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Systematic Survey Analysis of the Application of Artificial Intelligence Base Network on Grid Computing Techniques

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ABSTRACT

A smart grid is a contemporary electrical system that supports two-way communication and utilizes the concept of demand response. In order to increase the smart grid's dependability and enhance the consistency, efficiency, and efficiency of the electrical supply, stability prediction is required. The true test for smart grid system designers and specialists will therefore be the increase of renewable energy. With the goal of integrating the electric utility infrastructure into the advanced communication era of today, both in terms of function and architecture, this program has achieved great strides toward modernizing and expanding it. In this study, researchers used the Systematic literature review method which identifies, evaluates and interprets all relevant research results related to certain research questions, certain topics, or phenomena of concern. The study review on how a smart grid applied different deep learning techniques and how renewable energy can be integrated into a system where grid control is essential for energy management. The article discusses the idea of a smart grid and how reliable it is when renewable energy sources are present. Globally, a change in electric energy is needed to reduce greenhouse gas emissions, prevent global warming, reduce pollution, and boost energy security.

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1. INTRODUCTION

A developing idea in today's power infrastructure, the smart grid (SG) allows data and electricity to move back and forth between peers in electricity system networks (ESNs) and their clusters[1]. Peers can take an active role in ESN thanks to SG's self-healing properties. Generally speaking, distributed energy resources (DER) will take the role of the fossil fuel-heavy conventional grid in the smart grid[2], [3]. It does this by combining a variety of current and developing know-hows, such as digital communications and information technologies, to manage a multitude of operations. By doing this, the SG will be able to handle various problems and "detect, react, and pro-act" to changes in usage.

Guaranteeing timely grid operations. However, the full potential of DER-based SG's "detect, react, and pro-act" capabilities can only be realized with the utilization of cutting-edge technologies such as Blockchain (BC), Internet of Things (IoT), and Artificial Intelligence (AI)[4], [5]. Neural networks, fuzzy logic, and knowledge-based systems are some of the AI approaches. They have improved the control of SG based on DER. Numerous services, including data sensing, data storage, and safe, transparent, and traceable digital transactions between ESN peers and its clusters, have also been made possible by the Internet of Things and BC. Over the last ten years, these promising technologies have undergone a rapid technological evolution, and the applications of these technologies in ESN have grown significantly [6], [7] Massive data sets are used in artificial intelligence (AI) approaches to build intelligent machines that can perform tasks that need human intelligence[8]. AI includes machine learning (ML), however the terms are sometimes used synonymously. ML is only one method, though, of creating AI systems. Neural networks, robotics, expert systems (ES), fuzzy logic (FL), and natural language processing are other, more comprehensive approaches to creating AI systems[9], [10]. In general, AI methods facilitate quick and precise decision-making. Artificial Intelligence (AI) in smart grid applications refers to the computer mimicking of the cognitive functions of grid operators in order to attain self-healing capabilities. In other situations, AI might not be able to take the role of grid operators, though[11], [12]. While AI systems have the potential to be more accurate, dependable, and thorough, the smart grid's application of AI technology still faces numerous obstacles[13], [14].

In the smart grid, virtual and physical artificial intelligence (AI) systems are both feasible. Informatics is one aspect of virtual AI systems that can assist grid operators in carrying out their duties[15], [16]. Self-aware AI systems that can optimize and manage particular grid activities with or without human intervention are examples of physical AI systems. Artificial narrow intelligence (ANI) and artificial general intelligence (AGI) are two further classifications for AI systems in the smart grid[17], [18]. Artificial neural networks (ANIs) are AI systems designed to accomplish certain tasks within relevant requirements and limitations. An example of an ANI would be a system that uses various datasets to forecast load. AI systems created to learn and evolve on their own, much like humans, are referred to as AGI systems. In the future, creating AGI systems may aid in the realization of actual smart grid systems.

1.1 Techniques for Artificial Intelligence in smart grid

Due to the modern power system's rapid revolution, a larger electrical power network and the underlying communication system are encompassed by more distributed smart grid components, such as distributed energy resources, smart metering infrastructure, communication infrastructure, and electric vehicles. These components are tightly integrated into the power system. These components provide enormous volumes of data in order to enable a wide range of applications, including distributed energy management, cyberattack security, system state forecasting, and automation of the smart grid [19], [20]. Artificial intelligence (AI) techniques have garnered significant attention due to their capacity to process the massive amounts of data supplied by smart grid systems, a capability that conventional computational techniques lack. These artificial intelligence (AI) techniques were the focus of a lot of research efforts because they leverage large-scale data to further enhance smart grid performance.

The following categories can be used to broadly group the AI methods used in smart grid systems [2]

1. ES: A human loop technique expert utilized for certain issues. 2021's Smart Cities: 4,550
2. Supervised learning: An AI paradigm wherein the outputs of fresh inputs are predicted by studying the mapping of inputs and outputs.
3. Unsupervised learning: A machine learning lesson that uses unlabeled data to identify similarities and differences in the data.
4. Reinforcement learning: Its intelligent agent technique, which tries to optimize the idea of cumulative reward, sets it apart from supervised and unsupervised learning.
5. Ensemble model: To get around an algorithm's shortcomings and outperform it overall, combine the output of other AI systems.

1.2 Smart Grid (SG) and AI

The distributed generating units (DGUs), energy storage systems, smart meters, smart home appliances, and other components are dispersed among several sites and serve as multiple ports of entry to the grid. For cybersecurity to endure mild calamities, the grid's physical security is just as important. SG is making every effort to guarantee the security of distributed components through the use of ICTs, utilizing an advanced control and communication system[21], [22]. [23] describe how critical information such as user authentication keys can be compromised and how malicious programs can be implanted into smart appliances to get access to any area of the grid. Every system in the actual world has weaknesses and complexity, even the SG. The cyber-physical system (smart grid) can be made secure against cyberattacks by using AI techniques like ANN[24]. Individual privacy, security, dependability in terms of performance and communication, and denial of service are important SG issues.

2. RESEARCH METHOD

Explaining research chronological, including research design, research procedure (in the form of algorithms, Pseudocode or other), how to test and data acquisition.

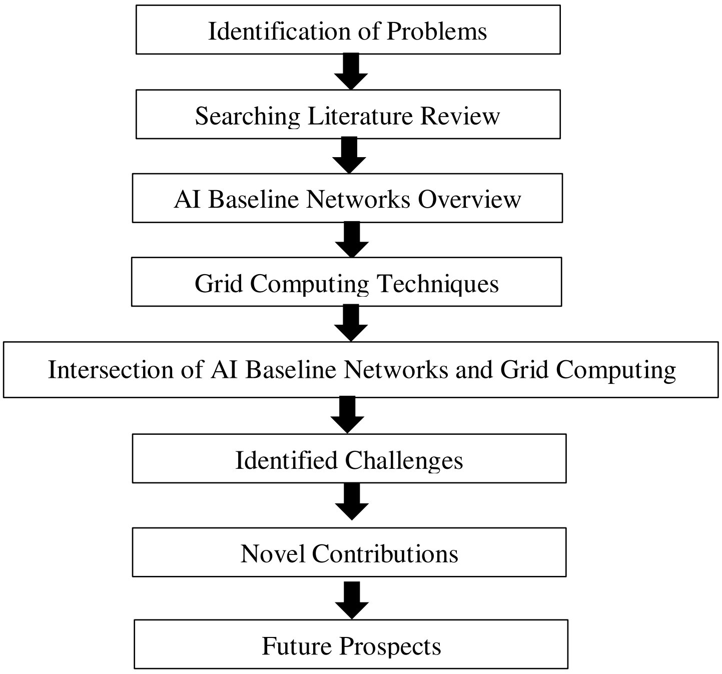

Figure 1. Research Design

1. Identification of Problem
Objective: Establish the need for combining AI baseline networks with grid computing. This section introduces the core concepts of grid computing, which deals with the large-scale sharing of computational resources, and AI baseline networks, which focus on developing foundational AI models that can adapt to various tasks.
Context: This section should describe the rapid growth in data and computing needs across industries and research sectors, leading to an increasing demand for efficient grid computing techniques. Highlight the importance of AI as a solution to these challenges, setting the stage for the survey.

2. Literature Review
Goal: Provide a comprehensive analysis of existing research in AI baseline networks and grid computing.
Content:
AI Baseline Networks: Present studies on foundational AI models (e.g., GPT, CNN, RNN) and their relevance to large-scale problem-solving tasks. Discuss how these models adapt to different tasks using minimal resources.
Grid Computing Techniques: Review key techniques in grid computing such as distributed task scheduling, resource allocation, fault tolerance, and load balancing.
Intersection of AI and Grid Computing: Identify prior attempts or studies where AI techniques have been integrated with grid computing infrastructures.
Gap Identification: Conclude by identifying the gaps in the existing literature where there's limited work on integrating AI baseline networks and grid computing.

3. AI Baseline Networks Overview
Purpose: This section dives into the specifics of AI baseline networks. Baseline networks are fundamental AI models that are trained on vast datasets and are then fine-tuned for specific tasks.
Topics to cover:
Key Characteristics: Discuss their generalization ability, scalability, and potential in various computational environments.
Architecture and Functioning: Explain how these networks process inputs and generate outputs. For example, explore how neural networks, especially transformer-based models, operate.
Relevance to Grid Computing: Argue that AI baseline networks can be used for predictive analytics, intelligent resource management, and decision-making in grid computing environments.

4. Grid Computing Techniques Overview
Objective: Lay the foundation by explaining how grid computing functions. Grid computing allows multiple computers to work on a problem simultaneously, dividing tasks across distributed systems.
Key Elements:

Architecture: Describe the structure of grid computing systems—centralized or decentralized grids, middleware, and communication protocols.
Techniques: Explain methods like:
Distributed Scheduling: How tasks are distributed among resources.
Resource Allocation: Techniques for optimal resource utilization, such as load balancing and job allocation based on computational power.
Fault Tolerance: Mechanisms to handle system failures without disrupting the entire process.
Use Cases: Provide real-world examples, such as scientific simulations, financial modeling, or big data analytics.

5. Intersection of AI Baseline Networks and Grid Computing
Purpose: This is the core section where the overlap between AI and grid computing is analyzed.
Topics to Discuss:
Enhanced Resource Management: How AI baseline networks can predict resource demand and allocate resources efficiently in a grid environment.
Intelligent Scheduling: AI models can optimize job scheduling by analyzing historical data and predicting execution times, reducing grid latency.
Improved Fault Tolerance: AI models can learn from past failures and optimize the fault tolerance mechanisms in grid computing.
Data Processing: AI's ability to process and analyze large volumes of data can enhance grid computing by improving decision-making on task prioritization and resource usage.

6. Identified Challenges
Objective: To outline the key technical and operational challenges that arise when integrating AI baseline networks into grid computing environments.
Challenges to Address:
Scalability Issues: Grid computing already handles large-scale systems, but integrating AI models requires significant computational power and scalability, especially with large AI models.
Data Processing Overhead: Running complex AI models may add a computational overhead to grid computing, which needs to be addressed through efficient algorithm design.
Latency and Real-Time Decision-Making: AI models must make real-time decisions in distributed computing environments, where latency can pose significant challenges.
Complexity in Integration: AI systems are complex and integrating them with existing grid computing infrastructures, which may have legacy systems, can be a significant challenge.
Security Concerns: AI models need to process vast amounts of data, which can raise concerns about data security and privacy in grid environments.

7. Novel Contributions
Goal: This section presents new insights and contributions from the research.
Innovations:
Novel AI Algorithms: Propose innovative AI algorithms specifically designed to enhance grid computing performance.
Resource Optimization Techniques: Explore new methods of using AI to optimize resource allocation in grid environments, leading to lower operational costs and higher efficiency.
Enhanced Fault Tolerance: Introduce new fault tolerance mechanisms, aided by predictive AI algorithms, to enhance grid computing stability.
Impact: Discuss the potential long-term impact of integrating AI baseline networks with grid computing, such as more efficient handling of large-scale computations in fields like climate modeling, genomics, and financial simulations.

8. Future Prospects
Objective: To predict the future of the integration of AI and grid computing.
Key Trends:
AI-Driven Autonomous Grids: Discuss the possibility of creating autonomous grid computing systems powered entirely by AI, where human intervention is minimized, and the system dynamically manages resources and tasks.
AI for Edge Computing in Grids: Explore how AI baseline networks can be applied to edge computing nodes within grids, enabling real-time processing at the data source.
Future Research Directions: Identify areas where more research is needed, such as improving AI model efficiency for grid systems, developing new security measures for AI-powered grids, and creating frameworks for seamless AI integration with existing computing infrastructures.
Commercial and Societal Impact: Predict how the advancements in AI and grid computing could revolutionize industries that rely on high-performance computing, from healthcare to finance, and what the societal impact of such technologies will be.

3. RESULTS AND DISCUSSION

Researchers Analysis

The analysis section systematically examines the interaction between AI baseline networks and grid computing techniques based on various factors like scalability, efficiency, and overall performance. The goal of the analysis is to evaluate how AI can enhance the existing grid computing infrastructure, as well as the specific challenges it presents.

3.1 Performance Enhancement with AI Baseline Networks:

Efficiency of Resource Management: One of the primary analytical focuses is on how AI baseline networks improve resource management in grid computing. The study likely evaluates whether AI can predict and optimize resource allocation, reduce idle resources, and ensure efficient utilization of the distributed computing system. Impact on Task Scheduling: The analysis examines how AI enhances scheduling algorithms. AI's ability to predict execution times for various tasks can streamline the process of job allocation, leading to faster and more efficient computation. Reduced Fault Tolerance Issues: AI models can dynamically learn from past failures in grid systems and help predict potential system errors. The analysis assesses whether AI integration helps in reducing system crashes or downtimes, ensuring continuous and reliable computing power.

3.2 Challenges in AI-Grid Integration:

Scalability Concerns: An important area of analysis involves the scalability of AI baseline networks within grid computing environments. The research evaluates whether AI models, which typically require substantial computational resources, can scale efficiently in grid computing systems that handle distributed workloads across large networks. Computational Overhead: The study likely analyzes the computational overhead introduced by AI. This includes how running AI models in parallel with grid processes affects the overall processing power, latency, and resource availability of the grid system. Security and Data Privacy Issues: The research assesses the challenges related to securing AI-driven grid systems, especially in environments handling sensitive or large datasets. AI might require access to a wide variety of data, which could raise concerns about data breaches and unauthorized access.

3.3 Evaluation of Novel Contributions:

Proposed AI Algorithms: The analysis focuses on evaluating any newly proposed AI algorithms that were developed during the study to optimize grid computing techniques. For example, new scheduling algorithms, fault tolerance mechanisms, or predictive models are tested against traditional methods to compare efficiency and accuracy. Comparison with Existing Techniques: The analysis compares the AI-enhanced grid computing system with existing, non-AI grid systems. This comparison likely includes performance metrics like: Job completion time. Resource utilization. Fault recovery rate. System overhead.

3.4 Long-Term Impact Analysis:

Scalability to Large Grids: The analysis also focuses on how scalable the AI-augmented system is for larger, more complex grid environments like scientific simulations, financial modeling, and large-scale data processing. Interoperability: The research evaluates whether AI-enhanced systems can work seamlessly with existing grid infrastructures and legacy systems without significant modifications. Learning Capacity: The ability of AI baseline networks to continuously improve through learning and adapting to new tasks is analyzed in terms of long-term sustainability in grid computing.

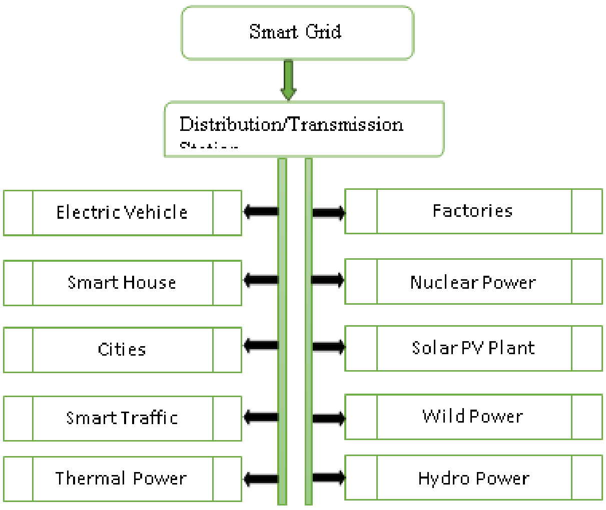

Figure 2 Smart Grid Application in Different technologies

Employ a deep neural network to successfully pinpoint the assault location through a case study and lessen the effects of cyberattacks on the power system at various levels [25].Threats are any number of potential events, whether man-made or natural, that have the potential to affect how well a system operates [26]. If the necessary steps are not done in a timely manner, these threats could be dangerous. Electronics 2020, 9, 1030 16 of 25 breaches of customer data privacy and malevolent control of smart home equipment and devices are the most common threats[27]. Because of the complexity of the system and the fact that sophisticated attacks are difficult to identify, it is impossible to include every potential hazard in the SG. Malicious threats are divided into three categories. according to their objectives: network availability, data integrity, and information privacy[28]. In addition to its technical difficulties, the SG presents regulatory difficulties. Changes are anticipated at random because politicians and stakeholders compete for domination. Designers of smart devices must guarantee compliance with SG standards[20].

3.5 Novelty in AI baseline Networks

AI technologies have been steadily advancing in a variety of VPP applications in recent years[29]. The economic dispatch was approached by the studies in utilizing either non-dominated sorting genetic algorithm or reinforcement learning (RL)[30]. There have also been other variations of intelligent energy management techniques based on RL and recurrent neural networks (RNN) [31], [32], [33]. For solar photovoltaic power prediction, the studies used explainable AI tools and artificial neural networks, whereas suggested an ensemble learning-based model for wind energy forecast. (. For solar photovoltaic power prediction, the studies in used explainable AI tools and artificial neural networks, whereas suggested an ensemble learning-based model for wind energy forecast. Based on a multilayer perceptron, demand-side energy management with a price forecast.

Combined the EV bidding technique with the RL method. In order to estimate EV energy consumption, a unique centralized energy demand learning system was presented in[27]. Given that the majority of these works conduct their tests on a single, centralized server, the system will inevitably run into the following issues. The center's collection and learning of all the distributed data may first cause a latency and cost constraint. Second, the centralized server plays a major role in maintaining the stability of the entire system. That is, all distributed nodes' requests will stop receiving responses once the server fails. Furthermore, it is simple for attackers to get or alter sensitive data once they have access to the centralized server. Conversely, in certain edge computing models the processing is shifted from data centers to nearby devices[34], [35], [36]. However, the edge nodes' speed and storage capacity are still constrained[37], [38].

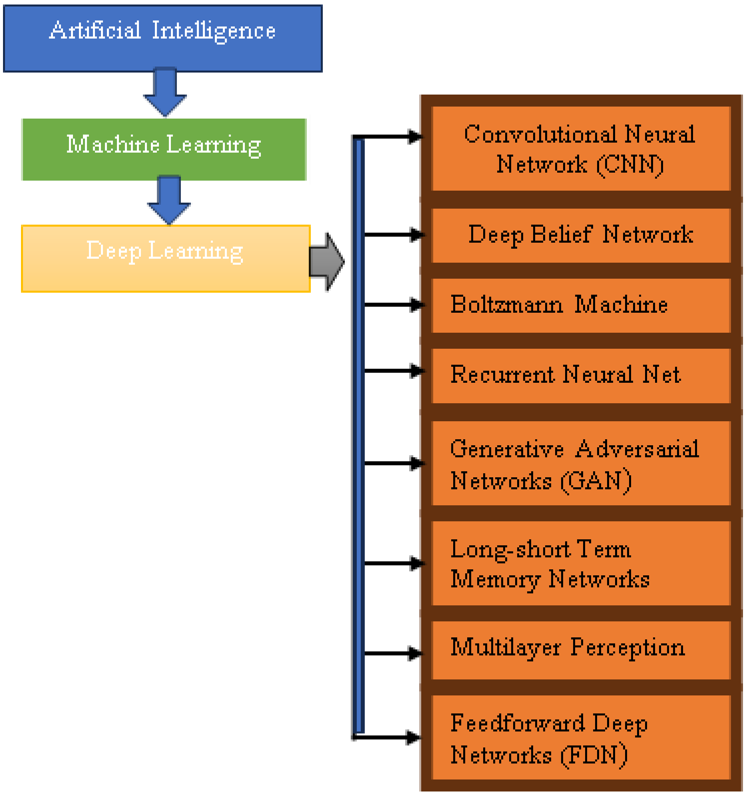

Figure 3 Techniques associated with Deep learning

With the aid of strong computer technology and a growing volume of data, new AI algorithms have emerged, propelling AI into the so-called AI 2.0 stage. AI is now able to address increasingly complicated issues. First applied to image processing, deep learning (DL), a subset of machine learning (ML), started with multilayer deep neural networks (DNNs). In recent years, deep learning (DL) techniques have advanced quickly. Several effective structures, such as deep belief networks, convolution neural networks (CNNs) ,recurrent neural networks (RNNs).

AI has advanced into the so-called AI 2.0 stage because to the development of new algorithms and the availability of an increasing amount of data[39]. AI can now handle problems that are getting more and more complex. Multilayer deep neural networks (DNNs) were the foundation of deep learning (DL), a branch of machine learning (ML), when it came to image processing. Deep learning (DL) approaches have made rapid progress in the last few years. To address issues with smart grids, a number of efficient structures have been proposed, including generative adversarial networks[40].

Table 1. Merit and Demerits of various deep learning techniques

Techniques	Merits	Demerits
CNN	CNNs are strong, very competitive supervised deep learning techniques. Its scalability is increased with the addition of CNN features, and the length of their training when paired with ANN features is improved. Because CNNs may dynamically learn functionality from raw data on protection, they provide potential uses for IoT privacy.	CNNs have substantial computational expenses. As such, their implementation to provide onboard safety features on commodity-constrained platforms is difficult.
RNN	In many situations, RNNs perform better than their equivalents when dealing with serial data. Serial data can occasionally be seen in IoT security data. RNNs could therefore be useful for IoT security.	The primary drawback of RNNs is the issue of gradients blowing up or disappearing.
AE	Theoretically, AEs are important for functionality extraction. Without any prior knowledge of the data, AEs can be used to minimize dimensionality and train features for representation learning that are superior to the manually constructed features used in conventional ML.	A lot of computer power is used by AEs. Even while AEs are easily trained to capture the properties of training data, they will not be able to reflect the qualities if the training dataset is not representative of the test data set. Instead, they will merely cause confusion in the learning process.
RBM	Multiple key features can be recovered using an unsupervised approach using a feedback mechanism on RBMs.	RBMs have significant computational expenses. Therefore, it is difficult to integrate them to enable onboard protection systems on IoT devices with limited resources.
DBN	DBNs are iteratively trained with unlabeled data to represent relevant features in non-supervised learning scenarios.	Because the lengthy initialization process generates a huge number of parameters, DBNs have substantial computing costs.

GAN	Similar to DBNs and RBMs, where the Markov network needs an arbitrary number of iterations, the only option to generate a sample with GAN is to go through the model.	GAN is erratic and requires advance planning. Learning how to use a GAN to create discrete data is a challenging undertaking.
EDLN	Combining different DL optimization algorithms can produce a wider range of models, improving the generalization and efficacy of the models.	The temporal complexity of the system can be greatly expanded.

3.6 Smart Grid's advances and Reform

Through the integration of modern metering infrastructure, control technologies, and communication technologies, the smart grid is making it possible to collect vast amounts of high-dimensional and multi-type data regarding the operations of the electric power grid. The limits of traditional modeling, optimization, and control technologies in handling data have led to an increasing recognition of the smart grid's potential for utilizing artificial intelligence (AI) techniques[41]. Technological progress has led to a transformation of power systems, bringing about institutional adjustments. The implementation of the smart grid necessitates cooperative processes involving technological, institutional, economic, and social issues. Since their founding, the RTOs and ISOs have battled to create an effective market-based decision-making structure that keeps all parties informed. The main concept is to open up the electricity market to new ISOs and RTOs, allowing them to enter the market and increasing the accessibility of electricity for medium- and small-scale consumers[42].

This would stimulate new market competition, which could result in breakthroughs and aid in the transition from centralized fossil fuel generation to green and clean energy as well. Energy-related problems are directly related to the consumer's lifestyle use numerous technical breakthroughs, including SM, to highlight pro-sustainability attitudes and values of power transition and consumption. The energy industry has seen significant changes as a result of market liberalization with far-reaching technical and financial ramifications. Policymakers and industry participants are working hard to implement effective strategies in order to keep up with the improvements as a result of the rising digitization. suggest an energy market design architecture that can integrate, coordinate, and manage intricate power sector systems thanks to AI technology and big data.

In order to provide new services, SM and ICT gather vast amounts of consumer and utility service management data, which are then used in conjunction with advanced communication equipment. It will also assist in controlling market prices for electricity. Investors in the power sector are becoming more and more interested in the ongoing liberalization of the energy market, or the transition from monopoly to competitive market structures. The virtual power plant (VPP) idea gives distributed energy resources (DERs) visibility and access to all energy markets. Businesses can maximize their location to increase the potential for their revenue creation by utilizing VPP market knowledge.

The results from this research would highlight the major findings based on the detailed analysis. Here’s what the results may show:

Improved Resource Allocation and Scheduling:

AI-Driven Optimization: Results are expected to demonstrate significant improvements in grid computing resource management, with AI baseline networks predicting and dynamically allocating resources more efficiently than traditional methods. Reduced Latency and Overhead: The results might show that AI-based scheduling and predictive load management reduced task latency and improved overall throughput in the grid environment. Faster Task Completion: AI-driven task scheduling likely resulted in faster job execution times, leading to a more efficient grid system.

Increased Fault Tolerance

Enhanced Stability: The findings could indicate that grid systems integrated with AI baseline networks exhibited higher fault tolerance, with AI algorithms predicting potential failures and taking preemptive measures. Less Downtime: AI models may have effectively reduced system downtime by detecting and addressing faults before they escalated, leading to a more reliable and stable grid computing infrastructure.

Challenges in Scaling and Integration:

Computational Costs: The research may highlight that while AI improves grid computing performance, it also introduces significant computational overhead, particularly in large-scale grids. The results may suggest that advanced optimization techniques or hardware support (like GPUs) are required to address these challenges. Security Risks: Another key result could be the identification of new security concerns, especially related to data privacy when integrating AI into grid computing. The study could propose mitigations or highlight areas where further research is needed to secure AI-driven grid systems.

Novel Contributions:

New Algorithms and Models: The study may present newly developed AI models or algorithms that outperformed traditional methods in terms of resource management, task scheduling, or fault tolerance. These contributions could demonstrate clear advantages in specific use cases, such as large-scale scientific simulations or financial data analysis. Adaptive Learning in Grids: Results might show that AI baseline networks significantly contributed to the adaptability of the grid computing system, where the grid could learn and optimize itself over time based on previous tasks and system behavior.

Prospective Developments:

Autonomous Grids: The research may project that AI-enhanced grid computing could evolve toward fully autonomous grids in the future, where human intervention is minimized, and AI models dynamically manage all aspects of the grid, from resource allocation to fault management. Future Research Directions: The results could open up new research areas, such as the need for lightweight AI models that can function with lower computational costs in grid environments or secure AI integration mechanisms that protect sensitive data.

4. CONCLUSION

In conclusion, the results of this systematic survey would likely emphasize the potential benefits of using AI baseline networks to enhance grid computing performance, especially in terms of resource management, scheduling, and fault tolerance. However, it would also highlight several challenges related to computational overhead, scalability, and security. The study's novel contributions would involve proposing AI models specifically tailored for grid computing, with recommendations for further research on optimizing AI integration and developing lightweight, efficient AI algorithms for large-scale distributed systems.The study reviewed on how a smart grid applied different deep learning techniques and how renewable energy can be integrated into a system where grid control is essential for energy management. The article discusses the idea of a smart grid and how reliable it is when renewable energy sources are present. Globally, a change in electric energy is needed to reduce greenhouse gas emissions, prevent global warming, reduce pollution, and boost energy security.

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