Charles Darwin University

Incentive Mechanisms for Smart Grid

State of the Art, Challenges, Open Issues, Future Directions

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Incentive Mechanisms for Smart Grid: State of the Art, Challenges, Open Issues, Future Directions

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Abstract: Smart grids (SG) are electricity grids that communicate with each other, provide reliable information, and enable administrators to operate energy supplies across the country, ensuring optimized reliability and efficiency. The smart grid contains sensors that measure and transmit data to adjust the flow of electricity automatically based on supply/demand, and thus, responding to problems becomes quicker and easier. This also plays a crucial role in controlling carbon emissions, by avoiding energy losses during peak load hours and ensuring optimal energy management. The scope of big data analytics in smart grids is huge, as they collect information from raw data and derive intelligent information from the same. However, these benefits of the smart grid are dependent on the active and voluntary participation of the consumers in real-time. Consumers need to be motivated and conscious to avail themselves of the achievable benefits. Incentivizing the appropriate actor is an absolute necessity to encourage prosumers to generate renewable energy sources (RES) and motivate industries to establish plants that support sustainable and green-energy-based processes or products. The current study emphasizes similar aspects and presents a comprehensive survey of the start-of-the-art contributions pertinent to incentive mechanisms in smart grids, which can be used in smart grids to optimize the power distribution during peak times and also reduce carbon emissions. The various technologies, such as game theory, blockchain, and artificial intelligence, used in implementing incentive mechanisms in smart grids are discussed, followed by different incentive projects being implemented across the globe. The lessons learnt, challenges faced in such implementations, and open issues such as data quality, privacy, security, and pricing related to incentive mechanisms in SG are identified to guide the future scope of research in this sector.

Keywords: Smart Grid; carbon emissions; energy; renewable energy

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1. Introduction

An electric grid is a power system network that delivers electricity from power producer(s) to consumer(s). This system comprises several significant components, including generating plants, transmission and distribution lines, sub-stations, and transformers, to provide electricity to meet energy demands. Power generation can be categorized as centralized or decentralized based on whether energy generation occurs far from or close to consumption. The energy thus generated is provided to the consumption points with the help of powerlines, transformers, and sub-stations. The energy consumers include residential, commercial, and industrial consumers based on their energy needs. Conventional electrical grids are demand-driven, have a hierarchical structure, practically no storage capability, and provide only one-way electricity supply and consumption control. However, they do not allow communication between customers and suppliers of electricity, which is beneficial for the effective and efficient management of power. Several problems arise in traditional electrical grids, such as peak-time management of electricity distribution, delay in detection of failures in lane/transformer, inability to predict the electricity demand, and so on [1]. These shortcomings of traditional electrical grids have necessitated the development of a smarter electrical grid/smart grid (SG) [2].

SG are electricity networks that enable the flow of electricity in two ways and also pro-actively detect and react to several issues, as well as changes/updates in usage. They enable active participation from the customers in the grid and have self-healing capabilities. An SG system can thus collect large volumes of heterogeneous data, which often makes a system complex and difficult to manage. The use of big data analytics on the SG data helps in achieving technical, economic, and social benefits [3].

Internet of things (IoT), big data analytics, and machine learning (ML) technologies are key enablers of the SG. Through these technologies, SG can effectively predict the electricity demand, detect/predict faults in lanes, enable smart metering, optimize the grid, and react faster to challenges [4]. SG ensure the quality of the power even in case of power outages. SG also reduce carbon dioxide and other poisonous emissions during power generation, thus focusing on green energy. SG can automate the power system, sense along the transmission lines, and enable better power storage. Through the deployment of IoT sensors and intelligent devices at several locations of the power transmission, it is possible to check the condition of the network and identify problems and abnormalities in the grid [5].

Although SG can provide significant services and applications, attracting consumers/ producers to participate in several operations of SG is still a significant challenge. Consumers/ producers and grid operators may have to be provided with some incentive to improve the operations of the SG. For instance, demand response is a crucial operation in an SG, where the customers may have to shed/reduce their power consumption in peak periods to balance the supply and demand of electricity. To motivate the consumers to shed/reduce their energy consumption during peak hours, grid operators can provide them with incentives such as reduced pricing based on their energy consumption [6]. Another example is the government incentivizing grid operators who provide electric charging at a lesser price to electric vehicles (EV) by providing some subsidies or reducing taxes and so on [7]. Similarly, the producers can be motivated by providing incentives for renewable energy generation so that the emission of poisonous gases can be reduced to a great extent [8].

Hence, developing incentive mechanisms using several technologies, such as game theory, artificial intelligence (AI)/ ML algorithms, blockchain, and federated learning (FL), to motivate the SG operators, producers, and consumers of electricity plays a vital role in maintaining the supply/demand balance of electricity, optimizing resource utilization, providing a fair price to the consumers, reducing carbon emissions, and so on. Considering the aforementioned aspects, a comprehensive survey on the incentive mechanisms for SG is provided in this paper.

Even though several surveys on incentive mechanisms and SG have been carried out separately, there is no survey focusing specifically on incentive mechanisms for SG. This is the first work attempting to review incentive mechanisms for SG, to the best of our knowledge. The main contribution of this work is surveying the state of the art of different strategies for incentive mechanisms in SG. From the survey, we identify some open issues and challenges that are yet to be addressed, and then we present future directions that will motivate researchers to carry out their research in this direction. Table 1 provides a summary of the existing surveys and identification of the relevant limitations.

Table 1. Summary of existing studies.

Ref.	Year	Paper Aim	Limitations
[9]	2015	Presented a survey on incentive strategies for participatory sensing	Did not consider incentive mechanisms for SG
[10]	2016	Presented a review on incentive mechanisms for participatory sensing systems	Did not consider incentive mechanisms for SG
[11]	2015	Presented a survey on incentive mechanisms for static and mobile peer-to-peer systems	Did not consider incentive mechanisms for SG
[12]	2017	Presented a comprehensive survey on the designing of incentive mechanisms through contract theory for applications in wireless networks	Focused on wireless networks Did not consider incentive mechanisms for SG
[13]	2015	A survey on incentive mechanisms to motivate people to volunteer contributions to MCS	Did not consider incentive mechanisms for SG
[14]	2020	Surveyed incentive mechanisms for crowdsensing	Did not consider incentive mechanisms for SG
[15]	2019	Presented a survey on incentive-based schemes for privacy-preserving metering in SG	Limited scope to privacy preserving and did not consider incentive mechanisms for SG
[16]	2019	Provided a survey on game-theory-based incentive mechanisms for incentivizing the participants with consensus mechanisms in the blockchain network	Scope limited to blockchain and did not consider incentive mechanisms for SG
[17]	2018	Presented a survey on the design of incentive mechanisms for motivating the members to participate in community networks	Scope limited to community networks and did not consider incentive mechanisms for SG
[18]	2018	Presented a detailed review on privacy-preserving schemes for SG' communications	Limited scope to privacy preserving
[3]	2019	Presented a survey on the application of ML and big data analytics in SG One of the significant applications is load forecasting	Focused on application rather than comprehensive survey
[19]	2019	Presented a survey of experiences and initiatives of SG in India	Did not consider incentive mechanisms for SG
[20]	2018	Survey on SG implementation in New Zealand	• Limited scope to implementation in New Zealand • Did not consider incentive mechanisms for SG
[21]	2018	Presented a survey on SG implementations policies in Ontario, Canada	Limited scope to Ontario, Canada, and did not consider incentive mechanisms for SG
[22]	2020	Surveyed the requirements for communication in SG and also presented a review on IoT protocols for SG communication	Major Focus is on IoT protocol Did not consider incentive mechanisms for SG
[23]	2021	Presented a detailed survey on cyber-physical attack mechanisms on SG and the defense mechanisms for the same	Did not consider incentive mechanisms for SG
[24]	2018	Provided detailed survey on standards for cybersecurity requirements in SG	Focused on security rather than providing incentive mechanism in SG
[25]	2019	Reviewed several use cases of blockchain for SG	Did not consider incentive mechanisms for SG
[26]	2021	Discussed the scope of big data analytics in SG emphasizing renewable energy networks	• Focused only on information and communication technology tools for big data analytics • Did not consider incentive mechanisms for SG

The unique contributions of the survey are as follows:

- Includes a detailed discussion of SG, the various incentive mechanisms' applications, and categories.
- Presents motivations behind the use of incentive mechanisms in SG
- Discusses several technologies used to design incentive-mechanism-based SG systems.
- Discusses research projects and use cases in incentivized SG systems.

- Presents the lessons learned from these implementations and identification of challenges, as well as open issues directing future scope of research.

The rest of the paper is organized as follows. Section 2 sheds light on the background of SG, the big data life cycle in SG systems, incentive mechanisms' applications and categories, and motivations for incentive mechanisms in SG. Section 3 provides the technologies for designing incentive mechanisms in SG. Section 4 provides the ongoing research projects and use cases on SG. Section 5 demonstrates the lessons learned, open issues, challenges, and future directions. Finally, the paper is concluded in Section 6. Key acronyms used in the article are summarized in Table 2.

Table 2. Key (repeated) acronyms.

Acronyms	**Description**
Renewable energy sources	RES
Artificial intelligence	AI
Machine learning	ML
Smart grid	SG
Federated learning	FL
Distributed file systems	DFS
Internet of things	IoT
Electric vehicles	EV
Practice incentives program	PIP
Mobile crowdsensing	MCS
Renewable heat incentive	RHI
Net metering policy	NMP
Real-time pricing	RTP
Demand-side management	DSM
Data concentrator units	DCU
Meter data management system	MDMS
Advanced metering infrastructure	AMI
Solar Energy Industries Association	SEIA
International Energy Agency	IEA

2. Background

This section discusses SG, the big data life cycle in SG systems, incentive mechanism applications, and categories.

2.1. Smart Grid

Electricity is generated from various sources, such as thermal power plants, nuclear power plants, hydropower plants, and other RES, which include solar parks and wind parks [27]. The sources of energy generators are termed "producers". In the present electric grid system, the generated electricity is consumed by the group called consumers, including actors such as industries, factories, and homes/societies. The electric grid can accommodate these two actors in the system structure, and the flow of electricity is unidirectional.

Figure 1 provides an overview of the actors involved in the SG's environment. Prosumers in the SG are capable of both producing and consuming energy. Prosumers could produce energy utilizing solar panels, EVs, and wind turbines. The energy flow between the grid and the prosumers is bidirectional. The excess energy produced by the prosumers through solar, wind and thermal sources is sent to the grid. Therefore, the grid is expected to be smart to accommodate the operations to reflect the quantity of energy generated from the individual prosumers, geographical locations, and intermittent power generation, and to cope with the new forms of load. The SG can accommodate this third actor in the system infrastructure. SG not only encourages a two-way energy exchange but also transfers data between the actors [28]. The data transferred includes information about the natural load that the consumer requires regularly. The amount of energy consumed by the consumers during the daytime will not be the same as during the night. Similarly, the load utilized at homes during the summer season is higher than in the winter. Therefore, under certain circumstances such as seasonal/climatic changes or shifts in a day, the consumption load may vary accordingly. However, the energy producers are assigned a threshold point, and despite the varying load consumption by the consumers, the energy generated from various sources, such as nuclear and thermal power plants, remains constant. Deploying SG allows the producer group to know the actual energy required by the consumer group and thereby generate the required energy only. The required data from the consumer group is collected from electrical appliances, smart meters, and EVs through appropriate sensors [29,30]. The collected data can be used for informing the SG infrastructure, to understand the home/society load, appliances' electricity usage pattern, and the power on/off condition of appliances [31,32]. The concept of a home area network/wide area network (HAN/WAN) is used to acquire real-time data from electrical devices. Moreover, consumers can benefit from making smart decisions based on the acquired data. To prepare for the rapid de-carbonization requirement and various awareness programs, incentivizing the appropriate actor in the system is essential. The necessity to incentivize the actors in the SG is discussed in this section. In the heating sector, the burning of fossil fuel technologies is replaced with renewable heat generators and producers. To motivate this activity, the renewable heat incentive (RHI) of Great Britain has introduced incentive schemes for domestic and non-domestic energy producers [33]. RHI incentivizes additional income for every unit of heat produced by the domestic/non-domestic producers.

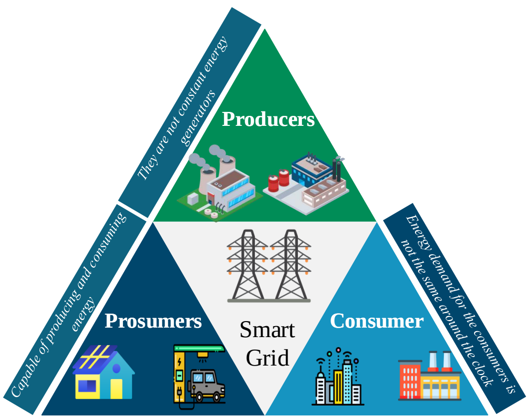

Figure 1. Actors involved in SG environment.

Among the three models available for participating in the energy demand/supply process, feed-in tariff (FIT), net metering policy (NMP), and energy auction, NMP is adapted in India by various states. One of the significant advantages that common users can enjoy is that the model offers consumers the privilege of comparing energy pricing and choosing their energy supplier. Additionally, in this model, the prosumers could sell their excess energy for more incentives than in other models. In another example, the Government of India is encouraging consumers to generate RES so that the excess energy generated can be sold through bidding [34]. Kappagantu et al. noted the fact that SG are a high-capital investment [35]. Besides such huge investments, stakeholders and investors need to be identified and incentivized. In developing countries like India, replacing the existing technology with new technology might burden the economic and financial situations of the nation and individuals. A lack of awareness of the technology and fear of a hike in electricity charges, new tariffs, and other health-related issues hinder the successful deployment of smart meters. Hence, along with necessary awareness programs, paying back incentives in the form of energy tokens or cash coins to the organizations, utilities, and individuals are the predominant elements to promote smart meters. Many countries have meticulously formulated regulations and policies concerning SG, which would make the stakeholders actively participate in the energy-generating and selling platform.

Tao et al. have put forth real-time pricing (RTP) mechanism as a way to incentivize efficient energy usage [36]. In line with this discussion, the authors also support the need for motivating incentive policies.

Energy producers such as RES are not constant energy generators. The energy demand of consumers is not the same around the clock. The variation in energy production and consumption leads to dynamic electricity pricing. The electricity pricing is directly proportional to the electricity demand. Hence, over a day, electricity pricing during the early morning, midday, and late evening can be low, high, and low, respectively [37]. Having the demand/price data in their smartphone, consumers can make smart decisions, such as using electric appliances [38] during morning/night and not recharging their car during peak hours [39]. These activities could be automated and are termed "self-healing systems" [40]. Whenever the demand on the consumer side is low, it will be communicated to the producer's side to generate energy accordingly.

2.2. Big Data Life Cycle in SG Systems

Big data technologies [41–43] help in the evaluation of data models and also improve data management in SG. The data sources in SG frameworks include large volumes of operational data generated in the form of electrical data from the grids, featuring the real-time and reactive demand response capacity, voltage, and reactive flow of power. The non-operational data include power quality data and reliability-related data. Apart from these, data relevant to meter usage is critical, as it helps in calculations of power usage and demand values, namely in terms of average, peaks, and delay timings. The event message data is collected from voltage loss or restoration information, fault detection, and exceptional events. Metadata organizes and interprets the aforementioned collected data from sources, namely smart meters, sensors, devices, mobile devices, mobile data terminals, distributed energy sources, intelligent devices, and various others. The integration of this data is done using advanced information and communication technologies that ensure improvement in SG reliability, efficiency, and performance. To be specific, service-oriented architecture (SOA) is used in demand systems, making data integration easier, as it can communicate using a single approach [44]. An enterprise service bus (ESB) enables monitoring, management, and divergence in the integration process, reducing cost and time. The common information models (CIM) help in achieving persistence in the case of critical data structures [45]. The messaging services help communicate data and other relevant information across various applications and servers. Data storage in SG is crucial, as it involves collecting data from dispatched data sources and ensuring delivery of data to the analytics tool in the case of accelerated input/output operations (IOPS). The data storage mechanisms predominantly used for this purpose are distributed file systems (DFS), and NoSQL databases [46]. Data analytics plays a significant role in making an SG function intelligently and efficiently. Five different types of analytics are used in SG implementations: signal analytics which is based on the processing of signals; event analytics relevant to events; state analytics, which help in visualizing the state of the grid; engineering operations analytics, which ensures seamless operation of the grid; and finally, customer analytics, which provides insight on customer data. Like any other system, big data analytics in SG is implemented in two phases. The first includes batch processing, which processes data in a particular period without response time constraints. The second is stream processing, which is performed for real-time implementations requiring low response latency. The choice of big data technology plays a vital role in achieving optimum results. Electrical companies often use multiple criteria decision making (MCDM) tools in the form of the analytic hierarchy process (AHP) model to ensure qualitative and quantitative performance [45,47].

3. Technologies for Designing Incentive Mechanisms in SG

From the existing literature, it can be seen that the incentive mechanisms for SG are designed using game theory, blockchain, and AI. This section discusses how these technologies can help design incentive mechanisms for SG and the recent state-of-the-art for the same.

3.1. Game Theory

Game theory deals with modelling strategies through which the players can make interdependent decisions by considering their competitor's decisions [48]. This science of strategies helps the player determine various mathematical and logical actions that need to be performed to reach the optimum outcome in the game. Games in game theory can be categorized into five types: (i) cooperative and non-cooperative games; (ii) normal form and extensive form games; (iii) simultaneous move and sequential move games; (iv) constant sum, zero-sum, and non-zero-sum games; and (v) symmetric and asymmetric games. Game theory provides noteworthy analytical benefits in various disciplines such as finance, military, energy, operations research, and more.

Various games in game theory can also be used to solve critical issues in the SG. Out of these, cooperation in the non-cooperative setting is best suited for designing incentive mechanisms in the SG. Players have partial or total conflicting interests in deciding the case of non-cooperative games, whereas an incentive is provided for players to act together in the case of cooperative games. SG constitutes various micro-grid elements, in which some grids may require excess energy, whereas some other grids have unused energy to share. A cooperative strategy can be applied here for exchanging energy between microgrids without requesting it from the main grid [49]. Demand-side management (DSM) is a significant part of the SG, as energy consumption can be controlled on the consumer side. Incentives can also be provided to those consumers who adjust energy consumption by considering the peak hours and using power when it is least loaded in the grid. Monetary incentives can also be provided for consumers who voluntarily shift their energy usage during the non-peak hours, thus balancing the energy load.

A scheduling mechanism based on incentives for energy consumption was proposed by [50]. The "energy consumption scheduler" is provided in the smart meter, thus enabling optimal energy consumption for every user. Smart meters are connected to both the power lines and communication networks. With the help of a flexible and appropriate pricing mechanism, the Nash equilibrium can be achieved by not deviating from the actual strategy, and by making sure that the strategy of every component is also optimal when considering the decisions made by other components. A detailed study on incentive mechanisms is carried out by [15]. Similarly, anonymous rewarding schemes in the SG were studied by [51].

A framework named "REWARDS" was proposed for assigning rewards in SG [52]. This privacy-preserving mechanism can provide incentives to consumers by assigning rewards anonymously to the token, which can be redeemed at any time. A hybrid demand response mechanism that combines real-time incentives and pricing using a 3-level Stackelberg game was also proposed. This model proved beneficial for the power grid, retailers, and users. Similarly, a demand response model based on a 2-level Stackelberg game that understands consumer–company interaction was proposed. This allows the consumers to be provided with benefits based on the power consumed [53]. In addition, a dynamic pricing model was proposed to ensure SG robustness.

Reinforcement learning algorithms can also be used for designing efficient energy trading games by providing the day-ahead details of pricing, thus enabling every player to understand strategies for energy trading that further increase average revenue [54,55]. In addition, incentive-based models from the viewpoint of grid operators were proposed. A two-loop Stackelberg game model was used by [56] to understand the interaction between different participants. The model considers different levels in the hierarchy, such as grid operators, service providers, and consumers. This incentive-based model works by the interaction between three hierarchical levels, which can help make significant demand reduction possible at the consumer end by assigning incentives based on their cooperation. The work was further extended in [57] by considering the intra-day market with demand response resources from multiple sectors. The Stackelberg approach could yield the best trading results and minimum procurement cost. Liu et al. [58] formulated a bi-level game that benefits both the consumer and aggregator by playing the game at the community level and the market level. An "energy demand partition-based market purchasing algorithm" is also proposed for solving the game formulated. Even though different games, in theory, can be used for formulating incentive mechanisms in SG, most of the research has been carried out with Stackelberg games, as they prove to be efficient in modelling decision-making problems.

3.2. Blockchain

Blockchain can be defined as a digital ledger of decentralized transactions in a peer-to-peer network. Due to the decentralized nature of blockchain, it offers various other advantages, such as transparency, security, privacy, traceability, cost reduction, efficiency, immutability, tokenization, and more [59]. Blockchain proves to be efficient in various domains, such as healthcare, SG, voting, real estate, banking, and insurance. The integration of blockchain with SG proves to be efficient in handling security, privacy, incentive mechanisms, penalty mechanisms, and standardization issues. Various use cases related to the use of blockchain have been carried out by [25]. Similarly, Mollah et al. provide an extensive study on the use of blockchain in SG [60]. In addition, Aderibole et al. surveyed the applicability of blockchain technology in SG about three important features: decentralization, incentives, and trust [61]. This section provides an overview of various research works on designing incentive schemes for SG using blockchain technology.

Incentive and penalty mechanisms are often related but complementary. Incentive schemes benefit customers by providing rewards in terms of cryptocurrency, reputation value, and carbon credit, whereas penalty schemes aid in preventing malicious activity by participating entities. Each electricity unit can be considered a virtual currency in blockchain technology. Wang et al. [62] proposed a blockchain-based energy system involving various energy trading transactions and crowdsourcing. This is carried out using a two-phase algorithm, where the initial phase focuses on grid operation and the second phase aids in balancing energy surplus or deficit using monetary incentivizing schemes. This system is implemented using the "IBM Hyperledger Fabric platform". As wireless networks can further improve the efficiency of an energy trading system, [63] proposed an energy management system for SG using wireless networks and blockchain technology. The smart contracts enabled in this system allow the producers to gain fair incentives for providing quality power generation.

A security-aware demand response management system named "ϵ-Sutra" was proposed by [64], which includes an "Ethereum-based smart contract" for incentivizing consumers as an effort to improve their energy-saving behaviour. Energy and carbon markets were also considered in a decentralized energy trading system proposed by [65]. In addition, incentive mechanisms prove to be useful in enhancing the grid connection behaviour of P2P trading systems [66]. Another breakthrough in the field was the introduction of a fully public blockchain to deal with the energy trading market [67]. A proof-of-stake consensus protocol alleviates the price gaps, thus rewarding the concerned party according to their energy behaviour. The integration of blockchain technology in the SG is still a hot research topic in energy systems, as more transparent and secure systems that benefit consumers and producers can be built using this. Figure 2 depicts the blockchain-based incentive mechanism for SG. Here, the data server publishes the task, the data owners upload their data, and the data miners verify the quality of data and the transactions. Based on the data uploaded by the users, appropriate incentives will be provided.

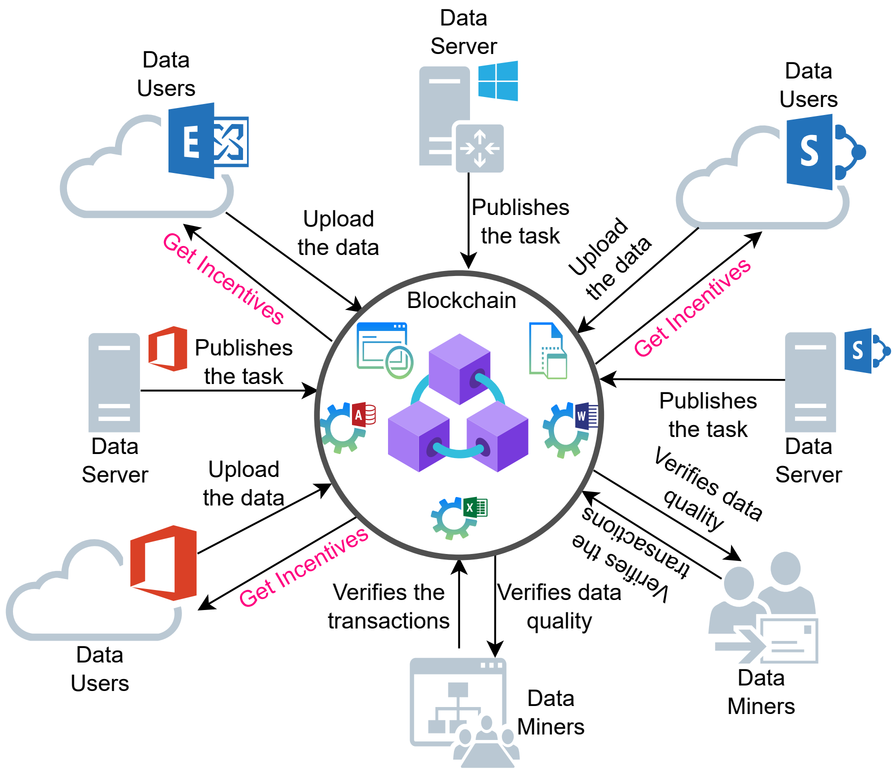

Figure 2. Blockchain model for providing incentives in SG.

3.3. Artificial Intelligence and Machine Learning

AI and ML techniques aid in developing intelligent systems [68–70]. These sub-fields of computer science, however, are not the same. AI can be referred to as the ability of machines to mimic human behaviour, thereby performing human-like activities. ML, a subfield of AI, refers to the machine's ability to learn from the data without being programmed explicitly. AI and ML prove to be efficient in dealing with various real-life applications [71].

Extensive research has been carried out in AI and ML to develop intelligent solutions for SG. Rahmani et al. [72] presented techniques for incentive-based demand response models, thereby enabling various levels of participation based on different loads. Another significant contribution was made by [73] in designing a real-time incentive mechanism for SG using deep learning and reinforcement learning approaches. This technique enables the service providers to purchase energy from their customers and thus provide incentives to deserving customers. Neural networks were used in this model to predict energy demands and prices, whereas reinforcement learning was used to identify the optimal prices considering the incentives. An extensive study on different incentive mechanisms that can be adopted for smart energy systems has been made by [74]. The study also focused on various challenges associated with implementing SG and presented a solution of contract-based systems that can enhance profit margins.

Dynamic pricing with incentive-based strategies has been presented by [75] by using potentiometers to monitor the energy load and thus enabling active participation from the customer side in reducing energy usage. The model further increases the reliability of SG to a great extent. Here, IoT and ML techniques play a major role in actively recording the customer's various activities and predicting the energy usage with which optimal decisions can be made in reducing the energy demand. In addition, Ref. [76] adopted a k-means algorithm and dimensionality reduction approaches in clustering the customers based on their energy usage and pricing during critical peak periods. An "extreme learning machine" (ELM) technique was used for clustering the energy load profiles and usages based on hourly measurements, which was then used for designing exclusive pricing mechanisms for every group using the "symbolic aggregate approximation" (SAX) technique.

Deep reinforcement learning-based models were also proposed for designing effective incentive mechanisms in the SG. One such mechanism to achieve real-time performance in the DR model was proposed by [73]. Customer diversity is taken into account while designing the incentive schemes. In addition, the service provider payments with and without demand response were studied to understand the different scenarios in the energy trading market. Another contribution was made by [77] in designing an incentive-based model that helps in maximizing the overall profits of consumers and producers, thus leading to a win-win situation.

FL techniques work by training a model collaboratively among distributed devices without the need to share the data to a centralized server. Data privacy can be ensured in SG with the help of FL mechanisms. Figure 3 depicts the FL-based incentive mechanism for SG. Training the data is carried out locally in the respective stations, and the result will only be shared with the cloud server. The parameters thus obtained can be used for global model updates. Appropriate incentives will be provided to the consumers based on the data obtained in the cloud server. A mechanism for privacy-preserving energy data sharing using edge-cloud collaboration was proposed by [78].

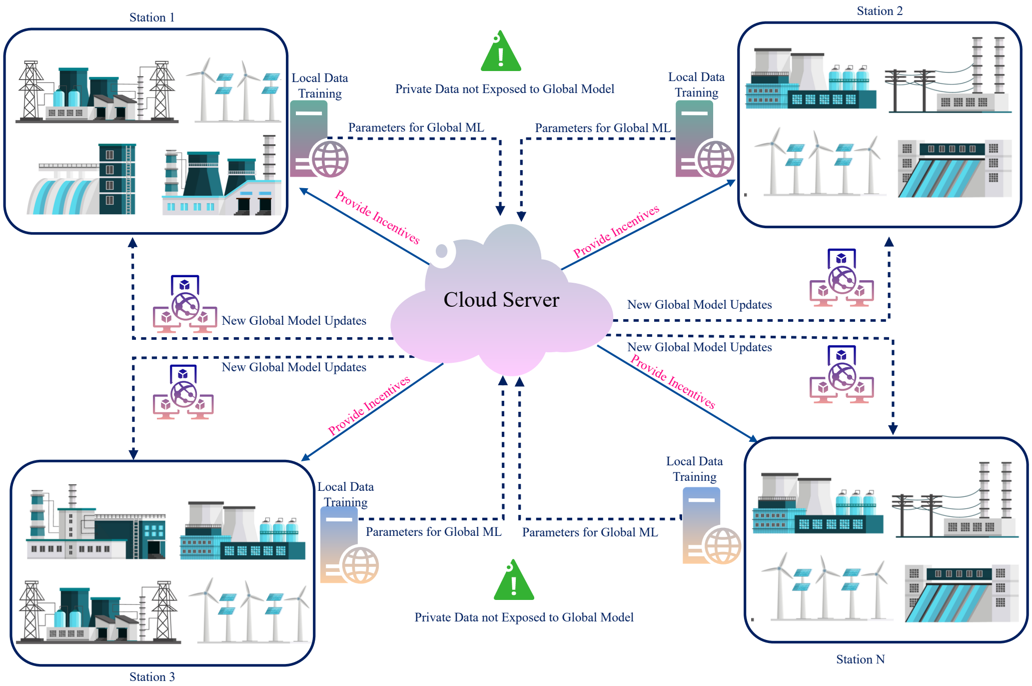

Figure 3. FL Model for providing incentives in SG.

To guarantee high-quality model collaboration, an incentive-based algorithm is also proposed. Biudko et al. [79] used FL techniques to collaborate efficiently in an energy-data-sharing environment. In addition, an incentive-based approach was proposed using reinforcement and deep learning approaches. Similarly, [80] proposed a mechanism for sharing the knowledge obtained from local data using FL approaches. The authors in [81] proposed a privacy-preserving approach based on FL. Here, an embedded incentive mechanism is employed for function encryption. In another interesting work, Lim et al. [82] proposed a task-aware scheme based on incentives for application in smart industries. Workers are rewarded based on their work, making it reliable for dealing with real-time applications. Literature shows that AI and ML models play a significant role in designing effective incentive mechanisms for SG, as the model can also be trained for big data sets, thus increasing the overall profit of customers and producers.

A systematic literature review approach is followed in this work to provide an overview of designing incentive mechanisms for SG. The relevant works were selected from reputable publishers such as IEEE, Elsevier, MDPI, Wiley, Springer, ACM, and reputable ranked conferences by searching in Google scholar. "SG AND Incentive mechanisms AND Game theory", "SG AND Incentive mechanisms AND Blockchain", and "SG AND Incentive mechanisms AND AI" were the search queries used in this work to retrieve the relevant peer-reviewed articles. The papers collected were screened based on their readability and quality. A summary of various enabling technologies for designing incentive mechanisms is provided in Table 3.

Table 3. Enabling technologies for designing incentive mechanisms in SG.

Technique	Ref.	Year	Contribution	Limitations and Challenges
Game Theory	[49]	2012	A cooperative game strategy is applied for exchanging energy between microgrids without requesting it from the main grid. This paper also provides an overview of the various applications of game theory in SG.	Addressed only three areas: microgrid systems, DSM, and communications
	[50]	2010	The energy consumption scheduler provided along with the smart meter enables optimal energy consumption. A distributed incentive mechanism is employed here.	Multiple energy sources, total daily energy consumption, and energy storage can be considered
	[83]	2021	A three-level Stackelberg game is used for modelling a hybrid demand response scheme that combines real-time incentives and pricing.	Different types of service providers in the different consumer/producer environments can be considered
	[53]	2018	A two-level Stackelberg game model is implemented for designing demand response models, where benefits can be provided based on the power consumed.	Can consider time-dependent pricing design
	[57]	2018	A resource-trading framework is presented from the point of view of the grid operator. The Stackelberg model could understand the interaction between different actors.	Renewable energy resources can be considered; ancillary services such as regulation services can be provided
	[58]	2015	A bi-level game model that benefits the customers and aggregators using community-level and market-level games is proposed.	Multiple energy sources, service providers, and customer needs to be considered

Table 3. *Cont.*

Technique	Ref.	Year	Contribution	Limitations and Challenges
Blockchain	[62]	2019	A framework for crowdsourced energy systems is proposed. A two-phase algorithm is also proposed that manages the distribution network while the crowdsources are being incentivized.	Distributed consensus mechanisms for the SG using blockchain can be considered; different types of threats also need to be dealt with
	[63]	2020	An incentive mechanism with smart contracts employing wireless networks is proposed. This enables the producers to be automatically paid with the incentives.	Different types of renewable energy resources can be integrated into the model
	[64]	2020	An ESC-based incentivizing mechanism for rewarding consumers, with the help of ϵ-Sutra scheme, is proposed.	Dynamic pricing techniques can be included in the system
	[65]	2019	A decentralized energy and trading scheme with a monetary incentive mechanism is proposed	Long-term investment in low carbon technologies can be considered
	[67]	2021	A PoS public blockchain that reduces energy gaps and thus rewards the consumers and producers is proposed.	Can be used for the distributed control of energy systems
AI/ ML	[72]	2016	Incentive-based and price-based demand response non-linear models are studied and implemented in different power markets.	Multiple energy sources can be considered
	[73]	2019	Considers the profitability of consumers and service providers in designing incentive schemes. Uses reinforcement learning for optimal incentives.	A technique for choosing the optimal weighting factor can be formulated. Multiple service providers and grid operators can be considered in the model
	[75]	2021	Dynamic pricing and incentive mechanisms are used in this demand response model.	Time-dependent pricing schemes can be considered
	[76]	2017	Customers are categorized based on energy usage and pricing during critical peak periods. The "Symbolic aggregate approximation (SAX)" technique was used for the pricing design of various groups.	Producer-based models can also be incorporated
	[77]	2020	A modified incentive-based demand response model that helps in increasing the overall profit of customers and producers is proposed.	Different types of customers, providers, and energy models can be considered
	[78]	2021	Each energy service provider uses DQN to develop the best payment model. An edge-cloud-based FL approach and a DRL-based incentive algorithm are used here.	Blockchain-based models and DP-based gradient perturbation can be considered

4. Research Projects and Use Cases

In an SG, there exists a need to meet users' ever-growing demands, and hence upgrading the power system by increasing its capacity becomes an absolute necessity. However, the inevitable consequence is an under-utilized power system, which leads to the wastage of money and resources. The normal generating capacity should be utilized efficiently and optimally to ensure sustainable development, which is possible only by implementing DSM techniques. The DSM technique is a tool for efficiently redistributing energy as per the demand over a specific period, enabling enhanced utilization in SG instead of opting for extensive constructions. It is also important to remember the need for environmental conservation, which is hindered due to inefficient use of power in most constructions, increasing environmental pollution and wastage of natural resources. The massive fluctuations in power generations compel thermal power plants to spend unnecessarily on extra fuels during peak demands, resulting in uncontrolled emission of greenhouse gases and inefficiencies. Thus, the development of DSM techniques becomes a dire necessity to reduce the wastage of resources and environmental pollution. The smart pricing method is one such technique that uses an auction mechanism to transfer information between users and providers. This enables them to meet the energy demand of the users by investing minimal costs in grid generation. However, when the users report their energy demand, there exist possibilities of cheating wherein they consume more while paying less, creating an extra burden for grid-operated meters, as mentioned in [84]. The study records users' consumption information and communicates the same to the energy provider. The patterns of consumption and their preferences are also modelled using utility functions. The Arrow–d'Aspremont–Gerard-Varet (AGV) technique is an incentive method wherein the user's payment is correlated with the consumption credit. The users in such circumstances are punished by being charged extra if a cheat record is identified in the consumption history. This mechanism helps achieve compatibility in the incentive mechanism, balancing the budget. Both the user and the energy provider reduce environmental pollution and resource wastage. The present study has identified the industry and research projects from reputed agencies by using the search query "Research projects AND incentive mechanism AND SG". The various incentive-mechanism-based projects implemented across the globe are discussed here and presented in Table 4.

Table 4. Incentive-mechanism-based projects in various regions across the globe.

Country	Game Theory	Blockchain	ML	Projects	Description
Spain	X	✓	X	SMILE	Manages all projects in the line of SG incentives
Spain	X	X	X	Innovgrid	Smart metering project that helps in collecting data on individual consumption, collective grid demands
India	X	✓	✓	POWERGRID	Large-scale integration of renewable capacity of SG
China	✓	✓	✓	5G SG	Automation of power distribution, ensuring load control, ultra-low latency, and security isolation
China	X	X	X	Honeywell Pilot project	Ensures efficient benefits of demand response
France	X	✓	✓	Pilot Linky	Logic controller that aids in the deployment of 300,000 smart meters, ensuring interoperability
France	X	X	X	ENR Pool	The virtual power plant integrates intermittent solar and wind energy, provides financial incentives for production modulation, solves issues relevant to the integration of grids in the renewable energy sector
USA	✓	✓	✓	ARRA-funded projects	Focuses on conservation of voltage reduction methods
USA	X	X	X	SGIG Projects	Reduction of customers' peak demand, which helps reduce capital investments in peaking power plants
USA	X	X	X	Smart Study TOGETHER	Evaluation of enabling technologies in SG considering time-based rate programs, impacts on energy consumption, and peak demand
Brazil	X	✓	✓	Big Push	Focuses on better promotion of public and private investment of sustainable energies, deploys incentive mechanisms for clean energy innovation

SG Incentive Program in Andalusia: Andalusia is an autonomous and highly populous community located in peninsular Spain. Various energy planning projects exist as part of the energy plan for Andalusia 2003–2006, the Andalusia Energy Sustainability plan 2007–2013, and the latest one, entitled Energy Strategy of Andalusia 2020 [85]. The end of the validation of these previous energy plans consequentially led to the development of the Energy Strategy of Andalusia 2020, wherein SG development has been one of the primary objectives. The idea was to modernize and implement innovative projects in the region, and hence an incentive line for SG was also included as part of the sustainable energy development program. This scheme is intended to e-connect the cities and the citizens, involving all the citizens, self-employed individuals, companies, the public, and various other entities. The program focused on three aspects of support—SG, sustainable construction, and sustainable SMEs, which helped promote improvement in energy-related actions. The energy demands in the household, business, and administrations were reduced, and energy usage was optimized in the most sophisticated and efficient way [86]. The SMILE project has helped in achieving a deeper perspective on the collaboration involving stakeholders who develop the projects [87]. It manages all the projects involved in the incentivization of SG. The Innovgrid project is a smart metering project that includes 30,000 consumption points, known as energy boxes, for collecting data relevant to consumption profiles, and collective grid demands integrating consumption management capabilities with metering functionalities using data analytics. The SET-UP project provides information on strategies for addressing challenges associated with integrating distributed energy sources in existing systems and identifies a way to convert traditional networks into smarter ones. It has also created an SG working group that explores various smart electricity systems and provides concrete solutions for the development of SG for the future [88,89].

SG Project in India—POWERGRID: the far-fetched dream of developing the modern Indian power system can only be fulfilled through the deployment of SG. This would contribute immensely towards improving the efficiency of the power sector in India. The SG vision in India has the core objective to "Transform the Indian power system into a secure, adaptable, sustainable and digitally-enabled ecosystem providing reliable and quality energy for all participating stakeholders". This objective is simultaneously aligned with the government's policy to provide access, availability, and affordability of power to all without compromising quality. The Indian SG Task Force (ISGTF) has identified fourteen SG projects to fulfill its goals. POWERGRID is one such initiative that emphasizes implementing SG technology in all verticals of the electric supply chain. Open collaboration with the manufacturers, academicians, solution providers, and consultants is initiated in the distribution phase of the pilot SG project. This open, collaborative effort helps design EVs' tariffs, net metering, and deployment through various renewables. The various SG attributes have been implemented and scaled up in this sector. For example, almost 1600 smart meters have been installed on customers' premises, integrated with data concentrator units (DCU) and Meter Data Management System (MDMS) by the control center at Puducherry. The Smart Home Energy Management System constitutes smart security, and microgrid controllers have been implemented to incorporate active customer participation. The visible benefits of such implementations include improved efficiency in metering and collection. Significant improvement is observed in the billing cycles due to advanced metering infrastructure (AMI), enabling concurrent meter reading collection from the vast customer base. In addition, AMI has helped detect anomalous consumer behaviour relevant to meter tampering, uninformed shifting of meters, excessive usage due to family functions, damaged wiring issues, and erroneous meter readings [90].

SG Incentive Mechanism Projects in China: China is the world's largest market for power transmission and distribution. It is also the major consumer of SG technology. The SG market in China is large and immensely influenced by two factors. First, the commitment of China toward green development creates a need for the adoption of SG technologies. Second, the market of China reduces equipment costs due to the active role of the Chinese government. However, appropriate utilization of such opportunities requires a structured vision, supportive policies, and incentives in the SG implementation. China emphasized a supply dispatch paradigm to respond to the dire need to expand generation capacity in the early 2000s. However, due to the rapid growth in urbanization and increase in distributed power, the need for demand/supply balancing has evolved. These smart energy systems allow the government to develop incentives supporting demand-side applications for SG concurrently with supply-side developments. The 5G SG project in China helps reduce faults in the distribution line by milliseconds and reduces power consumption in 5G base stations by using peak-clipping and valley-filling strategies. The Honeywell pilot project includes demand response, advanced energy management, and sub-metering, helping consumers manage the energy supply and demand efficiently, and reducing the burden on the utility infrastructure in China [91,92].

Incentive Mechanism Projects in France: The French administration uses its revenue cap within a regulatory period of four years. The revenues are predicted for each year, including the estimation of Opex and returns on the Regulatory Asset Base (RAB). Opex's (Operational Expenditure) and Capex's (Capital Expenditure) estimations are considered distinctly. The organization takes responsibility for any deviations from the estimations, and the difference in Capex is recovered from the revenue allowances of the following years. In the case of SG projects, different schemes are implemented, and there are investments producing reductions in Capex (DSM and storage). In addition, a significantly less than proportional increase in Opex is reprimanded. This is further incentivized in the case of SG projects, wherein Opex costs more than EUR 3 million and cost overruns are recovered through subsequent adjustments in the revenue cap. As an example, the pilot Linky smart meters provide residential participation using automation. The meters include G3-PLC communication that provides hourly data, creating business opportunities in renewable energy and integration for prosumers and EVs. The ENR Pool project in France builds a virtual power plant that combines wind and solar energy to provide services to industrial customers. It provides financial incentives to industries to modulate their production during a particular time frame to resolve problems pertinent to renewable energies [93,94].

Incentive Mechanism Projects in USA: SG technologies are being deployed enthusiastically by the Department of Energy to improve efficiency, reliability, and resilience, thereby efficiently ensuring integration and optimized utilization of the distributed energy resources (DERs). The most interesting aspect of the present deployment of SG technology includes the integration of information technologies, operational technologies, cloud computing, computer networks, and related services. The IEC61850 and IEEE1547 are being implemented to achieve security and interoperability. The total investment made by US utilities towards electricity generation, transmission, and distribution in 2016 was almost USD 144 billion. Apart from this, the investor-owned utilities, which include almost 73 percent of the total electricity customers in the USA, have spent almost 21 billion dollars and 27 billion dollars on transmission and distribution-related infrastructure, respectively. These costs are likely to increase by almost 13.8 billion dollars by 2024. In this regard, advanced and structured state policies combined with favourable business incentives have initiated the accelerated adoption of DERs.

The present challenge lies in the declining cost of distributed technologies in the case of rooftop solar and EVs. This needs to be accelerated in association with robust control capabilities in the states of the USA that have high incentives and targets pertinent to renewable energy. The smart meters and advanced metering infrastructures (AMI) enable the utilities to direct price-based signals to customers, incentivizing demand reduction during peak consumption periods. The favourable policies and incentive mechanisms have also triggered growth in distributed solar and utility-scale systems. The existing policies and incentives at the federal, state and local levels prefer the adoption of renewable energy at a huge amount in various distribution system levels, which acts as a motivation to develop renewable-energy-based projects. The energy storage systems and incentive mechanisms are relatively new, but almost five states have adopted energy storage incentives and investment programs. The state of California is in the leading position and has a self-generation incentive program that has provided almost USD 420 million since 2019 to develop residential storage projects. As per the Solar Energy Industries Association (SEIA), there will be a significant improvement in costs, policy incentives, and corporate demand, leading to almost 16GW of capacity by 2022. The notable SG projects that have implemented incentive mechanisms in the USA are the American Recovery and Reinvestment Act (ARRA)-funded project, the SG Investment Grant (SGIG) project, and the Smart Study Together project [95].

Incentive Mechanism Projects in Brazil: In Brazil, the Energy Big Push Project (EBP) was initiated as part of the 17 Sustainable Global Development Goals included in the Paris Agreement and its agenda of 2030. The project focused on sustainable development, energy transition, and international cooperation to support investments in sustainable energies and related innovations. The project was proposed considering four dimensions: Axis 1, Axis 2, Axis 3, and Axis 4. Axis 1 focused on developing processes that involved collecting, structuring, and managing data pertinent to various private and public investments in research and development activities in the energy sector. Axis 2 surveyed social, economic, environmental, and technical performance indicators with the help of low carbon energy solutions. Axis 3 identified strategic policies and guidelines that helped accelerate investments in the energy sector. Finally, Axis 4 ensured the establishment of innovative and efficient communication strategies pertinent to project results specific to decision-makers. The present incentive mechanisms implemented in Brazil for low-carbon energy technology development are classified into four categories by the International Energy Agency (IEA). The four categories are as follows.

Resource push: To be successful in technology innovation in the sector, incentivizing requires consistent funding for conducting research and development activities, for skilled professionals, and for well-defined priorities that help to fill the gaps that channel innovative activities. These aspects as a whole help to push the technology forward.

Knowledge management: The incentive mechanism for innovation in the energy sector and the development of related products and services require new ideas and efficient knowledge management so that the knowledge is disseminated with the help of dynamic networks and transmitted seamlessly across the value chain, ensuring intellectual property rights are maintained.

Market pull: It is also important that innovative ideas reach markets properly at the right time. Performance-oriented market instruments, namely the quotas, standards, carbon pricing, tax incentives, and public and pre-commercial procurement, help attract innovative activities, create scope for early deployment of incentive mechanisms, and ensure new incentive-mechanism-based products and technologies achieve a position in the market.

Socio-political support: The socio-political environment acts as a seedbed for technology innovation. Energy innovation strategies involving incentive mechanisms must receive the necessary support and engagement from all relevant stakeholders, which include the customers and industry [96].

5. Lessons Learned, Open Issues, Challenges, and Future Directions

5.1. Open Issues and Challenges

Data Quality: Data quality plays a critical role in SG to facilitate all private and governmental business applications [97]. Due to the huge data generation from SG, data quality assessment and improvement remains a challenging task. Some of the key techniques to maintain data quality are record linkage, business rules, and similarity measures [98].

Data uncertainty: Data uncertainty is the subset of data quality prevailing as a significant concern in designing incentive-based SG, wherein the attributes of consistency, completeness, and accuracy contribute as important factors in decision making. However, the data set includes missing/inconsistent values and noises, leading to erroneous results when making important real-time decisions. Various factors contribute to data loss and related data uncertainties, such as noise, missing/inconsistent data, unsynchronized data, physical damage to equipment, cyber-attacks, communication latencies, sensor imprecision, sensor inaccuracies, and so on. The level of data or information availability and public trust are the key challenges in designing and adopting incentive-based SG [99]. Thus, these aspects need to be considered critically during the design of an incentive-based SG [100].

Issues such as malicious attacks interfering with the incentives of data control and acquisition or sensor aging can lead to errors in sensor readings [101] in smart grids. Data analytics and mining techniques are the predominant choices to resolve such data uncertainties. In this regard, uncertainties can be modelled as stochastic processes within given limits for probabilistic data mining and data analytics. Data pre-processing techniques should be considered when designing incentive-based SG, such as data conditioning, data integrity, and data cleaning, which can be utilized to smooth out or eliminate noise, correct inconsistencies, find missing values and resolve redundancies.

Data Security: Financial transactions, commercial secrets, and consumer privacy information are significant data security concerns [102,103]. Consumer data security issues should be considered when designing an incentive-based SG. Blockchain and FL can be used to preserve data security. Integrity is improved due to the focus given to the development of equipment within traditional power delivery systems [104]. It can be seen that the reliability of the power industry has been supported by modern communication equipment and technologies until recent times. However, cyber security concerns have emerged as critical issues for power systems due to increased connectivity in recent years. Communication and IT issues have been inclusively covered in the cyber-security of power systems in recent times. In particular, it is established that the security of power grids would help prevent, prepare, protect, mitigate, and respond to unfortunate cyber-attack events or natural disasters.

Data Privacy: SG collect data regarding the user's power consumption, as they reflect informative insights relevant to the user's behaviour, but this has associated critical privacy concerns. In addition, in some scenarios, organizations feel reluctant to share the data despite the incentives being appealing, as they remain suspicious of their non-public and sensitive data being compromised. The prominent approach used for addressing such concerns is data aggregation. In such cases, data aggregation from the consumer and service provider's point of view should be considered when designing incentive-based SG [105]. Various techniques such as differential aggregation, distributed aggregation, and storage aggregation can be considered when designing an incentive-based SG to address privacy concerns. Economic management and smart control of energy consumption require higher interoperability between the service provider and consumers [106]. Privacy invasion in incentive-based SG is likely to occur when energy-related data remain unprotected. Radio waves in AMI have the potential to reveal information about users' whereabouts and activities, making user privacy vulnerable to potential attacks. Customers and regulators lack confidence in the adoption of SG where privacy concerns are not addressed, especially in the case of incentive-based SG. To eliminate such issues, blockchain and FL can be implemented to preserve data privacy in SG.

Data Integrity: The maintenance of data and ensuring consistency in data accuracy are highly important in achieving the objectives of accurate incentive-based SG systems [107]. Data integrity is ensured by preventing unauthorized changes to users' information. Different techniques, such as cryptography blockchain, should be used to keep consumers' data protected from malicious entities in the smart incentive grid. Risks of physical and cyber-attacks are of equal concern in the power industry due to the close interdependencies between communication and power infrastructure. There are possibilities of financial transactions being modified deliberately due to these cyberattacks, which would also result in misleading the operational decisions pertinent to utility management. Data integrity can be ensured by a privacy-preserving data aggregation (P2DA) scheme using a message authentication code or digital signature in smart incentive grid frameworks. Data security techniques such as MES, blockchain, and FL can be used to preserve data security.

Data Authentication: The accurate distinguishing of legitimate and illegitimate identities can serve as the basis of authentication for designing incentive-based SG data. For example, if an illegitimate identity enters the incentive-based SG system, there exists a high possibility of errors in distributing incentives. Here, intrusion detection, trust management, and implementation of encryption techniques act as important security mechanisms for preventing, detecting, and mitigating network attacks [108]. Various techniques, namely the signature generation and data encryption, are used for security management and data authentication in SG. Grid recognition authentication can also be used to authenticate data.

Latency: Delay of data transmission between incentive-based SG components is measured by latency. As the immediate transmission of data is needed, latency is one of the key constraints, for example, in some mission-critical applications, such as non-tolerance of DR or WASA linked to HEMs or AMI latency. Therefore, minimum delay requirements should be satisfied by incentive-based networking solutions for time-sensitive applications [109]. Latency can be improved by the integration of FL and edge devices.

Bandwidth and Networking Issues: Specific roles are based on the radio frequencies in the low, medium, and high ranges for the incentive-based SG application requirements. Medium and high frequencies are generally used for communication within short distances, such as HMS. Meanwhile, when the low frequencies are compared to higher frequencies, it becomes evident that linear and non-linear objects can be easily penetrated, and line of sight problems can be avoided [110]. Issues of sensor networks, wireless networks, and the internet, in general, would come under the umbrella of potential security concerns associated with the network of SG [111]. Similar to the contemporary internet, various networking technologies could be applied for incentive-based SG, including RS-232/RS-485 serial links, 3G/4G (WiMax), land mobile radio (LMR), fiber optics, Wi-Fi, 4G, 5G, 6G, and many more. The grid environment's requirements determine the need for specific networking technology, which remains an open issue in developing communication standards for SG.

Throughput: Within a specific time interval, the total sum of data exchanged between incentive-based SG components is referred to as the throughput. The characteristics of the application determine the throughput utilization by the incentive-based SG for communication [112]. For example, the throughput needed for TLM or WASA would differ from what is needed by AMI or DR communication. Throughput can be handled by using FL, which is a distributed learning system, to boost the throughput.

Reliability: Reliability in incentive-based SG can be achieved using explainable AI. To assign the incentive, the decision must be fair and reliable. Similarly, for the timely exchange of messages in a successful manner, the specifications of a communication system determine the reliability [113]. The specifications associated with reliability would vary across different SG applications. Hence, the communication nodes need to have the reliability to ensure a timely and successful exchange of information in the incentive-based SG.

Anomaly Issues: Timely and accurate detection of an outlier, faulty devices, and anomalous events are needed for carrying out reliable operations in incentive-based SG [114]. It is necessary to review methods of error detection and methods for coping with them to deal with the faults within the power grid. It is necessary to study the models, including systematic and malicious manipulation in these systems. ML and deep learning techniques can efficiently detect and mitigate anomalies early.

Multiple Energy Sources, Service Providers, and Consumers: Incentive mechanisms for the SG are usually designed with the primary focus on rewarding the customers and the service providers [83]. However, very few research works have focused on the different types of customers, service providers, and energy sources in the SG. If the incentive mechanisms are designed based on the unique energy groups, it will benefit both the customers and service providers, thus leading to a win-win situation.

Pricing: RTP schemes can be used for benefiting the power grids, retailers, and consumers [115]. Pricing schemes can be designed by considering the preferences of the subscriber and their usage patterns. Such a time-dependent pricing scheme can be used for providing real-time incentives to the user as well. Interactions between the service providers and customers prove helpful in this scenario.

5.2. Future Research Directions

Sustainability of SG: The capabilities of data collection, communication with computers for analysis, and advising for carrying out necessary actions were added for SG systems in SGI 4.0. This self-customization, self-optimization, and self-cognition empower power grid systems to operate independently or reduce human interventions to provide quality electrical services. These mechanisms should be added during the design of incentive-based SG. Hence, close cooperation and interconnections are created among stakeholders such as customers, workers, and systems [116].

An enormous volume of data is generated in a large-scale SG by autonomous and multi-function equipment. The current approaches and environments for information exchange are not suitable for handling the increased amount of data, which has dramatically further intensified the complexity of systems, resulting in higher uncertainties. Meanwhile, regarding flexibility, reliability, scalability, efficiency, latency, bandwidth, and data rates, communication requirements for SGI 4.0 have increased. Hence, the trustworthiness of information is assured by a non-traditional ICT infrastructure in real-time, across power generation and distribution processes [117].

Need for Modernized SG: A variety of advantages are targeted in designing smart incentive grids by using advanced ICTs for intelligent electricity. These goals span reliability, security, efficiency, environmental concerns, safety, and RES [118]. Although some contributions have been made by academia to address the challenges in the smart incentive grid, there remain many unexplored issues in industry 4.0. An incentive SG paradigm offers a platform, vision, and architecture with high-quality EGD. The significant principles of smart incentive grids are service orientation, real-time capability, virtualization, decentralization, modularity, and interoperability. At the same time, the core features of SG are service orientation, electricity generation process, optimization, intelligence, self-organizing capability, secure communication, flexible adaptation, data integration, and interoperability. The cost improves with the economic benefits of the smart incentive grid, as the average energy production price is reduced. All of the above concerns should be taken into consideration during the designing of incentive-based SG [119].

Human Role and Job Opportunities in Incentive SG: Despite the automation of processes brought by SG, humans remain important for improving real-time grid performance in terms of incentive security, efficiency, productivity, and power quality [120]. Hence, improvements in the design are anticipated for engineers and workers seeking better personal, professional, social, and methodical proficiencies for achieving greater efficiency of power generation at lower costs and lower consumption of resources in the grid. Various jobs, ranging from process monitoring to machine controls, are created in SG. Higher mathematical and computer programming competencies related to various simulation tools, Internet of Things (IoT), Cyber-Physical Systems (CPS), iOS (https://www.apple.com/ca/ios/ios-15/, accessed on 6 March 2022), and web technologies are needed to design incentive-based SG. Furthermore, the smart incentive grid needs information processing, analysis, problem-solving, data management, cyber security, networks, installation, cyber hardware, and software-related hard skills. In addition to these, various soft skills cannot be ignored in terms of their importance among IT specialists in this area, such as ethical, innovative, leadership, interdisciplinary, and professional communication skills, learning capability, adaptability, and systemic and proactive thinking. Hence, a detailed analysis of the roles is needed.

Big Data: Complexity and knowledge intensification is introduced in SG by aggressive developments in CPS and IoT technologies in SGI 4.0 [121]. Consequently, higher accessibility and abundance of data emerged in SGI 4.0. Pervasive integration of radio frequency identification, controllers, sensors, actuators, web-based applications, transactional applications, and interactive servers in SGI 4.0 results in data accumulation for SG applications. The purpose of data accumulation surrounds various applications in the SG, such as demand and response, grid systems' health data, energy-use data, metering data, electricity price data, advanced control, and monitoring.

It is anticipated that with an increased number of CPS in distribution and advanced electricity generation, data will grow dramatically in SG. However, academia has overlooked an important amount of data. Hence, advanced collection, integration, processing, storage, analysis, and data presentation systems must be developed for big data, linking all the data and entities. This remains a major challenge for realizing the industrial processes of SGI 4.0.

Cloud Computing: High-performance computational techniques, along with big data mining, cleaning, and storage, are needed by the intensive data generated from IoT-enabled CPS sources in SG [122]. Cloud is a potential technology for employing service-oriented technologies, IoT, CC, and virtualization, to aid the EGD model in transforming resources into services. Cloud offers scalability and remote service access for any end-user of the SG. The cloud is currently an essential platform for offering a stable connection between the application and network layer components. Hence, the intelligence offered by the cloud has suitable potential for covering the EGD life cycle inclusively, right from the inception of its design to the testing and maintenance phase in SG. Virtualization technology in the clouds empowers CC with flexible extensions, resource sharing, and other computational layer features. Therefore, a wide range of services is offered by CC technology for users, based on application requirements such as storage, hardware, software, access to systems, and security in SG.

FL: Data privacy and data security are the two key concerns associated with data sharing. FL techniques come to the rescue by training a model collaboratively among distributed devices without the need to share the data with a centralized server [123,124]. This can be defined as a decentralized form of ML. This proves to be advantageous for SG since local energy data remains private and need not be shared, even for cooperatively training the model. After the inception of this technique by Google in 2016, various researchers have focused on FL for finding privacy solutions associated with data sharing. Even though researchers have focused on designing incentive mechanisms for various smart industries using FL approaches, very few works have focused on its specific application in SG. However, with the benefits FL provides, especially regarding privacy, this area will benefit the researchers in finding real-time solutions to the critical issues in the domain.

Power System Security: Apart from cyber security, physical vulnerabilities in the power grid must also be investigated in future studies [125]. Massive deployment of new devices will result in uncertain security, and suitable modifications in relevant standards and regulations will be needed accordingly. There is a need to develop a graph-based model combining both electrical and cyber grids to ensure the security of power grids. Cause-effect relations in cyber-attacks can be studied using such models, and further research could be done before the large-scale application of such ideas.

Accountability: It is well known that cyber security technologies can protect all levels of current network infrastructure [126]. However, for the particular framework of the SG, new risks and vulnerabilities continue to appear. Accountability is needed to ensure integrity, confidentiality, and privacy for SG. Built-in accountability mechanisms can identify the responsible elements even if a security issue exists. Such detection can help fix problems through predefined programs, while expert evaluation presents valuable information.

Table 5 presents the summary of challenges for incentive-based SG and possible solutions.

Table 5. Challenges for Incentive-based SG and Possible Solutions.

Challenge	Description	Possible Solutions (Future Directions)
Data Quality	• Many techniques have been proposed to assess and improve the data quality; however, due to huge data generation from SG, data quality assessment and improvement is still a challenging task.	Record linkage, business rules, and similarity measures
Data Uncertainty	• Data uncertainty is one of the major concerns for designing an incentive-based SG, as its attributes include consistency, completeness, and accuracy in making decisions.	Cooperative game theory
Data Security	• In incentive-based SG, financial transactions, commercial secrets, and consumer privacy information are critical security concerns. • It is critical to assess integrity, authentication, and private data security.	Blockchain and FL
Data Privacy	• User insights into the behaviour of other users can be gained through data on power consumption, and grid data present critical privacy concerns. • In some cases, data companies are reluctant to offer the data even if the incentives are appealing, as they will be cautious of their non-public and sensitive data being compromised.	Blockchain and FL
Data Integrity	• Maintaining and assuring the consistency of data accuracy is highly important to achieve the objectives of accurate incentive-based SG systems	Homomorphic signature scheme
Data Authentication	• Authentication of data preserves privacy and ensures the integrity of data. • Distinguishing legitimate and illegitimate identities can serve as the basis of authentication for designing incentive-based SG data. • For example, if an illegitimate identity enters the incentive-based SG system, there is a high chance of error in distributing incentives.	Grid recognition authentication
Latency	• Immediate transmission of data is needed; latency is one of the critical constraints.	Integration of FL and edge devices
Bandwidth and Networking Issues	• Specific roles are based on the low, medium, and high radio frequencies for the incentive-based SG application requirements. Integration of FL and edge devices • Medium and high frequencies are generally used for communication within short distances, such as HMS.	5G, 6G
Throughput	• The total sum of data exchanged between incentive-based SG components within a specific time interval is referred to as the throughput. • The characteristics of the application determine the throughput utilization by the incentive-based SG for communication	FL

Table 5. *Cont.*

Challenge	Description	Possible Solutions (Future Directions)
Reliability	• The timely and successful exchange of messages, considering the specifications of a communication system, determines the reliability. • The specifications associated with reliability would vary across different SG applications.	Explainable AI
Anomaly Issues	• Timely and accurate detection of an outlier, faulty devices, and anomalous events is needed for carrying out reliable operations in incentive-based SG. • It is necessary to review methods of error detection and methods for coping with them to deal with the faults within the power grid.	AI-based solutions
Type of Energy Sources, Service Providers, and Customers	• Incentive mechanisms should be designed to consider the different types of customers, service providers, and energy sources. • It is necessary to review the mechanisms through which incentive mechanisms can be designed for a unique group of customers/ service providers based on their energy usage.	ML-based solutions
Pricing	• Pricing schemes in SG should be designed by considering customers' types and usage patterns.	Time-dependent pricing schemes

6. Conclusion

Global warming is one of the most alarming issues threatening life. The elimination of this threat requires cooperation and support from all sectors of society to reduce global CHG emissions. The use of traditional electricity generation and distribution systems plays a significant role in CHG emissions, so efforts are being made to replace them with low-carbon devices based on RES. This transition is necessary and can be considered the only way to effectively reduce climate change, but it has associated challenges pertinent to controlling electric power systems and their operation. This establishes the reasoning behind the evolution of SG which use advanced sensing technologies to disseminate all voltage levels and distributes energy, ensuring flexible transmission using two-way communication networks. The SG infrastructure incorporates the integration of RESs that reduce carbon emissions, promising a greener and healthier planet for future generations. SG generates a huge amount of data that incorporate the smartness of the system. Big data technologies [127] is used to ensure efficient and scalable data management in SG systems. Big data technologies ensure the handling of all SG requirements, such as data processing, data storage, and data visualization. The present study presents a comprehensive survey of the state-of-the-art initiatives pertinent to implementing incentive mechanisms in SG. The state of this sector is discussed to establish the background behind the use of incentive mechanisms in SG. The state of the art in SG, the applications of incentive mechanisms in general, and the underlying reasoning involved in implementing incentive mechanisms in SG are discussed. The technologies and their relevant implementations in popular SG projects, namely AI and ML, game theory, and blockchain, are discussed, highlighting the relevance and utility of incentivizing SG in the present. To present a real-world perspective, various incentivized SG projects and use cases implemented in different countries, namely Andalusia, India, USA, China, France, and Brazil, are discussed. However, the present study emphasized technologies like game theory, AI, and blockchain as the enabling technologies to design incentivized SG frameworks. This could be further expanded by considering other techniques, such as multi-criteria decision making (MCDM), soft computing, and so on. The information discussed in all of these sections leads to the identification of various open issues in the aforementioned implementations, despite their promising benefits. These open issues are related to data uncertainty, data security, data privacy, data integrity, data authentication, latency, bandwidth/network issues, throughput, reliability, anomalies, pricing, multiple energy sources, service providers, and consumers. These open issues provide insight into possible future directions of research that would further help optimize incentive-mechanism-based SG implementations, thereby fulfilling the dream of a better and greener planet.

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