

AI-driven Demand Response Management in Solar-powered Smart Grids: A Review

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Abstract: Solar photovoltaic energy has become an important component of modern electricity systems, yet its variable nature creates challenges for grid stability, demand balancing and energy management. This review examines AI-driven demand response management in solar-powered smart grids, with emphasis on how artificial intelligence supports forecasting, load flexibility, battery coordination and renewable energy utilisation. The study adopted a structured narrative review approach and synthesised recent scholarly literature on smart grids, solar Photovoltaic (PV) integration, machine learning, deep learning, reinforcement learning, federated learning and explainable Artificial Intelligence. The findings show that AI improves demand response by enabling accurate load prediction, solar generation forecasting, dynamic pricing, automated appliance scheduling and real-time grid optimisation. Reinforcement learning and multi-agent systems were found to be particularly useful in solar-powered environments where consumers, prosumers, batteries and distributed energy resources interact under uncertain grid conditions. The review further shows that AI-driven demand response can reduce peak demand, increase solar self-consumption, minimise curtailment and strengthen grid flexibility. However, implementation remains constrained by privacy concerns, cybersecurity threats, black-box algorithms, infrastructure limitations and low consumer trust. The study concludes that AI-driven demand response is essential for the effective operation of solar-powered smart grids, but its success depends on secure data governance, transparent algorithms, interoperable technologies and supportive regulation. The review provides useful insight for researchers, policymakers, utilities and energy planners working toward intelligent renewable energy systems.

Keywords: artificial intelligence, demand response, solar photovoltaic energy, smart grids, energy management

1. Introduction

The transition from conventional electricity networks to smart grids has become central to global energy transformation because modern power systems must now manage decentralised generation, digital communication, flexible demand, and variable renewable energy as shown in Fig. 1. Solar photovoltaic energy is particularly important in this transition because it offers clean, scalable, and increasingly affordable electricity, yet its dependence on weather conditions, irradiance, and time-of-day generation creates operational uncertainty for grid operators [1, 2]. As solar penetration increases, traditional grid management approaches become insufficient because electricity demand does not always coincide with solar generation.

This mismatch makes demand response a critical mechanism for balancing supply and demand in solar-powered smart grids. Demand response refers to the deliberate adjustment of consumer electricity consumption in response to price signals, incentives, or grid conditions. In solar-powered smart grids, demand response can shift flexible loads such as heating, cooling, water pumping, refrigeration, electric vehicle charging, and industrial processes to periods of high solar generation, thereby reducing curtailment and peak-load stress [3, 4]. However, conventional demand response programmes often rely on static tariffs, manual participation, and rule-based control, which limits their ability to respond to rapid changes in solar output, consumer behaviour, and grid constraints [5]. This limitation has created growing interest in artificial intelligence as a more adaptive and predictive approach to demand response management.

Artificial intelligence provides the computational intelligence needed to process large smart meter datasets, weather information, solar PV output, electricity prices, and consumer load patterns. Machine learning and deep learning models improve short-term load forecasting, PV generation forecasting, anomaly detection, and energy consumption prediction, which are necessary for effective demand response decisions [6, 7]. In solar-integrated buildings, supervised machine learning models have been used to forecast electricity consumption and renewable generation, enabling day-ahead dynamic pricing and automated control of price-sensitive loads [8]. Similarly, AI applications in grid-connected PV systems have shown strong potential for fault diagnosis, maximum power point tracking, forecasting, monitoring, and grid-support functions [9]. Reinforcement learning has become especially relevant because demand response is a sequential decision-making problem in which the system must learn when to consume, store, reduce, or shift energy use under uncertain grid and solar conditions. Multi-agent reinforcement learning enables households, appliances, batteries, electric vehicles, and prosumers to act as intelligent agents that coordinate energy scheduling while preserving user comfort and reducing cost [10, 11]. Recent studies show that multi-agent and deep reinforcement learning frameworks can improve real-time demand response, manage price uncertainty, and optimise solar-powered residential appliances [12, 13]. These developments are significant because future smart grids will require decentralised decision-making rather than purely centralised utility control.

Energy storage also strengthens AI-driven demand response in solar-powered smart grids. Since solar generation is intermittent, battery systems can store excess daytime solar energy and discharge it during evening peaks. Machine learning supports this process by forecasting demand, estimating battery state, improving charge-discharge scheduling, and extending battery life [14]. AI therefore creates a link between solar generation, storage assets, and flexible consumption, allowing the grid to operate more efficiently and reliably. Despite these opportunities, AI-driven demand response still faces technical, institutional, and social challenges. Smart grid data can expose household routines, business activities, and consumption behaviour, making privacy and cybersecurity major concerns [15]. AI models may also operate as “black boxes”, making it difficult for utilities, regulators, and consumers to understand or trust automated demand response decisions [16]. Digitalisation studies further show that effective AI-enabled smart grids require interoperable devices, real-time communication infrastructure, secure data exchange, consumer acceptance, and supportive regulation [17]. Broader renewable energy research also indicates that AI can optimise energy systems, but implementation depends on high-quality data, appropriate algorithms, and practical deployment environments [18]. Against this background, AI-driven demand response management in solar-powered smart grids represents an important research area. It addresses the urgent need to improve solar energy utilisation, reduce peak demand, enhance grid flexibility, and support cleaner electricity systems. The study is therefore justified because it examines how artificial intelligence can transform demand response from a passive consumer-side programme into an intelligent, predictive, and automated system for managing solar-powered smart grids.

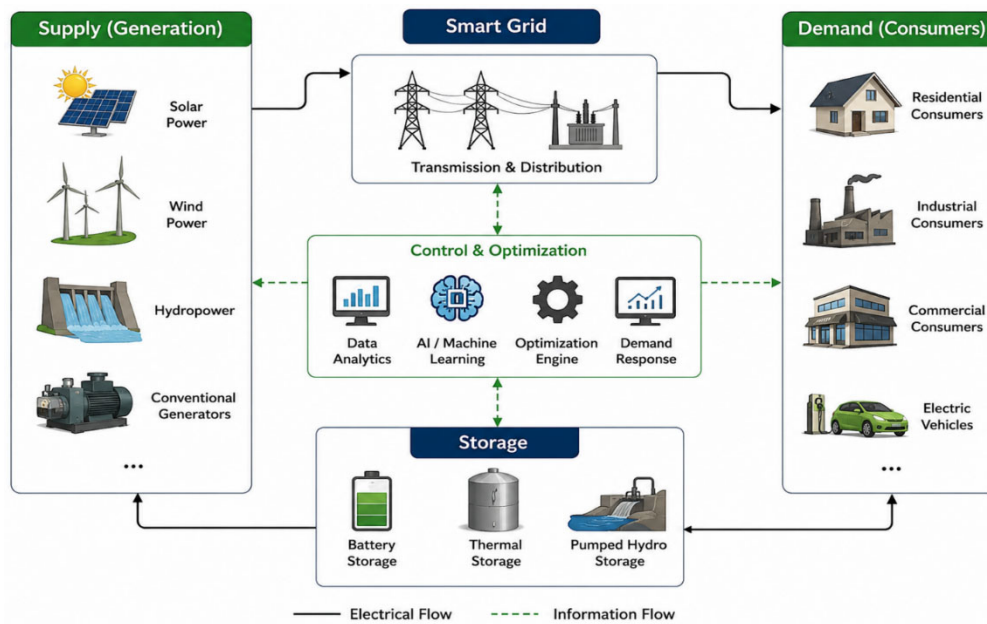


Fig. 1. Conceptual overview of AI-driven demand response management in solar-powered smart grids.

2. Related Studies

AI-driven demand response management in solar-powered smart grids has attracted growing scholarly attention because electricity systems are becoming more decentralised, data-intensive and renewable-dependent. Related studies generally show that artificial intelligence supports demand response through forecasting, optimisation, automated decision-making, consumer-side flexibility, privacy-preserving computation and real-time grid control. The literature also shows that solar-powered smart grids require more than conventional demand-side management because solar PV generation is variable and often mismatched with household, commercial and industrial demand patterns. This section reviews related studies under four subtopics: artificial intelligence and demand response management, solar photovoltaic forecasting and energy balancing, reinforcement learning and prosumer-based flexibility, and privacy, cybersecurity and trust challenges.

2.1. Artificial Intelligence and Demand Response Management in Smart Grids

Studies on artificial intelligence and demand response show that AI has shifted demand-side management from manual or rule-based intervention to predictive and adaptive optimisation. Lu *et al.* [19] reviewed artificial intelligence and machine learning approaches to energy demand-side response and showed that AI techniques are increasingly used to forecast consumption, classify user behaviour, and optimise demand reduction strategies. Khan *et al.* [20] similarly found that AI-enabled demand response improves grid sustainability by supporting load prediction, dynamic pricing, consumer participation, and renewable energy balancing. In a broad review of demand-side management, Sarker *et al.* [21] established that optimisation-based demand response reduces peak demand, improves load scheduling, and supports grid reliability when integrated with smart meters and communication systems. Arévalo and Jurado [22] further indicated that AI improves the planning and operation of distributed energy systems by enabling intelligent control, distributed optimisation, and flexible use of renewable energy resources. Alam *et al.* [23] added that AI-integrated grid systems contribute to monitoring, fault detection, control, and grid-wide energy management. These studies collectively suggest that AI-driven demand response is not only a load-reduction tool but also a strategic mechanism for coordinating consumption, distributed generation, and real-time grid stability.

2.2. Solar Photovoltaic Forecasting and Smart Grid Energy Balancing

Solar PV forecasting is central to demand response because flexible consumption can only be scheduled effectively when future solar generation is reasonably predictable. Bouquet *et al.* [24] demonstrated that AI-based solar forecasting improves smart grid efficiency by supporting better energy management and operational planning. Iheanetu [25] reviewed solar photovoltaic power forecasting and showed that accurate PV prediction is necessary for reducing uncertainty in renewable energy integration. Gaboitaolelwe *et al.* [26] compared machine learning techniques for solar PV forecasting and argued that AI models can improve short-term and medium-term prediction accuracy when trained with weather and generation data. Massaoudi *et al.* [27] also showed that deep learning has become increasingly relevant in PV forecasting because it captures nonlinear relationships between irradiance, temperature, cloud cover, and solar output. Qu *et al.* [28] proposed an attention-based Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model for day-ahead hourly PV forecasting and showed that hybrid deep learning architectures can improve temporal prediction. These studies are important to solar-powered smart grids because demand response decisions depend on knowing when solar generation will be high, low, or unstable. The literature therefore suggests that AI-based forecasting creates the informational foundation for load shifting, battery scheduling, peak shaving, and solar self-consumption.

2.3. Reinforcement Learning, Prosumers and Automated Load Flexibility

Recent studies show that reinforcement learning is highly suitable for demand response because energy scheduling requires repeated decision-making under uncertainty. Lu *et al.* [29] proposed a deep reinforcement learning model for smart facilities energy management and showed that intelligent agents can reduce electricity cost while maintaining user satisfaction. Zhang *et al.* [30] extended this direction through a testbed implementation of reinforcement-learning-based demand response, demonstrating that RL can move beyond simulation into practical energy management environments. Wan *et al.* [31] examined price-based residential demand response and found that reinforcement learning can help consumers adjust consumption patterns in response to electricity price variation. Sangoleye *et al.* [32] focused on smart grid systems with prosumers and showed that reinforcement-learning-based demand response can model interactions among consumers, prosumers, energy management systems, and utility companies. Amer *et al.* [33] further developed a deep reinforcement learning home energy management system that considers both consumer and operator perspectives. These studies show that reinforcement learning is useful where solar-powered smart grids include controllable appliances, rooftop PV, batteries, and prosumers. The reviewed evidence suggests that automated load flexibility can reduce peak pressure, increase solar energy use, and improve economic outcomes for both users and grid operators.

2.4. Privacy, Cybersecurity and Trust Challenges in AI-Driven Demand Response

Although AI improves demand response management, related studies also emphasise privacy, cybersecurity, and trust as major implementation barriers. Su *et al.* [34] proposed secure and efficient federated learning for smart grids, showing that edge-cloud collaboration can support intelligence without exposing raw consumer energy data. Fernández *et al.* [35] demonstrated that privacy-preserving federated learning can improve residential load forecasting while protecting sensitive smart meter data through secure aggregation and differential privacy. Grataloup *et al.* [36] reviewed federated learning in renewable energy applications and showed that decentralised learning is promising for distributed forecasting, consumption management, and renewable-energy coordination. Sarker *et al.* [37] integrated federated learning and explainable AI into smart grid load forecasting, highlighting the need for both security and interpretability in AI-based energy systems. Chen *et al.* [38] reviewed cybersecurity risks in distributed energy resource systems and found that connected DERs introduce attack surfaces that can threaten grid reliability. These

studies indicate that AI-driven demand response cannot be judged only by forecasting accuracy or cost reduction. Its success also depends on secure communication, privacy-preserving data governance, explainable decision-making, and consumer trust in automated energy control.

3. Methodology

This review adopted a structured literature review approach to examine existing scholarly works on AI-driven demand response management in solar-powered smart grids. The methodology was designed to identify, select, analyse and synthesise recent studies that address the use of artificial intelligence in demand response, solar photovoltaic integration, smart grid optimisation, load forecasting, energy storage coordination and consumer-side energy flexibility. Since the topic cuts across electrical power systems, renewable energy, artificial intelligence and energy management, the review focused on multidisciplinary literature from engineering, energy systems, computer science and sustainability studies. The purpose of the methodology was to ensure that the reviewed studies were relevant, recent, credible and suitable for drawing meaningful conclusions on how artificial intelligence supports demand response in solar-powered smart grids.

3.1. Research Design

The study employed a structured narrative review design. This design was considered appropriate because the topic is broad and interdisciplinary, involving several connected areas such as smart grids, solar PV systems, machine learning, deep learning, reinforcement learning, demand response and distributed energy management. A structured narrative review allows the researcher to organise existing studies thematically while still maintaining a systematic approach to searching, screening and synthesising literature. Unlike a purely statistical meta-analysis, this approach was suitable because the reviewed studies used different methods, including simulation models, experimental testbeds, optimisation algorithms, conceptual reviews and case-based energy management models. The review therefore focused on interpreting patterns, identifying areas of agreement, discussing gaps and presenting research directions rather than combining numerical effect sizes.

3.2. Sources of Literature

Relevant literature was obtained from reputable academic databases and scholarly platforms, including ScienceDirect, IEEE Xplore, SpringerLink, MDPI, Taylor & Francis Online, Wiley Online Library, Google Scholar and other recognised journal repositories. These databases were selected because they contain high-quality publications in renewable energy, artificial intelligence, smart grid systems, electrical engineering and sustainable energy management. The review prioritised peer-reviewed journal articles, systematic reviews, review papers and conference papers where necessary, especially when they addressed recent advances in AI-based demand response or solar-powered grid systems. Institutional reports were used only where they provided background information on renewable energy trends, smart grid development or global electricity transition, but the main analytical foundation of the review was based on peer-reviewed scholarly literature.

3.3. Search Strategy

The literature search was guided by carefully selected keywords and keyword combinations that reflected the major concepts in the topic. Search terms included artificial intelligence and demand response, AI-driven demand response, smart grid energy management, solar-powered smart grids, solar photovoltaic forecasting, machine learning for demand response, deep learning in smart grids, reinforcement learning for energy management, demand-side management, smart meters, battery storage optimisation, renewable energy integration and AI-based load forecasting. Boolean operators such as “AND” and “OR” were used to combine

search terms and improve the relevance of search results. For example, searches combined terms such as “artificial intelligence” AND “demand response” AND “smart grid”, as well as “solar photovoltaic” AND “machine learning” AND “energy forecasting”. This helped to identify studies that directly linked AI techniques with demand response and solar-integrated smart grid systems, as illustrated in the PRISMA flow diagram Fig. 2.

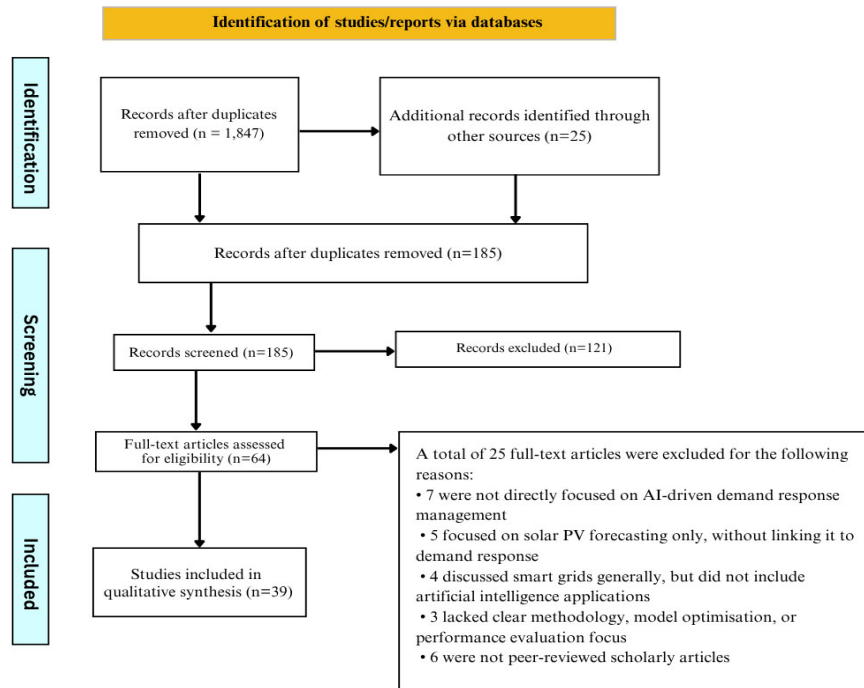


Fig. 2. PRISMA flow diagram.

3.4. Inclusion and Exclusion Criteria

3.4.1. Inclusion Criteria

- Studies published from 2020 onward
- Peer-reviewed journal articles and relevant conference papers
- Studies focused on AI, demand response, smart grids or solar PV integration
- Articles with clear methodology, findings or technical contribution
- Studies written in English
- Articles with accessible DOI or verifiable publication details

3.4.2. Exclusion Criteria

- Studies published before 2020, unless foundational
- Non-academic blogs, opinion pieces and unreliable web sources
- Studies unrelated to AI, solar energy or demand-side management
- Articles with unclear methods or weak scholarly relevance
- Studies not available in English
- Articles without traceable publication information

3.5. Screening and Selection of Studies

The screening process involved reviewing the titles, abstracts, keywords and full texts of identified studies to determine their relevance to the topic. At the first stage, studies were screened based on their titles and

abstracts to remove publications that did not directly address artificial intelligence, demand response, solar energy or smart grids. At the second stage, the remaining studies were examined more closely to determine whether they provided useful evidence on AI techniques, demand-side flexibility, PV forecasting, load optimisation, smart metering, energy storage, dynamic pricing or renewable energy integration. Studies that only mentioned smart grids or solar energy without linking them to demand response or intelligent energy management were excluded. The final studies selected for the review were those that contributed directly to understanding how AI can improve demand response management in solar-powered smart grid environments.

3.6. Data Extraction Procedure

Data were extracted from selected studies using a thematic approach. The key information collected from each study included the author, year of publication, title, research focus, AI technique used, energy system considered, methodology, major findings, limitations and relevance to demand response management. Particular attention was given to whether the study examined machine learning, deep learning, reinforcement learning, optimisation algorithms, federated learning, explainable AI or hybrid AI models. Information was also extracted on whether the study focused on residential buildings, commercial facilities, microgrids, electric vehicles, battery storage systems or utility-level smart grids. This extraction process helped to organise the reviewed literature into meaningful categories and made it possible to compare the contributions of different studies.

3.7. Method of Analysis and Synthesis

The selected literature was analysed using thematic synthesis. The studies were grouped into major themes such as AI-based demand response management, solar PV forecasting, smart grid energy balancing, reinforcement learning for load scheduling, energy storage optimisation, consumer participation, privacy, cybersecurity and explainable AI. This thematic approach was suitable because the reviewed studies applied different models and methods, making direct statistical comparison difficult. The synthesis focused on identifying common findings, contrasting methodological approaches and highlighting gaps in existing research. For instance, studies that used machine learning were compared with those that used reinforcement learning to show how different AI models support demand response. Similarly, studies on privacy-preserving AI were examined separately to understand the ethical and security concerns associated with smart meter data and automated demand response systems.

3.8. Quality Appraisal of Selected Literature

The quality of the selected studies was assessed based on relevance, credibility, methodological clarity and contribution to the field. Studies were considered strong when they had clear objectives, appropriate methods, verifiable publication details, recent publication dates and direct relevance to AI-driven demand response or solar-powered smart grids. Greater weight was given to studies published in reputable journals and those that provided empirical results, simulation outcomes, testbed validation or systematic review evidence. Studies that lacked methodological clarity, used weak data sources or made broad claims without technical support were treated cautiously. This quality appraisal helped to ensure that the conclusions drawn from the review were based on reliable and academically sound sources.

3.9. Ethical Considerations

Since this study was based on the review of existing published literature, it did not involve human participants, personal data collection or direct experimentation. As a result, formal ethical approval was not required. However, ethical academic practice was maintained by ensuring that all ideas, findings and

arguments drawn from previous studies were properly acknowledged through citation and referencing. The review also paid attention to ethical issues raised in the literature, especially concerns about privacy, cybersecurity, consumer consent, algorithmic transparency and fairness in AI-driven demand response systems. These issues are important because smart grid technologies depend heavily on consumer energy data and automated decision-making.

3.10. Limitations of the Methodology

The main limitation of the methodology is that the review adopted a structured narrative approach rather than a full systematic review with statistical meta-analysis. This means that the review provides a broad and critical synthesis of existing literature but does not calculate pooled quantitative effects across studies. Another limitation is that the review depended mainly on English-language publications, which may exclude relevant studies published in other languages. In addition, because AI-driven demand response is a rapidly evolving field, some very recent technical developments may not yet be fully represented in peer-reviewed journals. Despite these limitations, the methodology was appropriate for examining the current state of knowledge, identifying major research trends and highlighting future directions in AI-driven demand response management for solar-powered smart grids.

4. Results

This section presents the results of the review based on the three objectives of the study. Since the study is review-based, the results are drawn from the synthesis of existing scholarly studies rather than primary field data. The findings are organised in tables to show how previous studies have examined AI-driven demand response management in solar-powered smart grids. The first table presents studies on artificial intelligence techniques used for demand response management. The second table focuses on how AI improves solar energy utilisation, forecasting and grid flexibility. The third table presents the major challenges affecting AI-driven demand response in solar-powered smart grids. Each table is followed by an interpretation that explains the meaning of the findings and their relevance to the present study. This presentation helps to show the patterns, contributions and gaps in the existing literature on AI-based demand response, solar PV integration and smart grid optimisation.

Table 1. To Examine AI Techniques Used for Demand Response Management in Solar-Powered Smart Grids

Author(s) and Year	AI Technique or Focus	Key Finding
Antonopoulos <i>et al.</i> [19] (2020)	Machine learning for demand-side response	AI improves load prediction and demand response decisions.
Xu <i>et al.</i> [10] (2020)	Multi-agent reinforcement learning	Home energy management becomes more adaptive.
Zhang <i>et al.</i> [30] (2021)	Reinforcement learning testbed	RL can support practical demand response control.
Lu <i>et al.</i> [29] (2022)	Deep reinforcement learning	Smart facilities reduce energy cost and peak demand.
Wan <i>et al.</i> [31] (2022)	Price-based reinforcement learning	Consumers can adjust demand according to price signals.
Balakumar <i>et al.</i> [8] (2023)	Machine learning in PV-integrated buildings	ML improves demand response in solar smart buildings.
Khan <i>et al.</i> [20] (2023)	AI-enabled demand response	AI improves prediction, pricing and user participation.
Sangoleye <i>et al.</i> [32] (2023)	Reinforcement learning with prosumers	Prosumers can support grid-side flexibility.
Amer <i>et al.</i> [33] (2023)	Deep reinforcement learning HEMS	DRL balances user comfort and operator needs.
Xie <i>et al.</i> [11] (2023)	Multi-agent attention-based DRL	Buildings become more responsive to grid conditions.
Boopathy <i>et al.</i> [6] (2024)	Deep learning for smart grids	Deep learning improves intelligent demand response.
Wang <i>et al.</i> [7] (2024)	AI for smart energy consumption	AI supports forecasting, anomaly detection and demand response.
Sarker <i>et al.</i> [37] (2024)	Federated learning and XAI	Forecasting becomes more secure and interpretable.
Shantanu <i>et al.</i> [12] (2025)	Multi-agent RL with solar uncertainty	RL manages demand under solar and price uncertainty.
Singh <i>et al.</i> [13] (2025)	Blockchain-enabled multi-agent DRL	Secure real-time demand response is improved.

Table 1 presents studies on AI techniques used for demand response management in solar-powered smart grids. The studies show that artificial intelligence has become a major tool for improving how electricity demand is predicted, controlled and adjusted in smart grid environments. Machine learning models are commonly used for load prediction and consumer behaviour analysis, while deep learning models support complex forecasting and real-time energy decision-making. Reinforcement learning is particularly important because it allows smart appliances, buildings, batteries and prosumers to learn optimal energy-use patterns under changing solar generation and electricity prices. The findings also show that multi-agent systems are useful in decentralised smart grids where several users and energy devices interact at the same time. These studies confirm that AI-driven demand response is more flexible than traditional demand-side management because it can respond automatically to grid conditions. The table therefore shows that AI improves demand response by making energy control more predictive, adaptive and efficient.

Table 2 presents studies on how AI improves solar energy utilisation, forecasting and grid flexibility. The findings show that accurate solar PV forecasting is one of the strongest contributions of AI to solar-powered smart grids. Since solar generation changes with weather, cloud movement, temperature and solar irradiance, smart grids need reliable prediction models to know when solar supply will increase or decline. The reviewed studies show that machine learning, deep learning, CNN-LSTM models and hybrid forecasting methods improve the prediction of solar PV output. These forecasting improvements help the grid to schedule flexible loads, charge batteries during periods of high solar generation and reduce electricity demand when solar output is low. The table also shows that AI supports grid flexibility by coordinating solar energy, battery storage, smart meters and consumer-side demand response. This means that AI does not only predict solar generation but also helps the grid use solar energy more efficiently. The findings therefore support the view that AI is essential for reducing solar energy curtailment and improving grid stability.

Table 2. To Assess how AI Improves Solar Energy Utilisation, Forecasting and Grid Flexibility

Author(s) and Year	Study Focus	Key Finding
Ahmed <i>et al.</i> [1] (2020)	Solar PV power forecasting	Forecasting reduces uncertainty in PV generation.
Qu <i>et al.</i> [23] (2021)	CNN-LSTM PV forecasting	Hybrid deep learning improves day-ahead forecasting.
Massaoudi <i>et al.</i> [22] (2021)	Deep learning for PV forecasting	Deep learning captures nonlinear solar patterns.
Iheanetu [14] (2022)	Review of PV forecasting	Accurate forecasting supports grid planning.
Gaboitaolelwe <i>et al.</i> [12] (2023)	ML-based PV forecasting	Machine learning improves PV output prediction.
Bouquet <i>et al.</i> [8] (2024)	AI-based solar energy forecasting	AI improves solar energy management efficiency.
Khalid [15] (2024)	Renewable energy and smart grids	Smart grids need flexibility for solar integration.
Kiasari <i>et al.</i> [17] (2024)	ML and energy storage	Storage and ML improve renewable integration.
Mahmood <i>et al.</i> [21] (2024)	Digitalisation of smart grids	AI improves prediction and energy optimisation.
Husein <i>et al.</i> [39] (2024)	Deep learning PV review	Transformer models show strong forecasting potential.
Gülmez [40] (2026)	AI-driven smart grid optimisation	AI improves monitoring, control and grid optimisation.
Banad <i>et al.</i> [41] (2025)	AI and ML for smart grids	AI supports demand response and storage management.
Khouili <i>et al.</i> [42] (2025)	Deep learning in solar PV forecasting	DL improves PV prediction but needs better benchmarks.
Cestero <i>et al.</i> [43] (2025)	RL and physics-informed models	RL improves smart grid energy optimisation.
Soleymani and Mohammadzadeh [44] (2023)	Solar irradiance forecasting	ML improves solar irradiance prediction for smart grids.

Table 3 presents studies on the challenges affecting AI-driven demand response in solar-powered smart grids. The findings show that although AI improves forecasting, energy scheduling and grid optimisation, its practical use still faces several barriers. Privacy is a major concern because smart meters and connected devices collect detailed consumer energy data that may reveal household routines or business operations.

Cybersecurity is another serious challenge because distributed energy resources, smart meters and communication networks can be exposed to cyberattacks or false data injection. The table also shows that explainability remains a problem because many AI models operate as black boxes, making it difficult for consumers, utility companies and regulators to understand how automated demand response decisions are made. Infrastructure limitations, poor interoperability and weak consumer trust also affect implementation. These findings indicate that AI-driven demand response cannot succeed through technical optimisation alone. It also requires secure data systems, transparent algorithms, supportive regulation and active consumer acceptance.

Table 3. To Identify Challenges Affecting AI-Driven Demand Response in Solar-Powered Smart Grids

Author(s) and Year	Challenge Area	Key Finding
Machlev <i>et al.</i> [20] (2022)	Explainable AI	Black-box AI reduces user and operator trust.
Fernández <i>et al.</i> [11] (2022)	Federated learning	Privacy can be improved without sharing raw data.
Su <i>et al.</i> [31] (2022)	Secure federated learning	Edge-cloud learning improves smart grid data security.
Chatuanramtharnghaka <i>et al.</i> [9] (2024)	Demand response with EVs and renewables	Coordination becomes difficult with many flexible loads.
Grataloup <i>et al.</i> [13] (2024)	Federated learning in renewable energy	Data heterogeneity affects decentralised learning.
Reka <i>et al.</i> [24] (2024)	Big data privacy and security	Smart meter data creates privacy risks.
Sarker <i>et al.</i> [28] (2024)	XAI and federated forecasting	Secure forecasting needs interpretability.
Ukoba <i>et al.</i> [33] (2024)	AI in renewable systems	Data quality affects AI performance.
Zheng <i>et al.</i> [45] (2024)	Integrated energy management	Smart grid coordination remains complex.
Alam <i>et al.</i> [2] (2025)	AI-integrated grid systems	Deployment requires infrastructure and regulation.
Ali <i>et al.</i> [46] (2025)	Privacy-preserving federated learning	Differential privacy strengthens consumer protection.
Chen <i>et al.</i> [10] (2025)	Cybersecurity of DER systems	Distributed energy resources increase cyber risks.
Sinha <i>et al.</i> [47] (2025)	DRL and cyberattack detection	AI can detect attacks but needs robust training.
Singh <i>et al.</i> [30] (2025)	Blockchain and DRL	Security improves but system complexity increases.
Todorean <i>et al.</i> [32] (2025)	Smart building demand response	Interoperability and user acceptance remain challenges.

5. Discussion

This section discusses the findings of the review in relation to existing literature on AI-driven demand response management in solar-powered smart grids. The discussion is organised around four major areas that emerged from the reviewed studies: the role of artificial intelligence in demand response management, the contribution of AI to solar forecasting and grid flexibility, the importance of reinforcement learning and prosumer participation, and the challenges affecting implementation. These areas are important because solar-powered smart grids require intelligent systems that can predict generation, adjust consumption, coordinate storage and maintain grid stability under variable renewable energy conditions. The discussion therefore explains how the findings support, extend or reflect existing scholarly arguments on smart grid digitalisation, renewable energy integration and AI-enabled energy management.

5.1. Artificial Intelligence and Demand Response Management

The findings show that artificial intelligence has become central to demand response management because it enables electricity consumption to be predicted, scheduled, and adjusted more intelligently. This agrees with [19], who found that machine learning improves demand-side response by supporting load forecasting, consumer profiling, and automated decision-making. The finding also supports Machlev *et al.* [20], who

argued that AI-enabled demand response strengthens smart grid sustainability through predictive pricing, demand flexibility, and improved user participation. In solar-powered smart grids, demand response cannot depend only on static tariffs or manual consumer behaviour because solar generation fluctuates throughout the day. AI therefore becomes useful because it can process real-time data from smart meters, weather systems, PV units, and connected appliances. This position is consistent with Boopathy *et al.* [7], who noted that AI improves smart energy consumption through forecasting, anomaly detection, and demand response optimisation. The finding further reflects Balakumar [6], who observed that deep learning enhances intelligent demand response by modelling complex consumption patterns. This means that AI transforms demand response from a reactive mechanism into a predictive grid-management strategy. The reviewed evidence therefore suggests that AI-driven demand response is important for reducing peak demand, improving load scheduling, and supporting efficient solar energy utilization.

5.2. AI-Based Solar Forecasting and Grid Flexibility

The findings also show that AI improves solar-powered smart grids by strengthening solar PV forecasting and grid flexibility. This is important because solar energy generation is affected by irradiance, temperature, cloud movement, and seasonal variation. Ahmed *et al.* [1] emphasised that accurate solar power forecasting reduces uncertainty in renewable energy integration, while Iheanetu [25] noted that PV forecasting supports better grid planning and operational control. The present review supports these arguments because the studies showed that machine learning and deep learning models improve the prediction of solar output and enable demand response actions to be planned ahead of grid stress. Qu *et al.* [28] demonstrated that CNN-LSTM models improve day-ahead photovoltaic forecasting, and Massaoudi *et al.* [27] argued that deep learning captures nonlinear solar generation patterns more effectively than many traditional methods. These findings are also consistent with Bouquet *et al.* [24], who showed that AI-based forecasting improves solar energy management and smart grid efficiency. In practical terms, improved forecasting allows flexible loads to be shifted to periods of high solar generation and helps batteries store excess solar energy for later use. This confirms Kiasari's [14] view that machine learning and storage coordination are essential for renewable energy integration. AI-based forecasting therefore improves solar self-consumption, reduces curtailment, and strengthens grid stability.

5.3. Reinforcement Learning, Prosumers and Automated Energy Flexibility

The findings further indicate that reinforcement learning is a suitable AI technique for demand response because smart grid energy management involves repeated decisions under uncertainty. This agrees with Xu *et al.* [10], who found that multi-agent reinforcement learning improves home energy management by allowing household energy systems to learn optimal consumption patterns. Lu *et al.* [29] similarly showed that deep reinforcement learning can reduce electricity cost and improve smart facility energy management. The present review supports these studies by showing that reinforcement learning is useful in solar-powered smart grids where electricity prices, solar generation, and consumer demand change continuously. Zhang *et al.* [30] demonstrated that reinforcement-learning-based demand response can be implemented in a testbed environment, suggesting that the approach has practical value beyond simulation. The findings also align with Sangoleye *et al.* [32], who argued that reinforcement learning supports demand response in smart grids with prosumers. This is important because solar-powered smart grids increasingly include consumers who also generate electricity through rooftop PV systems. In such systems, users are no longer passive consumers but active participants in energy balancing. Amer *et al.* [33] added that deep reinforcement learning can balance customer comfort with operator requirements in home energy management systems. The evidence therefore suggests that reinforcement learning supports automated load flexibility, prosumer participation, and decentralised energy coordination.

5.4. Implementation Challenges: Privacy, Cybersecurity and Trust

Although the findings show strong potential for AI-driven demand response, they also reveal important implementation challenges. The most prominent issues are privacy, cybersecurity, explainability, infrastructure readiness, and consumer trust. This agrees with Reka *et al.* [15], who observed that demand response modelling depends on large volumes of smart meter data, creating privacy and security concerns. Smart meter data can reveal daily routines, occupancy patterns, and business activities, meaning that consumers may resist AI-driven demand response if data protection is weak. Fernández *et al.* [35] and Grataloup *et al.* [34] suggested federated learning as one way of addressing this concern because it allows AI models to learn from distributed data without exposing raw consumer information. The findings also support [16], who argued that explainable artificial intelligence is necessary because black-box models reduce trust in energy and power systems. Cybersecurity is another major concern because connected distributed energy resources, smart meters, and communication systems create new attack surfaces. Chen *et al.* [38] confirmed that distributed energy resource systems face serious cybersecurity risks in smart grids. These issues show that AI-driven demand response cannot succeed through technical performance alone. Its effective implementation requires secure data governance, transparent algorithms, interoperable infrastructure, user acceptance, and supportive regulation.

6. Conclusion

The review concludes that AI-driven demand response management is a critical pathway for improving the performance of solar-powered smart grids. The reviewed literature shows that artificial intelligence strengthens demand response by improving load forecasting, solar PV prediction, dynamic pricing, battery scheduling, appliance control and grid-side flexibility. Machine learning and deep learning models are useful for identifying demand patterns and predicting solar generation, while reinforcement learning supports automated energy scheduling under changing price, demand and weather conditions. The review also shows that AI enables consumers, prosumers, smart buildings and distributed energy resources to participate more actively in grid balancing. This is particularly important because solar energy is variable and often does not match peak electricity demand. However, the success of AI-driven demand response depends on more than technical accuracy. Privacy, cybersecurity, explainability, consumer trust, infrastructure readiness and regulatory support remain important concerns. The study therefore concludes that AI-driven demand response can significantly enhance solar-powered smart grids when intelligent algorithms are combined with secure data systems, transparent decision-making and consumer-centred implementation.

It is recommended that utility companies and energy system planners adopt AI-based forecasting tools to improve load prediction and solar PV generation planning. Smart grid operators should integrate demand response platforms with battery storage systems to increase solar energy utilisation during periods of high generation. Policymakers should develop clear regulations on smart meter data privacy, cybersecurity and consumer protection in AI-enabled energy systems. Researchers should design explainable AI models so that grid operators and consumers can understand automated demand response decisions. Energy providers should promote consumer participation through fair pricing incentives, education and user-friendly smart energy applications. Future smart grid projects should invest in interoperable communication infrastructure that can connect solar PV systems, smart meters, electric vehicles and controllable appliances. Developing countries should prioritise low-cost AI-enabled solar microgrid solutions for communities with unstable grid access and rising electricity demand.

This review contributes to knowledge by bringing together recent scholarly evidence on artificial intelligence, demand response management and solar-powered smart grids. It clarifies how AI transforms demand response from a passive consumer-side activity into a predictive, adaptive and automated grid-

management system. The study also shows that solar-powered smart grids require intelligent coordination between generation, consumption, storage and pricing because solar PV output is variable and time-dependent. By synthesising studies on machine learning, deep learning, reinforcement learning, federated learning and explainable AI, the review provides a broader understanding of the AI techniques shaping modern demand response. The study further contributes by identifying the main benefits of AI-driven demand response, including improved forecasting, peak-load reduction, solar energy utilisation, battery optimisation and prosumer participation. It also highlights the major barriers that must be addressed, especially privacy, cybersecurity, algorithmic transparency, infrastructure limitations and consumer acceptance. This contribution is useful for researchers, energy planners, policymakers and utility companies seeking to improve renewable energy integration through intelligent demand-side flexibility.

Conflict of Interest

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

Author Contributions

Larbi Kwadwo: Conceptualization, literature collection, methodology design, and drafting of the manuscript. Clinton Amponsah (Corresponding Author): Conceptualization, Supervision, critical review, editing, validation, and final approval of the manuscript. All authors had approved the final version.

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