays out the general research strategy. This thesis employs qualitative research methodologies primarily based on a two-way approach that includes empirical research on primary data collected from energy industry expert interviews and a Likert scale survey among energy sector representatives from Finland, Norway, and Nepal. On the other hand, the theoretical part is secondary data from current energy industry optimization models and a review of publications linked to a given research issue which intends to identify, evaluate, and interpret all empirical evidence that meets the pre-specified inclusion criteria to answer a specific research question or hypothesis (Snyder, 2019). According to (Bogner, Littig, & Menz, 2009), an expert is a technical person with expertise in their areas of competence and possesses more than simply systematic, ordered information with extensive knowledge of specific experiences arising from their actions, responsibilities, and obligations as members of a specific functional standing within an organization. The integrated energy optimization using AI environments appears to be a new beginning in the energy industry; the empirical study will be required, as discoveries based on structured experience and knowledge will be helpful in real-time operation.

The expert interview and Likert scale survey are the two most common approaches in empirical social research. It offers unique perspectives on expert knowledge, structural settings, and action system change processes. According to (Rynes & Gephart Jr., 2004), interview research aims to learn about the meanings and concepts used by social actors in their everyday lives and examine how various people or groups hold different meanings. The interview questions were created to investigate the research phenomenon in the form of an open-ended opinion to understand their work environment, culture, and description of AI approaches in integrated energy systems. On the other hand, using a 5-point Likert scale survey (1—Strongly disagree, 2— disagree, 3—Neutral, 4— Agree, and 5—Strongly agree) as a quantitative variable presents AI implementation as part of their real-life experiences. The performance grading criteria for the variable are measured using the listed by (Rubaish, 2010) shown below:

Performance Grading	Criteria	
	Mean	Cumulative (%)
High Quality	3.6 & Above	80% & Above
Acceptable	2.6-3.6	60%-80%
Improvement Required	Less than 2.6	Below 60%

3.1 Data collection

This study investigated the transformation process of an energy production and distribution system and the evolutionary impact of AI technology on the energy industry. The need to move away from traditional power generation and distribution systems necessitated developing a new optimized integrated model to commercialize the new system. The AI driven integrated energy system is a relatively new disruptive technology predicted to revolutionize the energy sector. However, not much practical deployment in real life or business has been witnessed as it is a new technology. Therefore, the expert interview on energy industries domain has been evaluated, and research is speculative and indicative of a possible future revolution in the energy business.

To broaden the scope of research, a data mining framework is developed that is based on a two-way approach that includes primary data from energy industry expert interviews and a Likert scale questionnaire survey, whereas secondary data were from current energy industry optimization models and a review of publications linked to a given research issue. An optimal model is formulated that answers the core research question and suggests potential system improvements. **Figure 19** shown the complete methodology of the present research study.

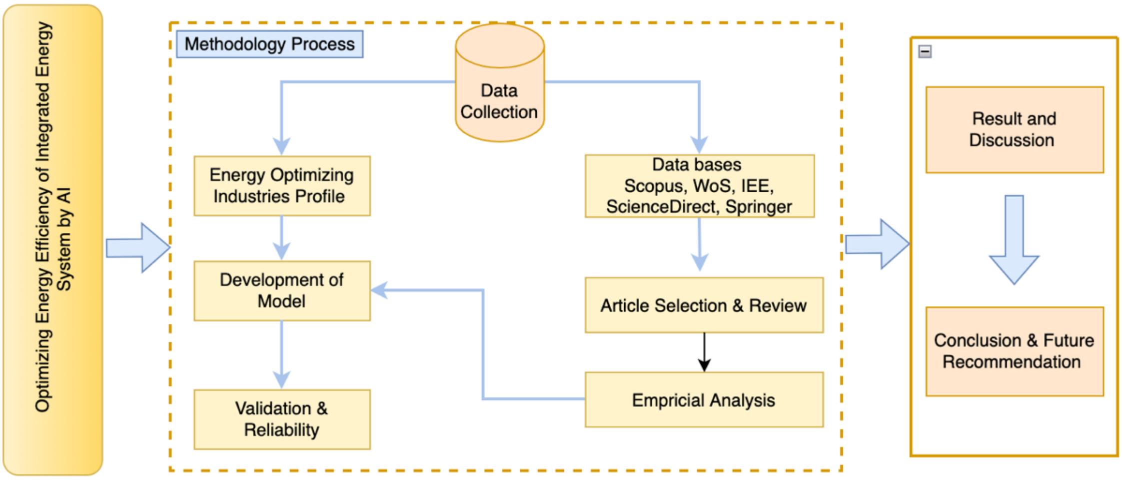


Figure 19. Research methodology process design.

The primary data for the empirical analysis of this study were gathered through energy expert interviews and a Likert scale questionnaire survey with environmental specialists and energy industry professionals. The empirical study entailed in-depth analysis and research on a specific subject to gather as much first-hand knowledge about the investigated phenomenon as possible which includes working culture, respondent experience, opinion on AI innovation, and their possible benefits and challenges in the future synergy. For the expert interview, data on energy industries in Finland that practice energy optimization were gathered. Then, they randomly sampled to reduce the search field based on inclusion criteria such as industries adopting AI technology for power solutions, automation solutions, and renewable power integration. Based on that information, ten energy companies are sort listed shown in **Table 3**: with their top priority, focus domain, expectation, and thoughts.

Table 3. List of reviewed energy company in Finland.

S. N	Energy Company	Priority	Focuses	Expection & Thougts
1	General Electric (GE) digital	Uses AI innovation to build,	Power, Renewable energy,	To supply businesses and

		move, power, and treat the world in the next industrial era.	Aviation, and Health Industries	consumers with various affordable and dependable energy solutions across the electrical value chain.
2	Wartsilla	Technologies innovative and lifecycle solutions for the marine and energy markets	Focuses on energy business and marine business	The objective is to design the most efficient power system for a future powered entirely by renewable energy sources.
3	VEO	Develop automation, drives and power distribution solutions for the energy and process industries	Automation and Power electrification solution for energy generation, distribution, and utilization	IoT and digitalization are energy businesses, making life easier for employees and clients.
4	Valmet Automation	Distributed Control Systems (DCS), industrial applications,	For the pulp, paper, and energy industries, develop and deliver	Services to reduce emissions, increase operational safety and

		Quality Control Systems (QCS), analyzers and measurements, Industrial Internet solutions and automation services.	technology, automation, and services.	dependability, and improve energy, water, and raw material efficiency.
5	EATON	Energy sustainability	solutions for efficient and long-term energy management	To improve people's lives and the environment with energy management technologies that are more reliable, more efficient, safer, and more sustainable.
6	Elomatic	To create solutions that improve people's and the environment's well-being.	Energy, machinery, equipment manufacture, marine, oil&gas, process industries	Recognized internationally and highly valued by our customers as industrial engineering and consulting

				services, software developers.
7	Hitachi ABB	Carbon neutral future, smart energy, resilience, e-mobility, and value to society	Utilities, industries, transportation, data center, and smart life	The global technology and industrial leader in power grids is speeding up its journey to carbon-neutrality as part of its Sustainability 2030 aim
8	EPV	With dedication and purpose, focus on emission-free, reliable energy generation.	CHP, Electricity generation from solar, hydro, wind, nuclear and energy management	The goal is to generate carbon-free electricity by 2030.
9	Danfoss	Climate, drive, and power solution	Automation, Energy and natural resources, energy integration, industry, building commercial and district heating	Danfoss' energy-efficient and climate-friendly products were designed to make the transition to green energy more affordable.

10	Etteplan	software and embedded engineering solutions, and technical documentation solutions	Industrial digitalization, energy, and power transmission	Assisting customers with their industrial transformation solution as well as developing and testing novel solutions

The interview respondents were chosen based on their energy background and contacted through email to inquire about the possibility of an interview at a convenient time. However, out of 10 respondents of those energy companies, only four respondents agreed for the interview session and all the interviewees have expressed a desire to remain anonymous. An interview guide was developed based on the existing literature and additional question were added shown in Appendix 1 if they helped answer overall research question. The interviewees were sent information about the study in advance through email to ensure they understood the objectives. The interview took between 30 minutes to an hour to complete. MicrosoftTeams Meeting was used for the interviews. During the interviews, comments were promptly interpreted to ensure that the interviewer had the exact interpretation of the responses. As a result, the researcher learned more about the issue in depth throughout the interviews. And for the 5-point Likert scale questionnaire survey 20 respondent were selected from Finland, Norway, and Nepal basis on their energy profile. The survey questions shown in Appendix 2 were send to the respondents via Google Forms and information is collected and further analyzed.

For the secondary data, several databases were used to conduct the research, including Scopus, Web of Science IEEE, Science Direct, Springer, and the digital library. These databases cover a wide range of topics, including engineering, business, management techniques, corporate strategies, and many others (Bhatti, 2018). In addition, energy industries practicing AI algorithms for energy optimization published videos and reports, and their application background and blog have been considered as secondary source of data for this study that build profound understanding of the involvement of different AI approaches in the energy industry optimization. The used secondary data are from sources, such as available research articles and reports, to compile a complete list of information on an interconnected grid system, renewable energy sources, disruptive technologies, and business models related with an integrated energy system. From which an overall optimized integrated model concept is developed that addresses the main research question and recommends optimized protocols.

3.2 Data analysis

The research included an in-depth analysis and study within a specific field to gather as much reliable information as possible about the studied phenomenon at the energy integrated system, such as optimized model development, environmental challenges, demand management, customer requirements, and importance.

Data can come from various sources and be analyzed in several ways. However, since first-hand data is inherently raw and complex, it is always necessary to transform it into a more understandable and concise format. According to (Bernard, 2000), content analysis, narrative analysis, grounded theory, and interpretive analysis are the commonly used data analysis methods in qualitative or quantitative research. The main approaches used in this study were content and descriptive analysis. Content analysis was employed consistently throughout the expert interview. On the other hand, interpretive analysis aided in examining secondary data. Most of the secondary data were gathered from peer-reviewed journals and online publications. Finally, descriptive analysis was used to describe the critical characteristics of the Likert scale survey questionnaire.

The information gathered was evaluated with Microsoft Office and a Microsoft Excel spreadsheet. These tools calculate and present the finding as a model diagram, tabular data, system flow charts, histograms, decision diagrams, and simulation results. The criteria for analyzing data and producing results pass via four crucial areas of AI application research: (a) Energy and load forecasting; (b) fault forecasting; (c) AI-based IoT technologies for smart grid system optimization, such as energy storage, demand response, and grid flexibility; and (d) business value creation. The analysis criteria were examined to determine the possibility behind the energy industry's success through implementation of AI algorithms in integrated electrical systems.

The data analysis involves various significant steps; information gathered through interviews and a Likert scale survey was first transcribed into text. Themes were then created based on the literature reviews, expert opinion, and survey results. Next, the themes were narrowed down to make them more distinct and detailed, allowing for a better-organized presentation of the pertinent data. The essential takeaways from the interview and survey were then condensed and presented clearly and concisely in the results section. The findings were then analyzed and reviewed, and eventually, conclusions were drawn for the study's central questions.

3.3 Validity and reliability of the study

The terms "validity" and "reliability" are widely used in the qualitative research paradigm to assure study credibility through rigorous investigation and review. Validity refers to the techniques' integrity, applicability, and accuracy with which the research conclusions is meaningful (Noble & Smith, 2015). On the other hand, reliability relates to the consistency of analytical processes, which is essential because random or systematic measurement errors frequently influence the data collection during a study (Rosenthal & Rosnow, 1991).

The primary and secondary data gathering methodology emphasize this study's reliability. A huge proportion of scientific research are unreliable due to threats causes by the researcher bias, reactivity, and respondent bias thus it's crucial to know the difference between definitive and faulty evidence (R., J., N., & J, 2017). The search string is critical for locating relevant primary research, and as it is incorrectly generated, the review is likely to overlook essential information. Therefore, secondary data were selected from well-regarded scientific journals and publications to limit this risk. In addition, search phrases were derived from related work and validated using a control set of relevant publications. The previous subsection covers the data collecting and analysis methodologies.

It is possible that the main research questions do not cover all components of an integrated energy system. Therefore, the research questions were presented well to cover all of the significant components of a search-based integrated energy system formulation. Multiple databases were employed to offset the risks associated with database selection to prevent any potential limits imposed by a single database. Databases are chosen based on their relevance to the field of energy optimization. All of the searched databases returned articles that have been published in prominent venues in the specialized area.

The respondents for the interview were selected based on their expertise and experience in the energy industry. The energy industry in Finland was primarily focused on as a research site. Before the interview, the interviewees were given an interview guide, which assisted the researcher in brainstorming that broadened their grasp of the research issue. The responses from the interviews were carefully examined and used to reflect essential terminology employed in the research to get an accurate result. In addition, the various energy systems and capacity and their future prediction projections were also examined.

Furthermore, some questions were irrelevant to all respondents since their priorities were predefined. As a result, Likert scale questionnaires were provided to different individuals from diverse part of world engaging in energy industries to gauge their attitudes about future energy innovation. This adds to the research's credibility. The research objectives are also described in the findings. Proper preparation and tools were used in evaluating data, which contributed to the research's validity.

4 Result and discussion

This chapter goes through the responses to the research questions by analyzing all relevant publications from an AI-based integrated energy system optimization standpoint and empirical analysis of transcripts from four interviews with energy experts' opinions from Finland and 20 respondents to a Likert scale poll on digitalization in energy industries from Finland, Norway, and Nepal. The coding revealed the research findings in seven dimensions shown in Appendix 1.

4.1 Results

The result of empirical research included open-ended answers and Likert scale qualitative variables. The answers are not confined to "Yes" or "No" replies; instead, it include their opinion and understanding of the research topic. The research guidelines included a survey with nine Likert scale questions and seven open-ended interview questions based on the following themes:

- General questions about the interviewees' background to understand his/her expertise area and status.
- Questions about their view toward digitalization in energy integration, Challenges to the traditional energy system.
- The role of AI technology and the machine learning model in energy industries, possible challenges and solutions.
- The final part includes the interviewee's thoughts on the future shape of the energy sector due to AI innovation.

Based on above themes **Table 4** depicts the replies of the interviewees and their opinion on the research topic domain. This data revealed the respondent's understanding of the research topic and the role of AI in future energy innovation.

Table 4. Outcomes of the respondent interview.

Interviewee's	Status	Experties	Outcomes
Interviewee 1	Electrical Engineer, worked in electrical engineering services for 3 years	Electrical system integration and energy services	• The interviewee says an integrated energy system is conducting, planning, and operating different energy systems, i.e., power, transport, building, or various industrial systems across different time scales and vectors. • Most interviewees
Interviewee 2	Assistant Product Manager, worked in the field of automation, drives and power distribution for 3 and half years	Energy consulting, energy business marketing and sales	
Interviewee 3	Senior Electrical Engineering Manager, worked in industrial scale energy storage system for 3 and half years	Power Integration system, development of electrical vehicles battery	
Interviewee 4	Product Engineer, worked in energy management and product quality assurance for 17 years	Product development and verification, management of deliveries, product quality issues	

			believe that AI is the revolutionary enabler of the energy transition that provides energy transition of decentralized and variable renewables, ensuring interconnected networks reliably, securely, and efficiently. • Experts express that AI technologies and Machine learning techniques will turn out the energy management and distribution system in more effective way through

			accurate data interpretation for renewables energy fore-casting, smart grid controlling for intelligent power adjust-ment, and smart energy storage unit for sustainable and reliable power solu-tion. • The nature of the interview-ing companies varied; some were solely power solution providers, while others were both en-ergy genera-tors and solu-tion providers; yet they shared common themes that is

			development of innovative energy process technology. Most companies use automation solution which includes smart meters, IoT devices for connecting the smart device and providing constant surveillance and Machine learning algorithms are uses for optimizing and control of energy consumption and storage. • According to them challenges can be related to their flexibility towards

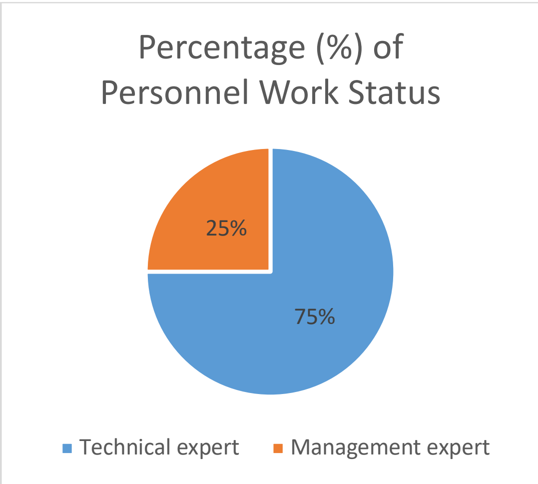
			renewable source vulnerabilities, energy efficiency needs to be understood broad, suggested solution are predictive maintenance, creation of market flex, flexible supply and usage, better utilization of data interpreter like ANN, VSM, and Regression, expansion of renewable energy trading. • They believe in nearby future we can see much potential of AI technology in real life science. They express those

			digital technologies will make energy system connected, intelligent, efficient, reliable, and sustainable. Mainly, they believe that it will innovate the application and will help solution for decarbonizing energy system.

Similarly, 20 people responded to the 5-scale Likert questionnaire survey, with 85 % of men and 15% of women. When the data is reviewed further, it is discovered that 75% of the respondents were energy industry technical professionals, while 25% came from a management background shown in **Table 5** and **Figure 20**. However, according to the number of respondents, most of them were unambiguous in their reactions to AI innovation in the energy sector's sustainability. This is because roughly 80% of respondents believe AI will play a key role in improving energy system efficiency and dependability, while 20% believe that AI technology is yet to be explored more.

Table 5. Respondent in Likert scale questionnaire survey.

Status	Frequency	Percentage (%)	Male	Female	Percentage (%)
Technical expert	15	75 %	17	1	85 %
Management expert	5	25 %	0	2	15 %
Total	20	100 %	17	3	100 %



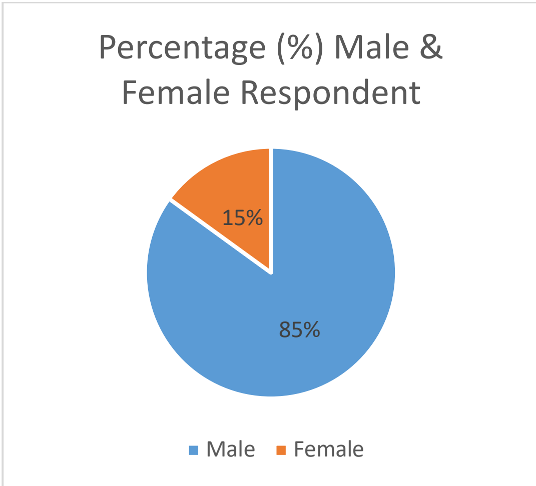
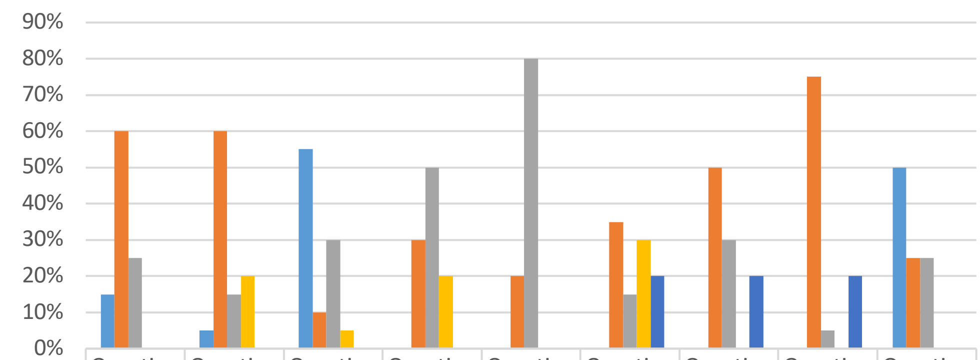


Figure 20. Percentage of personnel work status, male & female respondent.

The poll results are shown in **Table 6** and **Figure 21**, which indicate that not all respondents agree on the rise of AI technology, with a portion of respondents expressing opposition to the AI revolution in the energy sector. Respondents exhibit a high level of agreement on most questions. However, 5 to 30% of respondents disagreed with some questions. Overall, it was discovered that 80% of respondents believed AI technologies with high quality data has a favorable impact. On the other hand, 20% of respondents have data improvement requirements, indicating that AI technology should be further researched.

Table 6. Result of Likert scale questionnaire survey.

Questions	Total	Strongly Agree (%)	Agree (%)	Neutral (%)	Disagree (%)	Strongly Disagree (%)	Total
Question 1	20	15 %	60 %	25 %	0 %	0 %	100 %
Question 2	20	5 %	60 %	15 %	20 %	0 %	100 %
Question 3	20	55 %	10 %	30 %	5 %	0 %	100 %
Question 4	20	0 %	30 %	50 %	20 %	0 %	100 %
Question 5	20	0 %	20 %	80 %	0 %	0 %	100 %
Question 6	20	0 %	35 %	15 %	30 %	20 %	100 %
Question 7	20	0 %	50 %	30 %	0 %	20 %	100 %
Question 8	20	0 %	75 %	5 %	0 %	20 %	100 %
Question 9	20	50 %	25 %	25 %	0 %	0 %	100 %



	Question 1	Question 2	Question 3	Question 4	Question 5	Question 6	Question 7	Question 8	Question 9
Strongly Agree (%)	15%	5%	55%	0%	0%	0%	0%	0%	50%
Agree (%)	60%	60%	10%	30%	20%	35%	50%	75%	25%
Neutral (%)	25%	15%	30%	50%	80%	15%	30%	5%	25%
Disagree (%)	0%	20%	5%	20%	0%	30%	0%	0%	0%
Strongly Disagree (%)	0%	0%	0%	0%	0%	20%	20%	20%	0%

Figure 21. Respondent responses in Likert scale survey.

Furthermore, for the secondary data analysis chosen publications respond to the research's main thematic content, whether the study is from artificial intelligence (AI) and its various algorithms or the perspective of energy optimization. Certain publications employ distinct AI-based algorithm points of view to assist the energy optimization technique. The majority of the articles focus on AI-driven approaches to sustainable energy generation, distribution, and optimization. The results from the selected publications are reviewed, and synthesis is created based on the information gathered. In the discussion section, the findings are further examined.

The most recent research publication used as a primary source was published between 2017 and 2022, and it includes current perspectives and explanations of AI implications in energy optimization. The new technology is released regularly, and additional empirical research on that topic is carried out to reflect the theory in energy optimization case studies. The relevance of the article publishing year is evaluated based on inclusion criteria because AI ideas are continually evolving, and traditional power generation and distribution technology is no longer considered competent as it is today.

Table 7. gives an overview of the selected studies providing application areas, data source, used algorithms, outputs, and references. Following that, the research questions are answered using the information gathered. About 30% of the articles chosen are empirical research, while the remaining 70% are review articles and energy business overviews that usually summarize the available literature on a topic to describe the present level of understanding of the issue. This result suggests that additional empirical research is required to fully understand the phenomena and its ramifications and future development requirements.

Table 7. Application of data-driven AI techniques in integrated energy system optimization.

S. N	Application areas	Data sources	Algorithms	Outputs	References
1	Optimize the range of possible solar energy and power grid combination	Case study on HIS Smart power meter and radiation meter data	ANN/K means clustering	Estimate the amount of energy generated by any solar thermal system	Basurto et al. 2019
2	Energetics system improvement	Review article ScienceDirect database	Fuzzy logic, ANN, GA	AI provides users with secure, sustainable, and economical electricity from complicated sources and can use their energy more efficiently.	Ahmad et al. 2022

3	Sizing integrated renewable energy systems using optimization approaches	Evironmental technology review article data base	GA, ANN, FL, RBF	The best system configuration for scaling IRES is discovered using artificial intelligence (AI) technologies.	Kanase-Patil et al. 2020
4	Improve a forecasting model and a trading strategy for energy.	Case study on EPEX SPOT and Nordpool market data	ML, SVR	Demonstrates the viability of a data driven concept with significant implications for use in power management functions.	Carriere & Kariniotakis, 2019
5	Microgrid (MG) management and scheduling in virtual power plants (VPP).	Experimental data from real load parametric device of northern Malaysia	ANN-BBSA, ANN-BPSO	ANN-based controllers' advantages in terms of cost reduction and efficiency	G.M. Abdolrasol et al. 2021
6	Data-driven model for estimating	Review article based on ANN	ML, ANN	Accurate prediction of	Rahman et al. 2021

	renewable energy output such as solar, wind, or hydropower.	approaches databases		renewable resources	
7	Artificial intelligence and data analytics in integrated smart grid initiatives.	Review articles based on empirical data	ML, DL	AI-based data analytics initiatives demonstrate the importance of project execution and the complexity that determines project success.	Khosrojerdi et.al, 2022
8	Role of AI IoT and Block chain in Distributed energy resources	Review article data set	AI, IoT, BC	AI, IoT, and BC provide autonomous services to peers	Kumar et.al, 2020
9	Deep reinforcement learning for improving energy conversion in an	Experimental data set	CNN	The system operator's running costs are reduced by using a renewable energy	Zhang et.al, 2019

	integrated electrical system			conversion algorithm.	
10	Resync's enegy cloud platform	Data collected from smart metering device	ML, DL	Smart energy efficiency solution	Resync Technologies Pte Ltd., 2021

Table 7 shows that Artificial Intelligence (AI) and Machine Learning (ML) are employed as major technologies to deliver real-time decision-making with large-scale data interpretation. These data-driven approaches are used to address various issues, including picking the best group of customers to react to, understanding their characteristics and preferences, dynamic pricing, scheduling, and device management. As a result, AI may be considered to play a crucial part in enhancing the energy grid's ability to run more efficiently.

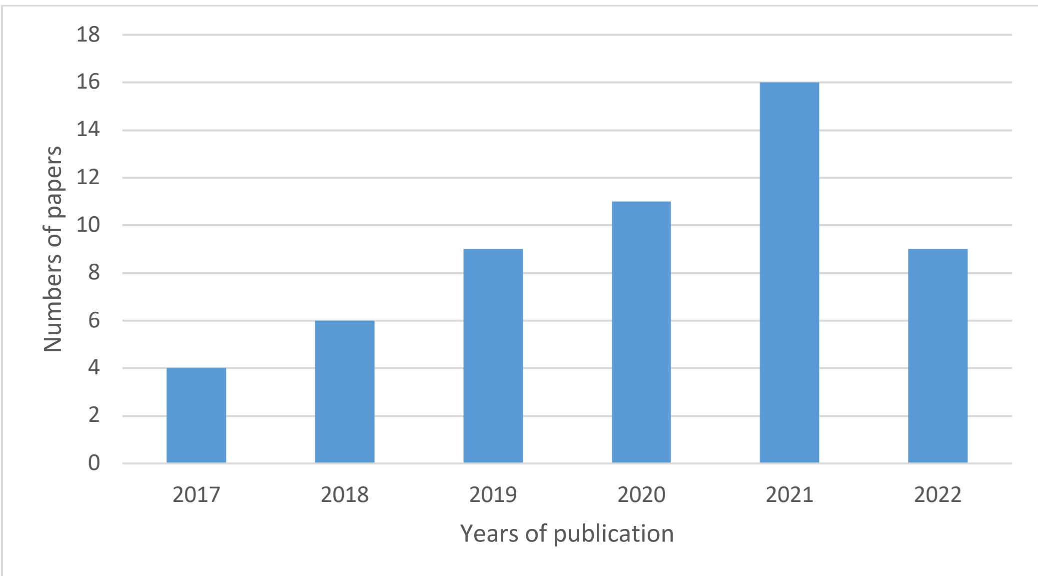


Figure 22. Number of papers published per year in AI based IES optimization.

The fast surge in research interest in AI-based energy optimization solutions reflects the growing interest in this topic. The number of publications published each year is seen in **Figure 22**. According to this graph, the number of papers peaked in 2021. The number of scientific papers incorporating AI techniques has risen, with the majority utilizing AI techniques for energy optimization.

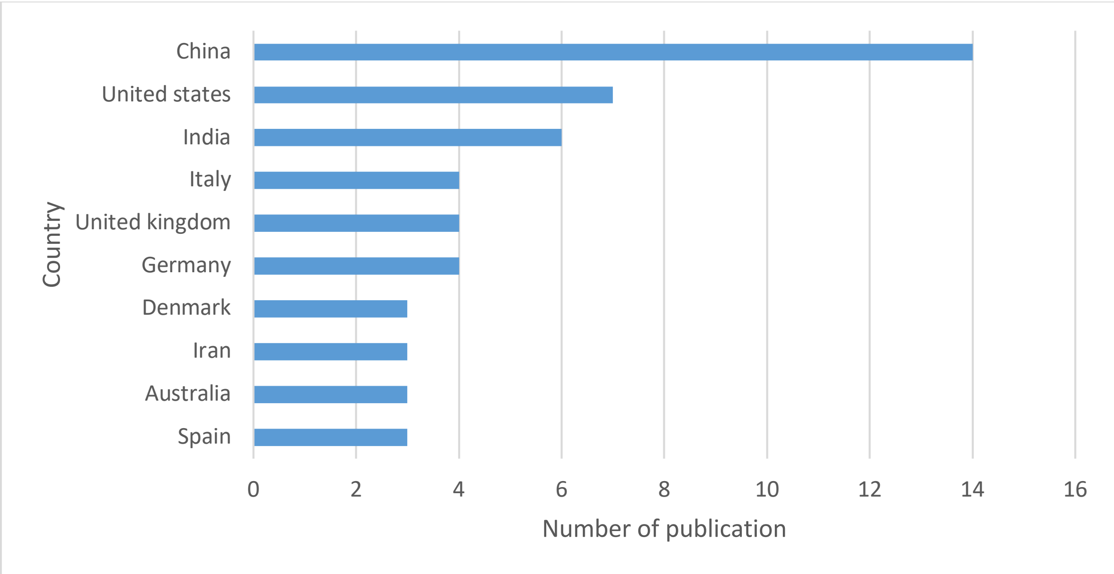


Figure 23. Number of papers published per year in AI based IES optimization.

The study was conducted based on the authors' nationalities to identify groups working on energy optimization challenges based on AI algorithms. **Figure 23** depicts the nations where articles on AI-driven techniques for IES optimization have been published. Authors from two or three countries collaborated on several themes, such as China and the United States; India and China; the United Kingdom and Spain; China and Italy; and China and Germany. The writers from China collaborate with other nations, and the most publications 14 articles. The United States and India, on the other hand, placed second and third in terms of paper publishing, with seven and six papers, respectively. China (Zhang et al., 2019) has one of the most referenced articles on AI-based energy optimization cited by 38 papers.

(Basurto et al., 2019) aimed to anticipate the energy output inside a solar thermal system using supervised and unsupervised learning methods such as ANN and K-clustering in a case study. In Spain, these approaches were integrated and used in a real-world exhibit. The suggested model is compared and evaluated using data from the entire year in the case study. The result identifies that the new model machine learning algorithms calculate solar energy with more precision, with an error of 10-4 in 86 percent of cases. According to a survey (Ahmad et al., 2022) on Kuwait National Petroleum Company (KNPC), leveraging AI results in significant improvements in energy utilization. To reduce CO2 emissions and KNPC's carbon footprint, the corporation deployed AI-based simulation software to reduce energy use by $15 million yearly and maximize energy efficiency among available utilities.

According to (Kanase-Patil et al., 2020), employing artificial intelligence (AI) technologies is the optimal system architecture for scaling the integrated renewable energy system (IRES). IRES is optimally sized using AI methods like fuzzy logic and genetic algorithms. This method provides an intelligent coordinating layer across the power supply, monitors and collects data, and analyzes it to find patterns and insights in the data. The resulting forecast possible outcomes and helps to select optimal power generation solution modules. (Carriere & Kariniotakis, 2019) introduced two techniques to renewable energy trade forecasting and decision-making functions. Meta-optimization forecasting models are the first way, and data-driven decision-making is the second approach. As a result of case studies on energy trading on the EPEX SPOT electricity market for PV electricity and the NordPool market for wind power. It is being evaluated that the second data-driven strategy is more efficient for energy trading than the first, with a minor penalty per imbalance.

(G.M. Abdolrasol et al., 2021) used an artificial neural network (ANN) as the primary method for managing and scheduling microgrids (MGs) integrated into virtual power plants in their test experiment. Actual data from data recorders in Malaysia's northern regions are used in the experimental model. The test results show that the ANN algorithm generates an appropriate schedule for each DG to minimize fuel consumption and CO_2 emissions and boost system efficiency in smart and cost-effective VPP operations and grid decarbonization. Similarly, article reviews by (Rahman et al. 2021) and (Khosrojerdi et al., 2022) found that AI-based data analytics projects such as ML and DL are widely used for accurate forecasts of renewable energy generation, such as solar, wind, and hydropower. These models can forecast short-term time series in renewable energy sources and use previous information to impact the future prediction value. Furthermore, according to DER research conducted by (Kumar et al., 2020), AI and its sub-components, such as IoT and block chain, provide automated services that assure reliability, availability, resilience, and stability, security, and sustainability of energy system networks. The simplified energy network system is shown in **Figure 24.**

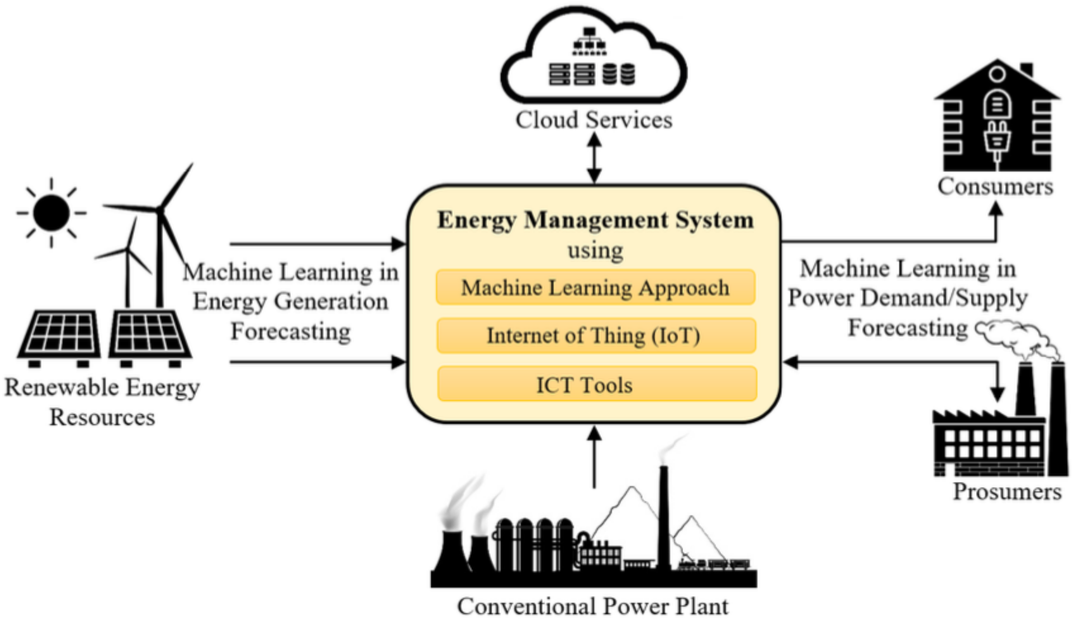


Figure 24. Schematic diagram of advanced energy network system (Rahman et al. 2021).

Compared to traditional energy network systems, the Integrated energy system offers greater flexibility in smart energy conversion since it can meet supply needs in various ways, enhancing overall reliability. (Zhang et al., 2019) claim that utilizing a deep reinforcement learning technique can help energy system operators choose the appropriate energy conversion model. According to the numerical simulation results, the proposed renewable energy conversion method might significantly lower the system operator's operating expenses.

According to an analysis of information from energy solution firms (Resync Technologies Pte Ltd., 2021), employing data analytics alone, they may enhance their stakeholders' energy efficiency by up to 30%. Data is gathered using standard communication protocols from local energy meters and energy assets (solar, wind, and grid) to enable real-time control edge level optimization balancing to increase renewable energy while reducing costs. Depending on the customers' adjustable load requirements, IoT devices collect data from all energy assets in real-time and calculate the optimal set point. (Resync Technologies Pte Ltd., 2021)

4.2 Discussion

According to the empirical analysis and literature review presented in the preceding part, identify the innovative potential that data-driven AI technology gives in integrating renewable energy resources into current electrical power systems to build a speedy and cost-effective solution. The study's findings point to numerous digital technologies such as AI, machine learning, deep learning, and the Internet of Things (IoT) and their contributions to a more efficient integrated energy system solution. In addition, the result shows that AI has broadened its application areas and is playing an essential role in developing integrated grid configurations.

Furthermore, the proactive nature of the integrated system identifies system changes in function and energy consumption following timely grid operation. These IES system capabilities are fully realized using AI-based data interpreters and communication mediums like ML, DL, and IoT. Throughout the study, ANN is one of the most widely used algorithms in the literature, with most researchers attempting to utilize it for the reliable prediction of renewable energy output (Debnath & Mourshed, 2018). The model has a correlation coefficient of over 80% and is getting better every day (Ferrero Bermejo et al., 2019). The study discovered several advantages of AI in IES optimization, including improved efficiency, availability, resilience, stability, security, and sustainability (Kumar et.al, 2020). However, some technical challenges are yet to be addressed. The advantages, technical limitations, and main application areas of the AI approach in IES will be discussed in the following sub-section.

4.2.1 Benefits and technical challenges

A key objective of the integrated energy system is to make the energy system sustainable, economical, accessible, and secure. Artificial intelligence (AI) and machine learning algorithms have been effective methods of allocating and managing energy resources in recent years. They aim to increase the modeling process's accuracy and facilitate decision-making procedures as more reliable and efficient with fewer complex models (Ahmad et al., 2021). The main advantages of AI technology are its built-in smart control centers that provide insight into grid operations for improved control (Manoj Kumar, Ghosh & Chopra, 2020). It enables energy providers to adapt supply and demand intelligently by promoting maximizing energy asset utilization. Next, AI is being used to create an integrated microgrid system that balances energy flow by addressing quality and congestion concerns. As previously mentioned, AI increased the system's safety and reliability by assisting in understanding energy consumption patterns, energy leakage, and grid health (Kumar et.al, 2020).

Furthermore, AI integration aids renewable energy suppliers in expanding the marketplaces by providing new service models and promoting increased involvement. AI can work with intelligent energy storage systems to provide a long-term and dependable, smart power storage and delivery solution. (Ahmad et al., 2022.) Apart from the benefits of introducing AI-based technology into renewable energy systems, there are several obstacles to overcome. According to the literature assessment of (Ahmad et al., 2022), artificial intelligence in renewables energy systems has revealed difficulties in energy integration because the weather mainly determines the availability of renewable energy and supply. Thus, it induced different energy assets, renewable grid deployment, and a surge in self-generation. Integrating those various energy assets results in greater energy network complexity, and there is a higher requirement for expanded processing power for AI technologies to handle those complicated challenges (Rhodes, 2020).

The highlighted hurdles by (Kuhlmann, Mehlum, & Moore, 2021) are related to the reliability of datasets and the balance of data privacy versus data usage. This is due to competitive or privacy concerns and a lack of adequate data labeling accuracy. Standardization and pooling of high-quality data have offered possible solutions to this problem. According to (Ahmad et al., 2021), additional vital challenges include efficient network connectivity and interoperability with other AI technologies, quality data, trained specialists and data science skills, legal security, and technology functioning in the energy industry. Aside from that, the literature analysis identifies high energy infrastructure investment costs and cyber security as roadblocks. However, (Makala & Bakovic, 2020) claims that after the energy industry has recognized the hurdles and problems, AI optimization will overcome energy waste, expenses, and facilities, allowing for sustainable contemporary energy forms development. In addition, to avoid obstacles caused by a lack of skills or knowledge, (Jamwal et al., 2021) proposed that continuous learning reduces the risk of employees in a firm lacking the necessary skillsets for energy industry technology.

4.2.2 Energy and load prediction

AI is effectively employed in the energy sector for energy load prediction and diagnostics of energy consumption patterns. Load forecasting, economic dispatch, hydrothermal generation, and optimization scheduling are employed in AI models for operational and generation planning (Toopshekan et al., 2020). Efficient and accurate forecasting on both sides of the supply and demand curves is critical to the integrated energy system's optimal operation. The supply and demand balance characteristics are examined according to the prediction to give precise data support for the economy and energy savings of the complete system operation. (Ahmad et al., 2022.)

The accurate prediction of solar and wind farm power generation is critical as they are highly venerable and weather dependent. To effectively integrate the most renewable electricity into the grid, AI-based approaches such as ANN, SVM, and FL (Solyali, 2020) are commonly used to predict the power output of solar and wind assets by learning from historical weather data, real-time measurements of wind speed, and global irradiance from local weather stations, sensor data, and images and video data. These short-term power supply forecasts might then be included in operational systems that schedule the charging and discharging of local battery storage plants, reducing solar and wind farm curtailment. (Kuhlmann, Mehlum, & Moore, 2021.)

In terms of hydropower energy prediction, it is heavily reliant on the amount of water discharged and the size of the turbine. Power generation is influenced significantly by the changing seasonal impact. Thus, hydropower turbine size optimization and prediction are crucial. However, the size of the turbine and the amount of water discharged are nonlinear and complex (Rahman et al., 2021). According to (Bernardes et al., 2022), Artificial intelligence and machine learning techniques such as SVM, GA, and ANN (Hammid et al., 2018) are used to predict and optimize hydropower plant dispatch. The hydropower forecast, like other predictions, requires continually updated information regarding weather data and prior energy output to achieve effective system control (Rahman et al., 2021).

4.2.3 Fault prediction

Artificial intelligence has found its way into various applications in integrated energy systems. One of them is diagnostic and fault prediction in Electricals integrated grid systems. Compared to the conventional tendency, grid security and reliability are considerably more ensured with the rising accessibility of intelligent sensor data and artificial intelligence algorithms. Fault prediction is a novel technology that uses data-driven reliability algorithms for the early detection of potential faults. They can analyze data and build machine learning (Abubakar et al., 2021) or deep learning (Teng et al., 2021) -based prediction models for crucial energy faults related to solar photovoltaic systems and power grids.

Among the various renewable energy solar photovoltaics (PV) energy generation is promoted as a more efficient and reliable energy source. However, it needs ongoing maintenance to ensure consistent generating efficiency, and AI has been demonstrated to be a superior alternative to traditional maintenance procedures (Abubakar et al., 2021). The fundamental criteria that define fault detection and diagnostic approaches in PV systems were discussed by (Mellit & Kalogirou, 2018). The literature features rapidity in detecting defects, climatic and electrical data, and the capacity to discern between distinct issues. According to the literature study, there are two techniques for categorizing frequent forms of PV system faults: First, visual and thermal technique which are used to identify discoloration, browning, surface soiling, hotspot, cracking, and delamination. Second, electrical detection and diagnosis methods for arc faults, grounding problems, and diode failures in PV modules, strings, and arrays.

The I-V and P-V curve measure the capacity of the string to identify unique physical events associated with each type of defect. However, they are not always reliable as faults are mostly condition specific (Ning, 2021). Thus, appropriate artificial intelligence algorithms for fault detection are chosen based on fault phenomena of solar systems. (Abubakar et al., 2021) cited mainly used ML models, such as artificial neural networks, wavelets, fuzzy logic, decision trees, support vector machines, graph-based semi-supervised learning, regression model as failure detection, and diagnostic strategies for solar PV systems.

For example, **Figure 25** represents a schematic diagram of proposed AI-based fault diagnosis techniques for the Photovoltaic system. To detect the likely faults, the difference between the measured and simulated PV array output power is first compared to a threshold (Th). The detection and localization of faults are then accomplished by analyzing the primary features in each string I–V characteristic composing the PV array.

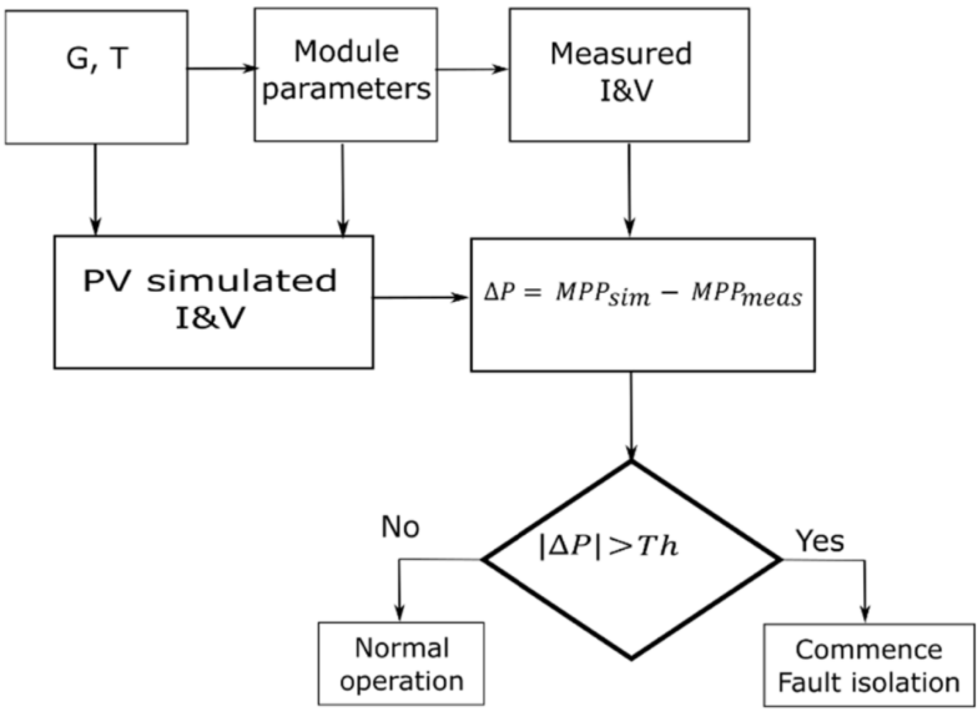


Figure 25. Fault detection technique for PV module by ANN (Abubakar et al., 2021).

Similarly, the integration of multiple producing units in the power grid network creates complexity, and the conventional fault detection approach fails to deal with the large amounts of data received by SCADA systems (Chai et al., 2019). Thus, AI technology is gaining traction as a special power grid fault allocation and rectification option. Power grid systems are vulnerable to faults and mistakes for various reasons. The most prevalent causes are power component failure due to lighting surges, human error, and equipment aging. The literature (Teng et al., 2021) and (Darab et al., 2019) mentions several intelligent methods widely used in the field of power grid fault diagnosis, such as expert systems, artificial neural networks, fuzzy logic, support vector machine, genetic algorithm, Petri nets, and so on, and analyzes their flaws in a practical way.

Figure 26 depicts the general structure of the artificial intelligence-based grid fault diagnosis application. The structural overview contains four layers: high-performance computing frame, data collection, algorithm application, and business scene. Their objective function is described in the following paragraph.

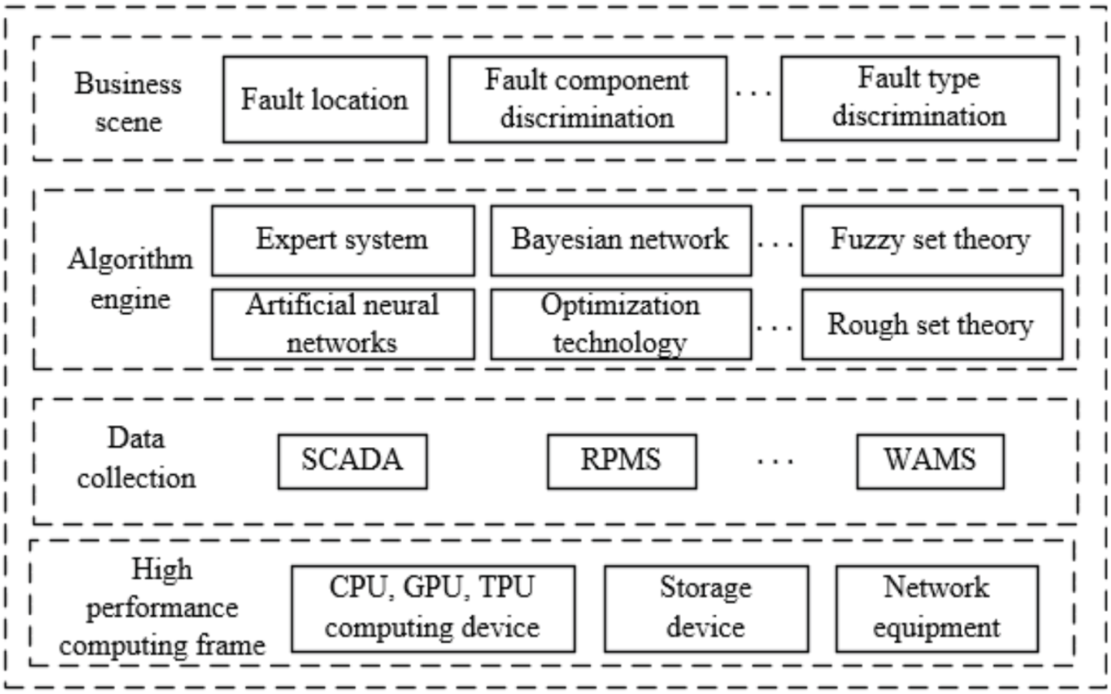


Figure 26. Framework of the artificial intelligence-based grid fault diagnosis (Chai et al., 2019).

The first high-performance computing frame consists of computing, storage, and network devices that execute computations for various algorithms to manage vast data and multi-level network parameters. On the other hand, Storage devices offer storage for the grid's vast operating data. The following layer is the data collecting layer, which collects data from the source and offers real-time monitoring and control functions through SCADA, RPMS, and WAMS. The algorithm engine then provides support for upper-layer applications by encapsulating various algorithms such as expert systems, artificial neural networks, and Bayesian networks. Finally, the business scenario analyzes and detects the physical and electric fault, employing different artificial intelligence methods to diagnose the issue and establish the fault component and type. (Chai et al., 2019.)

4.2.4 Energy storage, demand response and grid flexibility

The advancement of the energy sector is moving in the right direction; however, energy storage technology is still lagging (Barrett & Haruna, 2020). Energy storage systems (ESS) are projected to make critical leaps in the future smart grid development by employing AI and ML, as traditional power grid designs lack the energy storage infrastructure for high-efficiency energy understanding and consumption. AI approaches are being utilized to solve various problems, including determining the best time for a fixed energy supply, demand responses, grid flexibility, demand pricing, energy storage scheduling, and control, and rewarding them fairly and cost-effectively (Antonopoulos et al., 2020).

The power system does not store electricity; hence it is critical to always keep the grid flexible to satisfy unpredictable electrical demand responses. Thus, the concept of a reserved power plant, Energy Storage System (ESS) as Ancillary Services, is conceived to resolve any energy resource fluctuation or outage. Artificial Intelligence (AI) and Machine Learning (ML) are crucial technologies for making real-time decisions based on enormous data. First, they are utilized to forecast demand and power grid load. The data is then collected and analyzed by an AI-enabled system, giving insights into peak energy demand on the local grid and bridging the gap between renewable energy supply and demand to maximize power use. Using these methods, users can optimize their energy use habits and cost-effective flexibility to the broader power grid.

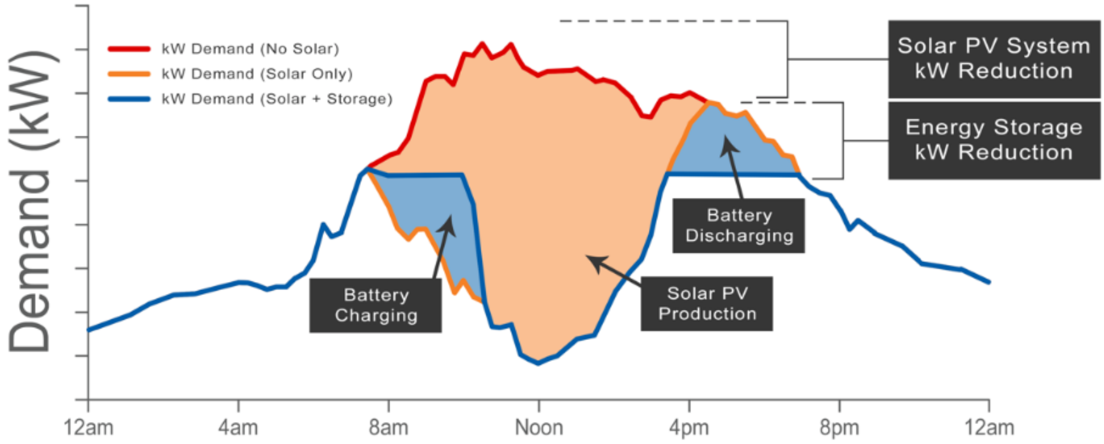


Figure 27. Energy optimization through solar and ESS (Ning, 2021).

Artificial Intelligence algorithms make real-time decisions for charging and discharging of the ESS. **Figure 27** depicts the integration of ESS with renewable energy supply, which results in peak shaving of the energy profile and lower demand charges. Through this optimization, financial gains are maximized. (Ning, 2021.) Artificial intelligence algorithms have been used in several studies to increase ESS performance, Demand responses, Grid flexibility, and Renewable energy supply. To solve the established optimum model, (Li et al., 2020) used an Artificial Neural Network (ANN) to construct a two-stage optimization that includes a day-ahead plan and an intraday adjustment to schedule the ESS and Renewable energy supply during each dispatch period, respectively. Similarly, (Lotfi, 2020) proposes a particle swarm optimization method that optimizes energy use by combining distributed grid with energy storage devices and taking demand responses into account. The suggested technique successfully enhances the integration of distributed generators, solar, ESS, and capacitors, resulting in a 26% reduction in energy loss and a 5.9% reduction in operational cost.

4.2.5 Business value and creation

The rise of the worldwide commercial business has been propelled by technological innovation, and now artificial intelligence is only a way in which the energy sector can meet up to today's innovation and boost energy business values. However, to get the most out of AI solutions, the energy industry must first grasp the fundamentals of AI, its influence on the business world, and the way to generate value and implement an AI strategy (Bolivar, 2022).

In terms of the energy business, every energy company that wishes to maximize profits and establish strong business values should implement sustainable energy policies, maximize energy resources, provide cost-effective services, and generate revenue. However, it is impossible to solve these issues due to the traditional business model. As a result, an intelligent AI-powered business model emerges that can analyze energy collection data and provide insights into energy usage. This data will help companies refine existing services (Ahmad et al., 2022), implement new operation models, dispatches energy with optimized resources, anticipate demand in advance, predict issues, and conserve resources wherever feasible. As a result, end-users will see decreased electricity bills and personalized services due to AI's energy-saving efforts, making AI a prominent energy industry player. (Martynova, 2021.) According to the report by (Deloitte AI Institute, 2021), there are six ways that AI may provide business value.

- Cost reduction: Artificial intelligence (AI) and intelligent automation technologies can help automate low-value, iterative procedures, resulting in cost savings and improved quality.

- Speed execution: By reducing latency, it achieves operational and business results. For example, it utilizes predictive data to design and optimize energy models.

- Simplified complexity: Analytics that are more proactive, predictive, and spot patterns in more complex sources improve comprehension and decision-making.

For example, production downtime can be reduced by forecasting equipment maintenance requirements.

- Enhanced participation: Changing people's perspective about technology by meeting consumer demands better, conversational bots that can comprehend and respond to client sentiment might be used

- Boosted creativity: Using AI to allow breakthrough new services, markets, and business models, for instance, depending on client demands and preferences proposing new service concepts and functionalities.

- Increased trustworthiness: Securing a business from threats like fraud and cyber-attacks while enhancing quality and consistency and increasing transparency to boost trust. Identifying and forecasting cyber assaults before they happen.

5 Conclusion and future recommendation

The final research outcome is concluded in this chapter. The written synthesis will recognize key findings and review the study for future development.

5.1 Key findings and conclusion

The research's key findings include the drivers and advantages of the AI approach in energy optimization of integrated energy systems and their significant role in transitioning towards a sustainable, environmentally friendly, cost-effective, accessible, and secure energy system. The study was initiated by examining the current energy generation trend in the global energy market, emphasizing alternative energy sources for system improvement and carbon emissions reduction. The study used a two-pronged approach, with primary data from energy industry expert interviews, a Likert scale questionnaire survey, and secondary data from current energy industry optimization models and a review from publications linked to a given research issue.

The expert interview outcome indicates that renewable energy sources such as solar, wind, and hydropower are the most significant way to cut the price of using traditional energy sources while also lowering carbon emissions. However, the inconsistency of renewable energy supply is a problem that needs to be addressed. They also considered that AI technology and machine learning approaches might be the game-changing facilitator of the future energy transition, with immense promise in data analysis, prediction, intelligent grid control, power adjustment, and smart energy storage for sustainable energy. According to the Likert scale study, 80% of respondents feel AI technology combined with high-quality data has a positive influence. On the other side, 20% of respondents said they needed data enhancement, indicating that AI technology should be investigated further.

The research also goes through a variety of published literature reviews and identifies AI's significant potential in electrically integrated energy systems, which includes a better understanding of energy consumption patterns, highly effective and precise energy load and fault prediction, automated energy management, enhanced ESS, more excellent business value, a smart control center, smooth monitoring, tracking, and communication of energy networks.

The study's findings point to numerous digital technologies such as AI, machine learning, deep learning, virtual power plant, and the Internet of Things (IoT) and their contributions to a more efficient integrated energy system solution. In addition, the literature shows that AI has broadened its application areas and is playing an essential role in determining the optimum system configuration for scaling integrated energy systems. For identifying the optimal size of the IRES system, algorithms such as Fuzzy based model, Genetic algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Neural Network (ANN) are being employed (Kanase-Patil et al., 2020).

This study has systematically investigated the rapidly developing subject of energy sector digitalization, providing an overview of essential characteristics of technologies, their applications in the integrated energy system with possible defects, and implementation issues. Decarbonization efforts have resulted in a high degree of decentralization in the power sector and a more integrated and electrified energy system. Digital AI-based solutions play a crucial role in managing this increasingly complex system and maximizing energy efficiency while minimizing carbon emissions. Researchers have done a significant amount of research, and all the related AI algorithms were reviewed and described in depth. Their application focuses on low-cost energy transition, enhanced power system efficiency, grid flexibility, distributed monitoring and control center, electricity and investment markets, and renewable energy resources management. However, most of the present integrated energy system's difficulties are related to unpredictable energy demand, limited adjustment ability of renewable weather-dependent output, and system security and stability caused by load variations. Thus, the integrated energy system must promote independence and reconcile benefits to improve system flexibility and lessen interconnectivity issues through AI-based technology.

To sum up, integrating and operating various renewable sources in a diverse energy market environment is complicated. However, the difficulty of the system operation can be reduced via digitalization and AI implementation. The research findings also supported the focus on integrated energy systems' unique characteristics, concluding that real-time AI technology may emphasize the renewable energy-dominated energy structure by controlling and monitoring parameters in real-time. The study delves into each part of the AI algorithm, exposing its possible answers to issues including carbon emissions, energy optimization, integration, and management.

5.2 Future recommendation

Incorporating AI techniques and data analytics into integrated energy systems discover an innovative way of defining intelligent electrical power networks. So far, electrical power grids have been viewed as modernized and enhanced power systems that include new ICT technology. However, the vast amounts of data generated by new electricity-generating devices, such as autonomous vehicles, smart buildings, and smart cities challenge our understanding of bidirectional power transmission and distribution system. Therefore, it is crucial to define the qualities of these energy producing resources that reflect a distinct identity, and future research will need to explain the technical characteristics and definitions of these fast-growing energy exchanging system models based on AI based IoT. In addition, another area of future research can be the energy conversion methodology in the Renewable-Integrated Energy System.

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Appendices

Appendix 1. Expert Interview Questionnaires

1. How long are you working in the field of energy industry?
2. How would you define integrated energy system? How important do you think the AI technology has on energy integration and their optimization.
3. In your thought, how can AI technology address the challenges faced by the power system industries of the present and future.
4. How is your company functioning to attain energy sustainability?
5. Which AI technology or machine learning algorithm do your company uses for monitoring and controlling the energy synergy?
6. What do you think what would be the possible challenge of AI approaches in energy integration? How to respond those challenges.
7. What are your thoughts on what the energy industries will be shaped in future by deployment of AI technology?

Appendix 2. 5-Scale Likert Questionnaire and collected data

This questionnaire was developed for the Master's thesis research purpose at the University of Vaasa, Finland. The goal is to get input so that the research questions and main objectives may be answered.

All responses and information will be treated with the utmost discretion. Filling out the questionnaire takes 5 to 10 minutes. Information about the respondent: i) Gender: **Male/Female** ii) Occupation status: __________

Question	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. I am familiar with the concept of the digitalization in energy industries	1	2	3	4	5
2. What do you think adoption of AI techniques for energy integration aids process optimization.	1	2	3	4	5
3 Are artificial intelligence (AI) and machine learning (ML) techniques useful in the energy industry to harvest renewable energy and allow businesses to run more sustainably.	1	2	3	4	5
4. Was the unidirectional design of convectional energy system causes failure in adopting everchanging and expanding energy demand	1	2	3	4	5
5. Do you think AI based energy solution accelerate data value to drive energy business insight	1	2	3	4	5
6. Is the high dependence on smart access control system contributes to data security breaching	1	2	3	4	5

7. Can standardization and pooling of high-quality data will be the solution to the data reliability and usage	1	2	3	4	5
8. Do you think machine learning model remove energy system complexities, business cost and accelerate innovation	1	2	3	4	5
9. Do interacting of AI technology with integrated energy system leads optimization and balance in energy consumption patterns and improves the quality of life	1	2	3	4	5

Respondent	Question 1	Question 2	Question 3	Question 4	Question 5	Question 6	Question 7	Question 8	Question 9	Mean	Performance Grading
1	4	4	4	3	3	4	3	4	4	3,7	High Quality
2	3	2	3	2	3	1	1	1	3	2,1	Improve requirement
3	4	5	5	4	4	4	3	4	5	4,2	High Quality
4	4	3	3	4	3	3	3	4	4	3,4	Acceptable
5	4	4	5	3	3	2	4	4	5	3,8	High Quality
6	4	4	5	3	3	2	4	4	4	3,7	High Quality
7	4	4	5	3	3	4	4	4	5	4,0	High Quality
8	3	2	3	2	3	1	1	1	3	2,1	Improve requirement
9	4	4	5	3	3	2	4	4	5	3,8	High Quality
10	3	3	2	3	3	3	3	3	3	2,9	Acceptable
11	4	4	5	3	3	2	4	4	5	3,8	High Quality
12	5	4	5	4	4	4	4	4	5	4,3	High Quality
13	4	4	5	3	3	2	4	4	5	3,8	High Quality
14	3	2	3	2	3	1	1	1	3	2,1	Improve requirement
15	5	4	5	4	4	4	4	4	5	4,3	High Quality
16	4	4	5	3	3	2	4	4	5	3,8	High Quality
17	4	4	4	3	3	4	3	4	4	3,7	High Quality
18	3	2	3	2	3	1	1	1	3	2,1	Improve requirement
19	5	4	5	4	4	4	4	4	5	4,3	High Quality
20	4	3	3	4	3	3	3	4	4	3,4	Acceptable