Electricity Market Empowered by Artificial Intelligence: A Platform Approach

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Abstract: Artificial intelligence (AI) techniques and algorithms are increasingly being utilized in energy and renewable research to tackle various engineering problems. However, a majority of the AI studies in the energy domain have been focusing on solving specific technical issues. There is limited discussion on how AI can be utilized to enhance the energy system operations, particularly the electricity market, with a holistic view. The purpose of the study is to introduce the platform architectural logic that encompasses both technical and economic perspectives to the development of AI-enabled energy platforms for the future electricity market with massive and distributed renewables. A constructive and inductive approach for theory building is employed for the concept proposition of the AI energy platform by using the aggregated data from a European Union (EU) Horizon 2020 project and a Finnish national innovation project. Our results are presented as a systemic framework and high-level representation of the AI-enabled energy platform design with four integrative layers that could enable not only value provisioning but also value utilization for a distributed energy system and electricity market as the new knowledge and contribution to the extant research. Finally, the study discusses the potential use cases of the AI-enabled energy platform.

Keywords: electricity market; energy market; artificial intelligence; digital platform; peer-to-peer

1. Introduction

The energy transformation, so sought after world-wide, would only be effective via the increased integration of renewable energies that are supported and enabled by intelligent grids, or smart grids. Smart-grid technologies will make it possible to use the available renewable energy sources efficiently and sustainably to create added value to the energy service as well as reducing costs for energy consumers and prosumers while supporting a decentralized and open architecture and design for the energy system [1]. However, energy scholars focusing on power systems acknowledge the challenges with increasingly complex energy systems. As such, the electric grid is a massive infrastructure with e.g., physical limitations [2].

The European Commission [3] envisions that tomorrow’s power grids will be made up of interconnected and diverse systems, with a growing number of distributed energy generation and consumption equipment and appliances that generate a large volume of data [4]. Considering only smart meters, if the average packet size is about 200 bytes [5], with a reading interval of 15 min as suggested in the European Union (EU) regulations and the 200 million smart meters that are deployed in 2020 [6], the total amount of memory in Europe is 5 606 TB of information. Reduce the sampling size to every second for near-real-time network measurement, and this is around 5 exabytes of data to be collected within a year only from smart meters. In particular, the electricity industry demands big data capabilities and novel architectures that can enhance power system management of the more complex
and decentralized grids [3]. Thus, over the last few decades, research efforts and scholarly discussion around the world have been focused on ways to effectively predict and optimize energy use.

Artificial intelligence (AI) as an emerging technological field has been altering numerous sectors of the world’s industries and economies. AI is seen as an innovation front and enabling technology [7,8]. AI includes a broad collection of computational techniques to extract insights from a variety of data sources—including the so-called “small data” that is generated by the algorithm itself) that assist in decision-making [9]—and create actionable information [10]. Generally, AI is deemed a general-purpose technology that can have significant technological, social, economic and political implications [9,11,12]. Some describe AI as parallel to the steam engines or electricity technologies that have changed many aspects of human life.

Evidently, AI will radically transform the energy sector. General Electric (GE) estimates that AI can enhance the production of a wind farm by as much as 20% [13]. At the same time, as claimed by Nagy et al. [1], the AI transformation in the energy industry will directly influence the international energy stability and economic prosperity. For instance, the use of artificial neural networks is of great importance for electricity companies to improve their productivity, the quality, and safety of the productions, and the stability of the electricity. As a case in point, the Google Data Center utilized the DeepMind AI to effectively achieve 40% of the energy-saving for the data center operation [14].

However, as AI technology adoption and penetration rates increase in the energy sector, the existing AI and energy-related research remain under-explored without sufficient scholarly effort on AI applications in the energy and electricity market design on top of the physical and technical energy infrastructure.

The study of Quan and Sanderson [15] introduces a holistic framework to analyze AI systems and platforms, including AI core technologies, AI platforms, and AI applications. Based on this framework, the extant AI and energy research has been largely focused on AI core technologies. For example, AI technology has penetrated the technical applications rapidly in the industrial systems. Technically, in the power and electrical engineering domain, AI techniques, such as expert systems, neural networks, and fuzzy logic have been utilized to solve various technical challenges [16], including but not limited to (1) energy forecasting [17,18], (2) energy market price prediction [19], (3) smart grid fault detection [20], (4) demand-side management [21], (5) building energy management [22], (6) smart home demand response management [23], and (7) smart grid data security with AI and blockchain [24]. In terms of driving the energy transition process, the greatest potential in the use of AI is forecasting renewable energy potential, big data management and optimization of hybrid renewable energy systems, e.g., [25,26].

Research Gaps Relevant to the Study

Several gaps can be identified in the extant research. The first gap in the current research is the lack of AI platform discussion dedicated to energy systems and market design. As argued by Reich [27] and Singer et al. [28], to the present day, AI systems (including AI-empowered energy systems) have hardly reached broad use in practice for several reasons. Research has often focused on narrow and specialized technical subtasks, not on larger and more integrated problems. Specifically, for AI’s application in renewable systems, it is suggested by [29] that most studies discuss the utilization of AI approaches in wind- and solar-based systems. AI approaches have great potential, but their effective utilization in future research is needed to provide more novel approaches to managing renewable energy sources, such as in the case of AI for hybrid renewables.

Although AI is identified as a promising optimization method [25], there is little discussion on it at the systemic level. A “platform” as a system model or architecture can tackle this problem. As stated by Landahl et al. [30], when developing a variety of products for a large number of customers/end users, the producers strive for commonalities and distinguishing features of the developed product variants. A common approach for this is the adoption of a platform model [31], which is typically achieved by modularizing the product’s architecture [32].
As suggested by Ramos and Porto [2], some of the important problems in energy supply technology and in the energy market require capabilities such as (1) heuristic search, (2) logical thinking, (3) perception as well as (4) uncertainty tolerance. All these needs give rise to the opportunity for cross-investigation between energy research and AI technologies. At a broader systemic level (e.g., a system platform perspective), AI does not only enhance a certain operation but can be potentially an effective enabler of the new solutions in the energy ecosystem in the areas of enhanced artificial neural networking and decision making, operation, maintenance, market monitoring, as well as optimized trading in the electricity markets [2].

For another emerging paradigm of energy internet thinking, the energy internet is considered to be a new and advanced paradigm for smart grids with massive inter-connected devices and bi-directional power and information flows. This emerging paradigm also demands more advanced techniques to optimize the entire energy system rather than individual applications [33], including big data, AI-based control, and optimization as well as cloud computing. Thus, the AI platforms for energy system and market design at a systemic level is a research front that requires more attention and research effort.

The second gap relates to the synergy between AI applications and electricity market design. The research and development of AI focus primarily on developing new algorithms and software that tackle a focal problem [29]. While most of the previous studies cover the applications of AI techniques, such as fuzzy logic or artificial neural networks in renewable systems [29], in theoretical research there is relatively limited discussion on AI’s potential in the electricity market such as facilitating market trading and renewable matchmaking in the electricity marketplace, especially in the emerging context of massive renewable integration into the smart grids. In contrast, empirically, companies in the energy industry have started experimenting with different use cases. For example, ABB focuses on advanced testing methods of 3D-simulation of power plants with a holistic view of the system which is based on smart human-computer interaction systems [34].

Fundamentally, markets have played a key role in giving market participants (or market actors) the opportunity to profit from the trade. Market design literature (e.g., [35]) suggests that the design of a market needs structure and a diverse range of market operations and transaction mechanisms to operate efficiently [36]. Market design studies often delve into fundamental problems: how the market agents can learn the patterns of the market to determine the optimal transaction prices? Or, how the market agents can have an enhanced understanding of the market environment where they operate?

This research suggests that in the energy/electricity market, it is possible to harness the improved predictions provided by data and AI algorithms to enable the marketplaces to better predict consumer and producer demand and supply. This proposition is supported by the previous literature of Ramo and Porto [2], which calls for further study on the economic perspective of the energy industry. However, we need to develop a deeper understanding of how such a platform is constructed than an ontological description. This is addressed in this study.

The third gap pertains to the value utilization of the electricity market. As mentioned, existing AI technologies have been focused on how to optimize energy production and distribution for the legacy energy systems. The issue arises when the platform thinking is adopted for the existing energy systems that overemphasize on the energy production and energy supply chain. In platform literature, a platform-like marketplace is formed because of the participation from both supply and demand, or value provisioning and utilization that help create the network effect for a platform to succeed [37]. By adopting platform thinking, AI can impact the utilization side of the marketplace or platform is limited from the existing energy research and literature.

By developing a high-level systemic architecture framework for an AI-enabled energy platform, this paper contributes to the need for a better understanding and articulation of the potential AI platform in the energy industry as well as AI’s roles and applications in electricity market design and operation. More specifically, the research addresses two parallel research questions: firstly, what can be the AI-enabled energy platform for the electricity market? and secondly what are the potential AI
applications for the value provisioning and utilization of the energy platform in order to provide better services for energy consumers?

Overall, by addressing these two questions, the research contributes to the existing literature in three ways: (1) the study enriches the existing AI and energy research discussion with a more holistic view: expanding from the technical focus of narrow AI technical applications to the utilization of AI at a systemic level; (2) the research introduces platform thinking and a platform architecture/model for the potential integration of AI into the energy systems. An AI-empowered energy system can have the capability to manage massive data and complex grid and market operations when the shares of the renewables increase significantly; (3) the research explores and proposes a number of AI applications in managing and optimizing the market operation and design. Previous literature [2] only gives a proposition that AI technology can transform the energy market operation without providing details and in-depth discussion. This research gap is filled in this research, including discussing how AI and blockchain can transform the further electricity market based on the extant studies of [38–40].

As addressed by [1], the direction of AI development in the energy industry is still an open path. To facilitate more effective and efficient human–AI collaboration, more research efforts are required to progress towards the development of new synergies AI and other parts of the energy system. Thus, this study is inspired and built on this call for action. The research question of this study is as follows: “How can we integrate AI technologies into the future energy system architecture, in order to enhance transparency and participation of users in different markets?” The focus is on AI’s potential at the utilization side of the electricity market, in order to enable smart energy services and increase value utilization. The paper focuses on AI-enabled energy market architecture at the system level. Therefore, we are open to a variety of AI technologies that demonstrate potential in the energy industry rather than a particular AI technique.

This paper contains the following sections: Section 2 encompasses a number of definitions on AI, AI’s application in smart grid and renewable researches. This section further introduces and explains the platform thinking and elaborates on the research method. Section 3 shows the outcome of the study by constructing and articulating the architectural model of an AI platform in the context of smart grids by expanding the 4C (connection, content, context, and commerce) framework in ICT (information and communication technology) and digitalization research. Section 4 discusses the potential applications of AI in the electricity market through the framework created in the previous section. Finally, Section 5 provides the conclusions of this study and heads to further research direction.

2. Literature Review and Methods

Nilsson [41] defines that “AI encompasses the intelligent behavior in artifacts, which involves perception, reasoning, learning, communicating and acting in complex environments”. The main purpose of AI is basically considered as the creation of intelligent machines that can perform human-like capabilities and beyond. Furthermore, it is recommended by the scholars (e.g., [42]) that the capabilities of AI can be divided into subgroups or categories such as reasoning, problem-solving, natural language processing, perception as well as general intelligence [42] to solve complex problems [43].

From the computer science perspective, AI is deemed as an approach for the software programs to analyze focal problems and devise appropriate solutions. AI core technologies are classified as machine learning, artificial neural network, and heuristic search [44]. To this date, numerous studies have been conducted to explore, experiment and investigate the capability and use of AI in a variety of fields such as big data analytics, information system, production engineering, and medicine, just to name a few [29].

2.1. Artificial Intelligence (AI) Application in Smart Grids and Renewables

Based on the framework of Quan and Sanderson [15], AI in energy research is mostly directed in different techniques and solutions for designing, optimizing, and managing the operations of different
domains. In energy and renewables research, the literature review shows that AI has been studied in areas such as solar, wind, geothermal and hydro [29].

A substantial number of studies have focused on energy demand prediction [45, 46]. For instance, prediction models can be categorized into the following types [47]: physical-oriented, data-oriented, hybrid, and large-scale prediction methods. In the area of energy prediction, the artificial neural network technique is well-known for the accurate forecasting of energy usage [29]. However, there is a challenging issue related to accuracy when the scale is reduced (e.g., neighborhood or household level) although precise load forecasting is possible at the aggregated level (e.g., national level). In this vein, the study of Ahmadi [48] suggests that the artificial neural network is developed in as many as 40% of the energy artificial neural networking algorithms [49].

**The use of AI in solar energy:** AI applications in solar energy are reviewed in the literature [50–52]. Applications often involve the use of artificial neural network methods for solar modeling [51] in both single and hybrid approaches [53]. For instance, the use of machine learning can improve the solar forecasting accuracy with a range of 30% to 50% increase, e.g., [54, 55] compared to conventional forecasting models.

**The use of AI in wind energy:** empirical research and trial by industry incumbents like GE show that through the use of IoT (Internet of Things) sensors, data networks, and advanced analytics can optimize the wind turbines to have as high as 20% peak efficiency in artificial neural network energy production [13]. By reviewing the academic research, Jha et al. [29] identify a number of studies related to the physical model, statistical model as well as artificial neural network methods for wind modeling. Basically, the applications of AI techniques in wind energy cover several categories, such as neural, statistical and evolutionary learning [29].

Overall, the artificial neural network, reinforcement learning, genetic algorithms, and multiagent systems are common techniques for AI to solve the problems of classification, forecasting, artificial neural networking, optimization, and control [2]. The current literature and research also show the disintegrated gap and low visibility of studies that integrate ICT systems, power/energy systems as well as energy market research [2]. However, this research suggests that AI and machine learning is an emerging application in the power and energy field, quickly gaining a footing within the intelligent energy systems domain.

### 2.2. Platform Thinking and Approach

The literature offers numerous platform types with different definitions and properties. The platform concept and thinking can find its presence in both economic and technology/engineering literature [56]. The work of Gawer [56] seeks to integrate technological platforms.

Digital platform architectures can generally be classified into two types which can have multiple hybrid combinations [57]: the economic-oriented transactional platform and the engineering-oriented technology platform. First, an economic-focused transaction platform facilitates exchanges by fragmented groups of consumers and/or suppliers. The platform provides a matchmaking mechanism to connect supply and demand that are normally fragmented [58]. This definition is in line with an economic point of view, and digital platforms are seen as markets where the platform facilitates exchanges between actors who otherwise would not be able to do business with each other. An example of this type of platform is Uber, as the platform connects drivers with travelers and facilitates the transaction between the two groups as a two-sided market or platform [59]. The economic platform thinking can also be extended to multi-sided markets [60, 61].

The engineering/technological platform is seen as a digital platform with technological architectures that enable innovation [56, 62, 63]. Such a platform architecture builds a foundational technology and distribution system that enables the other technologies to be integrated into the platform, enhancing value for the whole system. For instance, the mobile app ecosystem of Apple (App Store) is a well-known case of such a digital platform [63]. The core idea is that the platform includes modules that can be used to decompose complex systems into manageable components connected by interfaces.
The modules provide information-sharing because each module does not need information about the entire system, which in turn allows access control over specific data [59,64].

The research of Gandia and Parmentier [65] shows that it is possible to combine and integrate both the economic and engineering/technological conceptualization of the platform. For example, economic thinking would consider the declining costs of information gathering and market mediation for the empirical multi-faceted platforms on the Internet, such as eBay, Amazon, and Airbnb. In parallel, the technological perspective of a platform is rooted in presenting the platform as an integral system of software and hardware that offers standards, interfaces, and mechanisms that enable supplement technology vendors or providers to be matched with the end users as well as interacting with other technology providers. In this vein, the platform innovators’ and the complementary partners’ success depend on the platform owner’s continuous innovation [65].

2.3. Research Method

In an effort to address the research gaps, this research adopts two approaches: First, system architecture thinking, e.g., [66], where a “systems architecture is the conceptual model that defines the structure, behavior, and more views of a system”, and action design research (ADR) [67]. In the paper, the 4C systemic framework is used: connection, content, context, and commerce [68] and the 4C layered typologies [69] that can incorporate both the value provisioning and value utilization of a digital system, which bridges the gap in existing energy research. The 4C framework can be reconciled with the market layer of the smart grid architecture model (SGAM) that is the formal system framework established by the standardization organizations in the European Union [70]. Furthermore, the paper follows the system architecture logic and align the discussion based on system architecture’s three key constructs: the system structure, the system (and the component) behavior, and the view of a system.

Second, this study utilizes the constructive and action-oriented research approach for theory building and concept proposition for the AI energy platform architecture as an IT (information technology) artifact, aiming at bringing novelty value to the energy system and market design studies. Information system research has rich literature on the relevant approaches for dealing with the development and design of system architecture. For instance, action research is one stream of studies that incorporate theory generation with researcher intervention to tackle organization-related research problems and connecting the theory with practices [67,71,72]. In another stream of information system research, design science is used to create IT artifacts with a constructive approach. The IT artifacts are “shaped by the interests, values, and assumptions of a wide variety of communities of developers, investors, users” [73].

Seins et al. [67] have proposed a new IT artifact (e.g., software architecture) development approach that combines action research and design science, namely, ADR. The ADR approach stresses the importance of the relevance cycle through explicit guidance for integrating the process of building, intervention, and evaluation in a concerted effort [67]. In the context of this study, ADR addresses two challenge areas for creating the system architecture of the AI-enabled energy platform; (1) addressing a problem situation in a specific organizational setting which is the ecosystem as an organizational form in the energy sector; (2) constructing and validating an IT artifact, that is the 4C platform architecture that addresses the issues/needs in the energy ecosystem. Thus, this paper follows the four processes of the ADR to formulate, build, reflect and formalize the AI-enabled energy platform as an artifact. This means that the aim of the research is to generate theory and a framework with the help of empirical data, rather than the deductive approach that uses hypothesis and theory testing based on stringent empirical data [74].

This study is built on two large-scale research projects, including the EU P2P-SmartTest European Horizon 2020 project [75] and the VirpaD Finnish national innovation project [76]. The EU-level P2P-SmartTest project focuses on the investigation of a more intelligent electricity distribution system through the incorporation of 5G technology, local energy markets and novel business models for future power grids. Peer-to-peer (P2P)-based distributed smart energy grids have the capability to integrate
multiple sources of distributed renewable generations at the local level, such as the microgrids. Such an approach can provide qualitative and quantifiable value from tremendously enhanced interaction and integration of the ICT technologies and energy networks at the systemic level. Furthermore, regulatory, standardization and commercial frameworks are proposed to enable distributed energy trading and market design (e.g., through the P2P platform).

The VirpaD project focuses on the digitalization of building and energy services. This project is under the umbrella of the Finnish national research and innovation project that promotes the utilization of IoT, the sharing economy ideology and AI to develop digital platforms in the built environment (e.g., smart buildings, energy efficiency). The project provides and supports the creation and operation of digital platforms that are enabled by big data and AI algorithms. Furthermore, the VirpaD project provides the inputs of how an AI platform can be designed and what are its capabilities at different levels/layers of the platform.

Following the ADR logic, this research involves two main stages and four specific processes. The first stage was to review the existing digital architectural design and models of platforms in the two research projects. The data was collected from the platform development and engagement workshops with a stakeholder engagement approach [77]. The workshops involved multiple stakeholders that participated in the projects, representing energy utilities, energy service companies (ESCO), ICT and telecommunication operators, consumers/prosumers, regulators and so on. Moreover, the project technical reports and relevant project deliverables were collected and utilized. The P2P-SmarTest project provided the inputs and models of the distributed energy market design, while the VirpaD project provided the digital platform architecture with AI integration. The second stage involved the use of the ADR approach [78–80] with four specific processes that enable the mapping and reconciliation of the platform design into one model, the 4C systemic model that is presented in detail in the next section. This action design-oriented approach is an established approach both in the information system and organization research domain.

Process (1) Problem formulation: in this process, the research focused on conceptualizing the formulated problem, which is the focal research question of this study: what is the potential of AI-enabled system architecture for the future energy markets? In particular, this question was posed to address the two challenges stemming from (1) incorporation of massive renewables that are integrated into the grids and create new operational, technological and economic challenges for the future energy market and; (2) an emerging shift from the utility-centric model to a consumer-centric model. As the World Energy Council [81] addresses, the dynamic consumer-centric energy utilities are 85% more likely to outperform their peers with respect to the rate of profitability growth, yet only 14% of energy companies today are in this category.

Process (2) Building and intervention: in this process, the research involved multiple stakeholders in the energy industry. Ecosystem actor workshops were organized that focused on the creation of the energy and AI platform architecture. The same 4C framework was utilized in both P2P-SmarTest and VirpaD projects, where the P2P-SmarTest project focused on a decentralized energy market as the context and VirpaD project focus was on the AI-enabled platform in smart building context (including building energy consumption). As suggested by [67], this process involved reciprocal shaping and concurrent evaluation.

Process (3) Reflection and learning: this is a continuous process and parallels the first two stages as suggested by Sein et al. [67]. This process involved iterative cycles of conscious reflection on the problem framing and the theories chosen to reach the target model or architecture as the conceptual outcome. In this process, the researchers had in-depth queries and discussion on the platform architecture from process 2 with energy ecosystem actors involved in the project and workshops.

Process (4) Formalization of the learning: in this process, the research formalized the results of the study to cast the artifact instance into the artifact class or a more generalized model. The architecture design outcomes (instances) of the P2P-SmarTest and VirpaD projects were cast into a more generalized 4C architecture. Furthermore, the study also used secondary empirical cases to validate the architectural
model developed. The empirical case information was collected from the industry reports, industry news media, case company websites and public reports as secondary data. It is of importance to note that the cases included in the invalidation step are only to demonstrate the explainability and usability of the proposed model. The cases are not from an exhaustive list of empirical companies.

3. Results

This study adopts the system architecture thinking and ADR approach for the design of the AI energy platform. Thus, the results are presented and discussed by focusing on the three key constructs: the structure, the behavior and components, and the view of the system [82].

3.1. System Structure: The Architectural Framework of the AI Energy Platform

The platform architecture may also define the business/market layer from the Smart Grid Architecture Model (SGAM) [83]. SGAM has three dimensions: domains on the x-axis (Generation, Transmission, Distribution, Distributed Energy Resources, Customer premises), Zones of ICT-based control systems on the y-axis (Process, Field, Station, Operation, Enterprise, Market), and the Interoperability layer on the z-axis (Components, Communication Information, Function, Business). Therefore, the AI platform architecture contributes to enhancing the smart grid platform as it exists at the moment to integrate the high penetration of renewable energy sources. From this point on, the business layer [84] is, therefore, decomposed into four layers, those from the 4C framework in Table 1 below.

| Layer  | Description                                                                 |
|--------|-----------------------------------------------------------------------------|
| Commerce | The information and communication technology (ICT) solutions that provide all stakeholders with an application or marketplace for trading alternative connectivity solutions, content or context data. |
| Context | The ICT solutions that provide data and information-related contextual-based services. |
| Content | The ICT solutions that provide any data, information, and content that the users would want or need. |
| Connection | The connectivity-related solutions to connect one or several networks. |

The 4C systemic framework is applied in various empirical-inspired digitalization studies [68,69,85], which is used in this study as the foundation for theory and framework building. The framework has been used in value-related research in smart energy and the smart grid. The framework encompasses four types of value typologies in a digital system (e.g., smart energy and renewable system): connectivity, content, context, and commerce (as shown in Table 1). The 4C framework resonates with the SGAM architecture as the formal system model in the EU. The framework connects the service logic and value-based provisioning and utilization [85] within the focal ecosystem.

Each of the 4C layers is formed from the smart grid architecture and shall integrate the different actors within the value chain of the smart grid infrastructure. Therefore, the AI platform is transversal between the energy actors but also throughout the domains and hierarchical zones of the smart grid. In the 4C framework, the content and context layers are particularly relevant to the field of AI as data and contextual-aware services from these two layers are empowered by the technological infrastructure. For instance, AI and more specifically deep-learning technologies have been used for price prediction for intra-day trade in Nordpool (the Nordic regional energy-trading platform) based on the research of [86]. The simplified conceptual framework developed and utilized in this study is shown in Figure 1 and the detailed interconnection and integration between the 4C framework as the business/market layer of the SGAM are presented in Figure 2.
From a technology perspective, the computation value of a digitalized ecosystem is realized through the integration of AI technology and algorithms into the existing ICT systems. In particular,

**Figure 1.** The simplified overall conceptual framework of the study.

**Figure 2.** Integrating the 4C framework within the smart grid architecture model (SGAM).
From a technology perspective, the computation value of a digitalized ecosystem is realized through the integration of AI technology and algorithms into the existing ICT systems. In particular, the AI algorithms are developed and trained through various frameworks (e.g., TensorFlow, PyTorch) and hardware and software computation resources. Building on top of the establishment of network connectivity and the extraction, collection, and storage of data, AI algorithms are trained to build meaningful models to enable the execution of automated tasks at scale.

3.2. System Behavior: AI Energy Platform from Market Design and Value Utilization Perspective

Conventionally, a “simple” market model suggests that the business model is to facilitate the value created in the market to flow from providers to users through a central entity as the aggregator. The concept paves the way to the simple platform model proposed by [58]. The platform models can be two- or multi-sided platforms that connect the heterogeneous groups of value providers and value users through market mechanisms such as matchmaking and bridging [87].

The work of Gandia and Parmentier [65] describes the design of a digital platform from the value utilization point of view. The platform operators normally need to subsidize one side of the platform such as the platform service users [65]. In a multi-sided platform, the end-user may consume the product, service or other value that is created and provided by the other actors on the platform while producing value to other actors. Furthermore, a multi-sided platform can bridge a variety of user groups to interact with each other and create positive network effects [88]. Expanding this stream of design for the AI platform market led to the incorporation of the work from Milgrom and Tadelis [37] that focuses on how AI can impact generic market design in two major ways.

First, AI can promote trust in digital marketplaces or platforms (hereafter, digital platform). According to Milgrom and Tadelis [37], trust is a critical issue on digital platforms, mainly due to the threat from anonymous trading and asymmetric distribution of information. Confidence and trust on different sides of the platform are essential for the platform actors to conduct transactions and form a market. The existing digital platforms use online review, feedback and reputation systems to establish digital trust among platform actors. However, Milgrom and Tadelis [37] argue that the current online reputation mechanisms potentially inflate the seller rating and do not provide accurate information for buyers. For instance, the average positive feedback for eBay merchants is about 99.4%. This can mislead the buyers to make the right choice on the platform today. AI techniques such as natural language processing can be implemented to access the online communication and provide more accurate evaluations of the quality and trustworthiness of the buyers and sellers [89].

Second, AI can reduce matchmaking friction. Existing literature (e.g., [37,90]) shows that a key deployment of AI and more specifically machine learning, for digital platform is to enhance and optimize the way in which potential actors engage with the platform through the search function. Today, search engines like Google or Bing also employ AI algorithms as their core technology provides better search result quality, enhances the matchmaking capability of the platform and provides a great user experience. The sharing economy platforms like Airbnb also utilizes AI to deliver better search results for the users from its platform to make customers happy. Therefore, on the utilization side of the platform, when the energy system and market become highly distributed, AI can impact, enhance and optimize for better user experience such as better trust mechanisms and matchmaking friction reduction.

3.3. System Behavior: AI Energy Platform from Technology Innovation and Value-Provisioning Perspective

The value-provisioning side of an AI platform is focused on the creation and development of AI functionality and capability to create value for the platform users. Here, the 4C framework is used for the AI platform as the model goes beyond the boundaries of a company and enables collaborative value creation and capture with other ecosystem actors [91] and for the joint and system-wide development of innovations [92].

The 4C concept is manifested as the stacks and layers of the platform model where lower layers serve as the foundations for the higher layers enable the commerce or electricity market trading [85].
The layered approach is similar to the EU’s SGAM model as the formal and technical-oriented model or architecture of smart grids, where there are five layers from bottom to top: physical component layer, component layer, data layer, functional layer, and business layer. Compared to SGAM, the layers in the 4C framework can also be dynamically combined and stacked to provide more versatile value to the energy system [85].

Overall, the value provisioning of the AI platform is more concerned with the creation of value by AI, for example, optimized grid operation and management (connection layer), the enhanced prediction of energy supply (content layer), load balancing (context layer) or market pricing for whole electricity market (commerce).

3.4. System View: the Proposition of an AI-Empowered Energy Platform

This study sees that an AI platform model/framework can be established as a market model of the energy industry. In such a platform, energy users and producers (e.g., consumers and prosumers) can contribute to the electricity market by providing distributed renewable energy supplies and network balancing capability in exchange for other types of value, such as a tangible monetary reward for active market participation or intangible value like environmental and social value. In this case, a multi-sided platform can be created not only for the exchange of monetary value but also to enable the market participants to capture other types of value [85]. AI can be utilized as an orchestrating entity to facilitate, optimize, manage and automate the market transactions. The increased number of market transactions and activity logs can serve as data and training input to improve the AI and algorithms (e.g., how Google uses neural networks to improve its data center operation’s energy saving). This type of AI platform builds on the existing electricity market transactions and operations that are dependent on human decision making and control.

4. Discussion

Referring to the framework in the previous section, the mapping of the AI platform model and validation of such an architectural model are discussed in this section. The initial mapping of the AI platform architecture is shown in Figure 3.

![Figure 3. How AI can impact the value provisioning and utilization on the energy platform.](image-url)
4.1. Using AI to Enhance Value Provisioning on the Energy Platform

AI has demonstrated its effectiveness in the smart grids in renewable integration. At the connection layer, AI can support artificial neural networking and scheduling for the electric grid and network operations such as optimal dispatch, network reconfiguration, and maintenance schedule. According to Ramos and Porto [2], a number of AI techniques such as artificial neural networks or fuzzy systems are frequently used to solve the issues related to these operation areas.

At the content layer, AI can provide enhanced energy supply and production. For example, GE utilizes intelligent algorithms to improve and optimize the operation of wind turbines. Furthermore, when massive nodes of renewable supplies are connected to the grids, AI can perform well in the areas of diagnosis and control. For example, intelligent tutoring systems are trained and experimented with by utilities to improve network control [29].

At the context layer, contextual information and data can provide input to train AI models for load and demand prediction [93] as load and supply predictions are not only used by the traditional energy utilities.

At the commerce layer that relates to market trading, fuzzy logic has been implemented to provide price forecasting for electricity markets. Moreover, deep learning as a recently popular technique is utilized in cross-border electricity trading and price prediction [86]. The study of [94] shows the progress in using AI algorithms to assist distribution system operators (DSO) in managing high levels of renewables on a local flexibility trading market.

4.2. Using AI to Enhance Value Utilization on the Energy Platform

Based on the framework of the research, a number of areas that AI can impact on the utilization side of the smart grids and renewables are identified.

First, similar to the market price prediction on the commerce layer that is mainly used by the energy utilities, aggregators and balancing service providers in the electricity market trading today, AI can provide similar data, information, and prediction for the consumers who are on the utilization side of the platform at the commerce layer. Moreover, the energy-intensive industry branches could use AI to schedule processes based on their energy intensity to maximize profits and minimize costs.

Second, as proposed by Milgrom and Tadelis [37], a potential use case of AI in the context layer is to enhance the way potential consumers interact with the digital user interface to search for products or services provided by the platform. In our case, it can be the renewable trading products and other energy services provided on a digital energy platform in the context layer. Moreover, there is also a market for storage capacity. Apart from providing emergency reserves in the intra-day market, there is also a vision that electricity consumers could not only buy battery power from public facilities but also sell.

Third, at the content layer of the value utilization, AI can improve and transform the trust mechanisms of today’s digital platform (e.g., at the content layer). As mentioned previously, natural language processing can be used to extract semantic information and meaning from the platform actors’ communication messages in order to provide better insight into the trustworthiness and quality of the platform actors so that it enables better use of the energy platform at the commerce layer. From a technical perspective, the study of Chui et al. [95] introduces a novel approach, the genetic algorithm support vector machine multiple kernel learning (GA-SVM-MKL) algorithm to detect 20 types of home appliances with improved accuracy of 7%. Such an application can support better optimization of home energy use at a more granular level.

At the connection layer, AI can be connected with other technologies such as blockchain to promote trusted and automated connections that enable advanced market matchmaking and transaction on other layers. By integrating AI, smart contracts and distributed-ledger technologies, there is potential to bridge the exchange of excess renewable generation, storages and electric vehicles (EV) through automated matchmaking with little or no human intervention, which can be a game-changer for tomorrow’s electricity market [38].
4.3. Validating the Platform Model with Empirical Cases

Based on the action design approach, this study includes a validation process on the proposed system architecture with the empirical cases collected with desk research. The findings from analyzing the empirical cases are two-fold (Figure 4):

- **First**, the existing empirical cases resonate with the initial argument of the paper in that the AI applications in energy are rather narrowly focused on a specific use-case domain. However, these cases can be mapped with the 4C framework on both value-provisioning and utilization sides. Second, there are emerging companies that have adopted the platform model to develop an AI-enabled energy platform, a platform that spans two or three layers within the 4C framework. Although these cases do not fully cover the whole 4C framework, the empirical results demonstrate that the 4C framework can be used to analyze and explain the architectural design of an AI-enabled energy platform in practice.

On the value-provisioning side of the framework, a number of examples show that AI has been applied at different layers. The context layer can be associated with supply prediction. Xcel, as one of the largest energy suppliers in the US, is utilizing AI technology in Colorado to address weather forecasting challenges. AI-based data mining approach is used to create in-depth weather reports with high accuracy. Xcel’s system collects data from local satellites, weather stations, and wind farms to identify data patterns and make predictions to better inform the company’s planning decision in terms of energy supply [96]. Google as an ICT and AI giant has used machine learning to make predictions for wind farms. For instance, Google’s London-based subsidiary DeepMind has utilized its own AI system to forecast wind-farm production. DeepMind can predict wind power output 36 h ahead by using DeepMind’s neural networks [97].

At the content layer, GE has used its Predix platform to optimize GE’s wind-farm production. The platform can integrate data from different sensors from the wind turbine and performs detailed analysis to predict production and operation failure in the machine before it happens. Furthermore, the Predix platform can also optimize a collection of wind turbine assets to maximize the electricity product output [96].
At the connection layer, AES (an energy company that has 36 gigawatts of energy capacity in 17 countries) has been developing advanced neural networks, natural language processing, and machine intelligence. The key application area of the AES’ AI is to improve the awareness, efficiency, and maintenance of the electric grids that connect the company’s solar and gas generation assets, as the so-called “preventative maintenance” for grid operations [98].

On the value utilization side of the framework, several new AI companies have emerged in the energy market. PowerScout [99] is a California–based startup that can be considered as providing the solution for the consumers on the commerce layer of the 4C framework. The company uses AI and machine learning to improve consumer awareness and participation in the energy market. PowerScout utilizes industry data and AI to demonstrate potential savings on power costs for the consumers. PowerScout’s AI platform collects data from over 100 billion data points that are connected to 45 million households. The data is collected from several sources and predicts whether or not a given household should be investing in solar energy and helps the solar installers to match with the potential buyers.

At the content and context layers, GE has been focusing on utilizing AI to optimize how electricity flows out of batteries and points of consumption [100]. Grid4C and Landis+Gyr (one of the leading smart meter manufacturers) have formed a partnership to provide utilities with granular real-time predictions and actionable insights for operations and customer-facing applications. The so-called “AI grid edge” solution is the core technology that enables the applications to achieve granular load forecasting as well as optimization for the distributed energy resources for home energy management at the appliance level. The new application can predict and detect faults in both grid assets and home appliances and can be used to reduce peak demand at consumer home premises [101]. These cases demonstrate that AI technologies are actually used for demand-side management at consumer locations.

In addition to the empirical AI applications that are focused on a single layer within the 4C framework, the research has also identified a breed of emerging AI platforms that span multiple layers of the framework and resemble the platform architecture proposed in the paper.

C3.ai [102] is an AI-as-a-Service (AIaaS) platform that enables the utility companies to utilize a variety of data sources (from the grid operations) that underpin AI and machine learning algorithms to optimize grid asset management and forecasting systems, enhance the energy efficiency, and enrich customer service engagement with real-time predictive insights. C3.ai’s AI energy platform offers solutions that can cover several 4C layers: (1) at the commerce layer, C3.ai has the software solutions for digital customer experience and customer segmentation and targeting; (2) at the context layer, the platform offers energy-management analytics to reduce utility operation costs and enhance operation via real-time tracking, analytics, and optimization. AI techniques are used to provide more accurate forecasting and enable more effective demand response; (3) at the content layer, the C3.ai optimizes DER management by integrating real-time energy data across systems and sensor networks. The platform can enable secure API (application programming interface) to access various data for a utility’s grid edge control and operational platforms. With the AI algorithms, the C3.ai platform enables the management of distribution asset capacity constraints and mitigation of active and reactive voltage issues; (4) at the connection layer, the C3.ai provides predictive maintenance that can estimate asset failures in advance for the generation, transmission, and distribution systems. Both supervised and unsupervised learning algorithms are used to process the data streams from sensors, SCADA (supervisory control and data acquisition) systems, and asset management systems to identify anomalies and predict malfunction probability of the assets.

Another empirical case is Verv [103], which is an AI energy startup that integrates AI and blockchain: (1) at the connection layer, the company’s device is connected directly to the smart meter in a home. Through the hardware device, Verv’s platform then monitors the whole electricity usage of the consumer premises. Verv’s device has a “sample rate” that is up to 5 million times faster than a typical smart meter [103]. This is known as high-frequency data which allows the Verv device to gain more detail from the electricity mains.; (2) the content and context are interconnected in Verv’s case, where the collected high-frequency electricity data allow the AI algorithms to recognize the
household appliances via their unique energy signatures, eventually identifying new appliances in consumer homes and providing smarter insights into usage patterns. (3) At the commerce layer, the company builds a blockchain-enabled electricity trading platform that enables P2P energy trading. The households can sell the excess solar generation directly to other consumers/prosumers through the matchmaking mechanism provided by Verv Trading. This approach helps provide low-cost electricity for the consumers without solar panels and more return on investment for the prosumers who have solar panels installed.

Overall, based on the outcome of the validation, the proposed platform model demonstrates the expandability of the empirical cases. On one hand, the proposed model shows that the stand-alone and hybrid empirical AI applications can be mapped on the architecture model at all four layers and two sides of value provisioning and utilization, except for the connection layer on the value utilization side. On the other hand, the results show that there is a gap between theory and practice. The AI energy concepts are developed ahead of the empirical cases that can actually implement. This is particularly true for the value utilization side of the platform. For example, there is no empirical case on automated trading at the commerce layer for consumers. However, Fortum as a Nordic energy supplier is providing the Nordpool spot market price for the electricity consumers today. There is potential to incorporate AI-enabled pricing prediction for the consumers and prosumers in the future.

The enhanced matchmaking (context) and platform trust (content) enabled by AI are missing. However, the ICT and eCommerce literature suggests that AI algorithms can be used to optimize and generate highly relevant results and reduce search friction and cost to the user [37] in other empirical cases. Currently, there is no massive energy platform like Amazon for eCommerce platforms or Airbnb for home-sharing platforms, which means enhanced matchmaking and search friction reduction is not critical at the time of this paper as the energy platform has not reached a critical mass to demand these functions. However, technology is mature enough to provide such capability. For instance, Google receives more than 63,000 searches per second on any given day, which is equivalent to 5.6 billion searches per day [104].

5. Conclusions

In the ever-increasing pace of renewable integration and the adoption of smart grids as the next generation of the energy system, the integration of massive distributed energy supply and resources is the key. Evidently, AI technology can tackle many of today’s energy-system challenges that have numerous non-linear and high-uncertainty issues.

The literature used in the paper represents two streams of scientific research, the energy market design literature and the information system literature. Our key contribution to energy market design is to use introduce platform thinking for the AI-enabled energy market. The platform is a well-established concept and theory in energy economics. For the information system literature, we bring in the business model perspective as the information system comprises the operation process and business process. Even though platforms and data have been related to both research streams, existing research has not incorporated both streams to investigate AI as a general-purpose technology [9] that can enable and influence the technical and market architecture of the energy platforms. It is key to distinguish that this paper focuses on the system architecture of the energy market, while deriving mathematical modeling is not within the scope.

Above all, a consumer- and prosumer-oriented electricity system architecture enabled by AI technology is becoming a crucial area for the energy sector and energy market worldwide [105]. A more autonomous, optimized and flexible design of an energy system can be enabled by AI technology that is supported by the advancement in big data, IoT technology as well as computing technology. Multiple studies show that AI can improve the operating efficiency, reliability and intelligent ability of the energy system. Overall, AI is expected to be one of the means to develop security, economy, and reliability of the power industry.
The key contributions of the study are as follows. First, the study proposes a new energy system/market design architecture that is enabled by AI and big data. AI techniques have been tested, experimented upon and proven effective in numerous technical areas of smart energy systems and renewable productions. However, the lack of a holistic view of how these AI techniques can be integrated from the energy system perspective has been missing. This study tackles this issue by utilizing the 4C framework that has earlier been used in the ICT and energy ecosystem studies [69,85]. The end results show how AI technologies can be integrated into various parts of the energy system architecture.

Second, through the proposed platform model, the study identifies the research gap that the current AI and energy studies have been focused on narrow AI applications. This paper discusses the possibility of an AI platform that can incorporate, coordinate and manage different AI applications so that to create extended value for a complex system of the energy industry and market. The study introduces platform thinking to AI and energy research, suggesting that an AI-empowered energy platform or marketplace can be a potential solution for the next-generation energy systems for the incorporation of massive distributed renewable resources. Companies like Google, Amazon, Airbnb have proven that AI has the capability to manage and automate a digital system and platform that can go beyond human limitations e.g., by handling tens of thousands of research queries per second without compromising the resulting quality.

Third, the advantage or benefit of using the platform approach is to see how extant energy research has focused on value provisioning for the energy systems. This is largely due to the fact that the legacy energy systems are built on the paradigm of centralization and where the energy supply chain thinking is dominant. Platform thinking brings forward a perspective shift to help us see not only value provisioning but also value utilization in the electricity market. Thus, coordination and optimization can and should take place on both provisioning and utilization sides of the market. This inspires us to see AI’s capability on the utilization sides of the electricity market in cases such as enhancing market trust, reducing research and matchmaking friction and cost to the market participants. It is important to note that AI’s capabilities on the value utilization side are not only limited to the areas discussed in this paper. In fact, this research encourages future research to explore and discover more on the utilization side of the energy platform to enrich energy research and literature.

The limitation of the study is that it is built on secondary data and is inductive research. AI platform thinking is a novel concept that steers us towards the future energy industry and new AI technologies, and applications are still emerging. The paper focuses on concept development and proposition rather than validation. It is recommended for future research to utilize the deductive approach to survey and collect more empirical case studies to further test and improve the framework developed in this study.

This paper contributes to how AI can be combined with platform thinking to develop a holistic view on the AI energy platform. We argue that this is a potential model and design for the future and for more distributed energy and electricity markets. In addition, theoretical research and the practical application of AI in energy markets are further encouraged. For instance, a more holistic energy system comprises more than just renewable electricity exchange, it also includes services targeted at smart cities, industries, and transportation among others [95]. From the geopolitical perspective, with the increased share of renewables entering the scene of electricity and the energy market, tough competition will be faced by traditional powerplants and utilities to stay profitable, although baseload power will still be required. Therefore, there is massive potential for the use of AI technologies today and in the future for a regional market beyond country borders, such as the pan-European energy and electricity market.

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