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Artificial Intelligence Applications in Improving Electric Load Management: Case Studies

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ABSTRACT

As the globe faces serious climate and energy concerns, Artificial Intelligence has shown to be a transformative force in the advancement of renewable energy technologies. This paper examines the existing and prospective applications of artificial intelligence in renewable energy. This work focuses on the transformative role of Artificial Intelligence (AI) in making renewable energy systems more efficient, reliable, and scalable. AI technology - from machine learning and deep learning to learning to learning - optimization of energy production, forecasts demand, future maintenance and management of decentralized energy networks. Looking ahead, emerging fields like quantum machine learning and AI-powered augmented reality offer exciting possibilities, with the potential to fundamentally reshape energy infrastructures. The survey highlights major innovations across wind and solar power, energy storage, and smart grids, emphasizing how AI helps address persistent challenges such as intermittency and variability. Equally important are the supporting technologies—big data, the Internet of Things (IoT), and real-time analytics—that drive the development of more advanced AI models. We also explore how AI is shaping energy policy and market modeling, paving the way for broader renewable energy adoption. Real-world applications bring these ideas to life. For instance, Google's collaboration with DeepMind has enhanced wind power generation using wiser forecasting, while Australia's National Electricity Market has looked to AI in order to enhance grid stability. These cases demonstrate that AI’s role in renewable energy is not just theoretical—it is already delivering measurable results and redefining what’s possible in the global energy landscape. In order to optimize AI's potential for advancing sustainable energy and combating climate change, this study identifies the obstacles preventing its implementation in renewable energy systems and makes suggestions for enhancing current technology.

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1. Introduction:

Because of economic growth, urbanization, and population expansion, the world's energy demand has increased dramatically in the twenty-first century, leading to a greater reliance on fossil fuels like coal, oil, and natural gas, which continue to be the primary energy sources despite growing environmental concerns. According to the International Energy Agency (IEA), global CO_2 emissions from energy increased by 1.1% in 2023 to a record 37.2 Gt, which is nearly 50% higher than at the beginning of the century and is a major contributor to climate change, global warming, and the increasing frequency of extreme weather events. A cleaner and more sustainable alternative is provided by renewable energy (RE) sources, especially solar, wind, and hydropower, which are naturally replenishable, less susceptible to price fluctuations, and emit little to no greenhouse gases. Global renewable capacity reached nearly 3,870 GW in 2023, an increase of 14% from the year before, and generate more than 30% of the world's electricity; projections indicate that this share could surpass 42% by 2028, with wind and solar expected to double or even quadruple their contribution. The wider use of renewables can stabilize electricity prices, improve energy security in underserved regions, and create economic opportunities, making them central to a sustainable energy future. However, despite regulatory barriers, intermittency, and grid stability, advances in storage systems and digital technologies like artificial intelligence are helping to improve forecasting, system integration, and energy management.

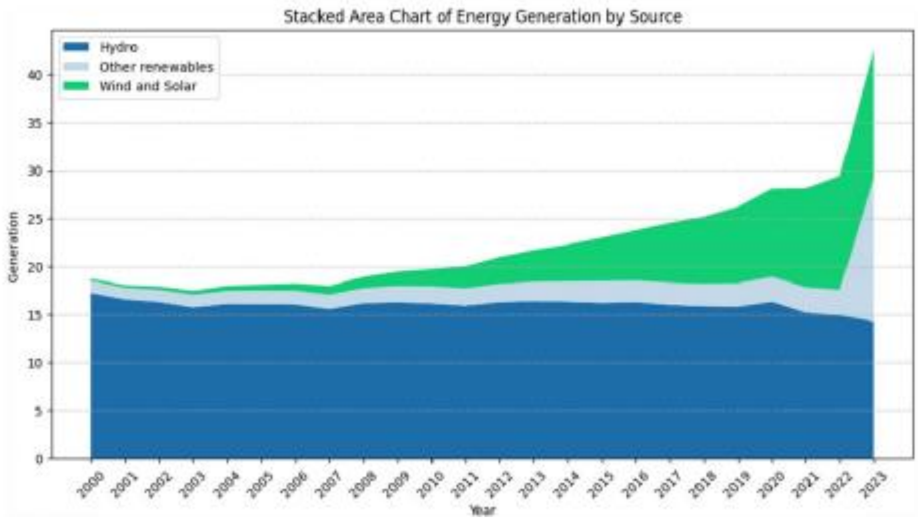

Fig (1): The expansion of renewable energy sources for power generation worldwide

1.1. Research question

This research addresses the following main question:

- What are the AI systems?
- What are the main AI technologies?
- What are the objectives of the intelligent systems?
- Where are the benefits and importance of AI technologies in electric power system?

1.2. Research Objectives

The main objectives of this study are as follows:

- Identify and analyze the AI system.
- How does AI system work?
- AI APPS.

1.3. Literature Review:

- An artificial intelligence-based 2.5 kW hybrid power plant model was created. Hydrogen conversion systems and renewable energy sources were hybridized. FCMSE = 2.4% and WEMSE = 1.96% performance prediction accuracy were attained. The WT and PV power generation was predicted by GSR and wind forecast models. Fuzzy logic constitutes the base of the energy management strategy for real weather conditions. V. Vallejo-Becerra and others (2013).
- • Artificial intelligence optimization has been used in Denmark to plan, design, and control hybrid energy systems. The most effective system design patterns as far as the optimal location, size, and kind of generation units for a node are determined by the algorithms. The system, through this, is able to satisfy the energy needs at least cost, thus proving the capability of AI in maximizing efficiency and economic feasibility in hybrid renewable grids.
- • Eid Gul et al. designed and implemented an artificial intelligence (AI)-tuned model of a power tower concentrating solar power (CSP) system with thermal energy storage (TES). Their research used a real dataset for eight years' hourly weather data (2015–2022) from the National Solar Radiation Database (NREL). Experimental procedure included data collection, data preprocessing, AI model construction, operational optimization, weather influence assessment, and economic analysis. Outcomes reported a

remarkable enhancement of performance and economic gains, emphasizing the potential of AI to drive CSP technologies and speed up the transition to green energy systems. The model's accuracy was verified using cross-validation, which reported an incredibly low Mean Squared Error of 0.0679 and almost perfect R^2 measure of 0.9999, indicative of the precision and expertise of the AI optimization process.

- • There have been a number of studies that explored the application of AI methods in developing renewable energy. Kalogirou and Sencan (2010) had an initial comprehensive overview of how AI would improve the efficiency of different solar energy systems. Based on this, Belu (2014) gave an overview of the most applicable AI methods used in solar energy, briefly mentioning neural networks, fuzzy logic, and genetic algorithms. Youssef et al. (2017) have studied AI-based applications in designing and controlling solar energy systems, while H. Elsheikh et al. have presented a comprehensive review on the use of Artificial Neural Networks (ANNs) in optimizing solar-based technology. Likewise, Oliva et al. (2019) presented a review on meta-heuristic strategies to enhance solar cell efficiency.
- • While useful, the scope of reviews such as this restricts the intensity of coverage of particular renewable technologies. In contrast, the present article takes a different approach—focusing in detail on the application of AI techniques to a very specific solar energy technology: the solar tower, or central receiver system.
- (Soteris A. Kalogirou ,2004 is demonstrated by the use of artificial intelligence techniques, such as genetic algorithms and artificial neural networks, to optimize solar energy systems and optimize their economic benefits. A TRNSYS computer program and Cyprus's climate, which is contained in a typical meteorological year (TMY) file, are used to model the system. A limited set of TRNSYS simulations was used to train an artificial neural network (ANN), enabling it to learn the relationship between collector area, storage tank size, and the system's auxiliary energy requirements. Based on this information, life-cycle savings can be projected. The ideal size of these two parameters is then estimated using a genetic algorithm to maximize life-cycle savings, which significantly cuts down on design time. The ideal magnitude of these two parameters is then estimated using a genetic algorithm in order to maximize life-cycle savings, which significantly cuts down on design time. The optimization of an industrial process heat system using flat-plate collectors is presented as an example. When considering both subsidized and non-subsidized fuel prices, the proposed optimization approach delivers notably better results than the traditional trial-and-error method. Specifically, it achieves life-cycle savings that are 4.9% and 3.1% higher, respectively, underscoring the effectiveness of this methodology. The current approach significantly cuts down on the amount of time that design engineers need to spend determining the best answer and frequently yields a solution that is difficult to identify using basic modeling software or trial-and-error, which typically relies on the engineer's intuition.
- Fathi et al. (2020) emphasize that university campuses are complex energy environments, characterized by diverse infrastructure, varying operational schedules, and the growing impact of climate change factors such as temperature, humidity, and solar radiation. They argue that accurate long-term energy forecasting, which accounts for these climate change effects, is crucial for improving energy management and reducing operational costs. In a related study, Kim et al. (2020) highlight how occupancy rates and weather parameters—particularly temperature—strongly influence summer energy loads. Incorporating these variables into forecasting models, they note, can significantly enhance prediction accuracy.

2. Method

2.1. The relation between AI and Electric power:

The power industry in developed countries has already started implementing artificial intelligence and other related technologies, which allow the communication between smart grid devices, including Internet of Things devices, and their possible utilization in enhancing energy management, efficiency, and consumption of renewable energy sources. Other challenges have been more severe in emerging markets, where inefficiency is particularly problematic. Other challenges facing electricity include weak and aging infrastructure, changing consumption patterns, rising demand, declining efficiency, and more.

Artificial intelligence is making its way into emerging economies, where it will significantly help solve the majority of the problems plaguing the electric power industry. . Simply put, AI has the potential to reduce electricity waste and lower costs, facilitate the use of renewable energy sources in electric grids, and accelerate the provision of unique functions, such as forecasting, monitoring, verification, and estimation. AI can also improve the planning, operation, protection, and control of electric energy systems. Predicting failures and their locations is one most important applications of AI in the electric power sector, along with scheduling and timing maintenance. . Failures of electrical equipment, such as generating units, networks, transformers, cables, substations, and others, are common events with potentially devastating consequences. Thus, when paired with the right sensors, AI may play a key role in equipment monitoring and failure detection before they happen, saving time, effort, and lives. Preventing and avoiding disasters, such as hurricanes, tornadoes, and other extreme weather events, is an effective application in predicting them, as is the case in some US states known for their seasonal hurricane belt. The most important applications of AI focus on boldly and efficiently preventing non-technical waste by stopping tampering and theft and controlling illegal receipts. These include managing, evaluating, maintaining, updating, and disposing of electrical grid assets effectively. AI also helps customers manage their consumption, as the technology can predict the total costs of future bills. As for electric vehicles, AI has found its niche through autonomous driving and the ability to stop and park the vehicle automatically. With the introduction of smart grids, which are powerfully and intelligently controlled by artificial intelligence, the future of the electric power industry looks promising, especially with the rise of smart grids. Unlike traditional grids, smart grids include an information layer that enables two-way communication between utilities and consumers. This connectivity makes it possible to respond more effectively to sudden fluctuations in power demand, improving both reliability and efficiency. Installing smart meters and sensors that allow data collecting and analysis afterwards creates this information layer. Artificial intelligence (AI) is used in smart grids to analyze data and improve power distribution and transmission efficiency, safety, and dependability; it can also help predict renewable energy production, enhancing the reliability of solar and wind power by analyzing vast amounts of meteorological data, creating forecasts, and deciding when to collect, store, and distribute solar and wind energy; it can help balance the electrical grid by analyzing its components by processing intermittent units and assisting in the resolution of grid congestion, which is genuinely advantageous for the grid operator. In the field of improving energy efficiency, AI monitors electricity consumption in buildings and factories to control, assess, and manage consumption. Accordingly, AI has the potential to control electricity use during peak hours, even identify, and flag sources of high consumption by detecting building equipment failures before they occur.

2.2. What Makes a Grid “Smart”?

Electricity travels from power plants to residences and commercial buildings in a one-way fashion under traditional systems. But smart grids are two-way. They allow energy generated in wind-turbine-driven and rooftop solar panels to feed back into the system. Smart grids are linked with smart meters that possess advanced metering technology for enabling real-time data, optimizing energy efficiency, and facilitating more elastic control. However, even the most advanced smart grid technology will be less effective without AI.

2.2.1. The Role of AI in Smart Grid Management

For example, when urgently energy demand surges, AI networks can instantly have rechanneled the power across the grid such that blackouts do not happen. When some region of the grid is showing signs of wear and tear, AI will detect it and alert before it leads to a breakdown and save money and time on maintenance. In so many ways, AI is the smart grid's brain—working behind the scenes to make sense of the mountains of data that these systems produce and keep everything working in harmony.

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2.2.2. The Benefits of Smarter Systems

1. Energy That Matches Demand

By analyzing data such as weather patterns, seasonal changes, and daily consumption habits, AI enables energy providers to anticipate customer needs more accurately. This ensures that electricity is delivered precisely where and when it’s required, reducing shortages and improving reliability.

2. Lower Costs, Fewer Wasted Resources

Automaton lowers the need for ongoing human interaction, hence lowering the operation costs for utilities. For consumers, this often translates into lower electricity bills, while providers benefit from greater efficiency and more sustainable use of resources.

3. A Smoother Path to Sustainability

Renewable energy, while essential for a sustainable future, faces challenges due to its intermittent and unpredictable nature. AI helps address these issues by managing energy storage—capturing surplus power in battery systems and releasing it when demand is high. This makes renewable energy more dependable and easier to integrate into existing grids

. This enables the maintenance of a steady supply even when the sun and wind are not present. Optimized grids also have the advantage of lowering greenhouse gas emissions.

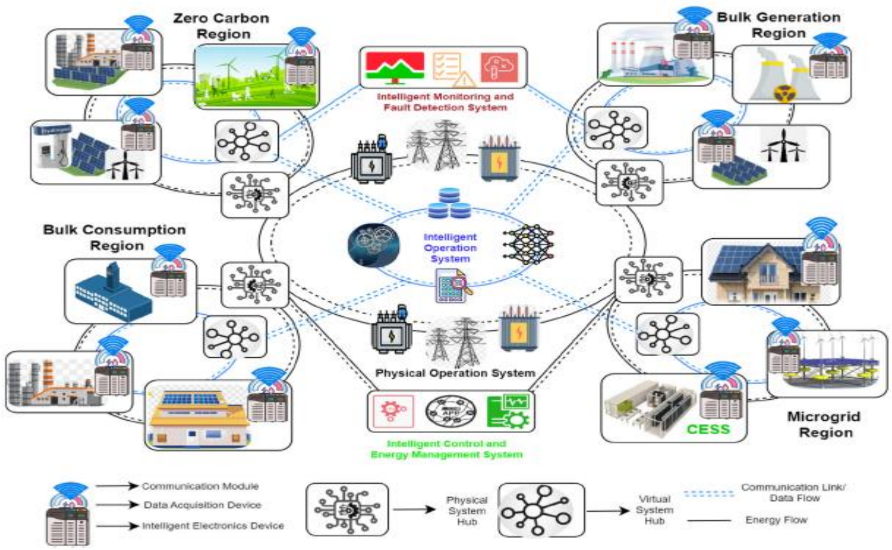

Fig (2): Framework of AI-based intelligent grid system.

2.3. Review of load forecasting in power systems:

Traditional grids and smart grids face different load forecasting challenges: traditional grids lack real-time data, which makes it more difficult to implement demand-response programs or seamlessly integrate renewable energy. Traditional systems usually depend on historical information and simple statistical models, and these can capture some idea of future demand but often fail to capture sudden changes in patterns of use and cannot respond to new circumstances. But smart grids have intelligent meters and sensors that continually take readings and feed them back for analysis through machine learning and deep learning methods to enhance the accuracy of prediction. Through more efficient and cost-effective grid utilization and management, and by influencing consumers to move usage when the grid needs it, it enhances real-time pricing. There are three core load forecasting methods. The first is spatial forecasting, where it investigates demand in various regions of the grid. The second is hierarchical forecasting, where it examines demand at national, regional, and local levels. The third is probabilistic forecasting, where it does not generate one number but a series of possible results and their probability. This latter approach serves to address the uncertainty arising from renewable energy and from changing markets

3. Result and discussion:

The smart network requires accurate load forecast to improve the transmission and consumption of electric power, which is necessary for effective energy management. Demand for energy is continuous, traditional forecasting methods is no longer enough. Instead, machine learning (ml) and deep learning (DL) approaches are quickly used to gain high accuracy and efficiency. By analyzing historical consumption patterns, weather conditions and other relevant variables, these models can predict more of future power needs than traditional techniques. In a smart grid, strain forecast plays an important role in increasing the efficiency and reliability of the power distribution. Recovery and decision trees such as ML models, with DL models such as nerve networks, are able to capture complex correlations within large data sets, enabling more accurate and dynamic forecasts. This future indicative capacity not only allows use companies to reduce grid load, adapt resource distribution and to prevent potential errors, but also strengthen consumers with insights to make more informed energy use decisions. Finally, integration of ml and dl in load forecast strengthens the operational efficiency of the smart network. It supports the development of a more intelligent, flexible and adaptive energy infrastructure that is well suited for the developed requirements for modern society (Zafar et al., 2023; Onteru and Vuddanti, 2023). Important artificial intelligence (AI) strategies for res:
Distribution, consumption and generational adaptation to renewable energy systems have made great strides, and data -driven methods are used on problems such as rapid supply variability, grid integration and maintenance scheme. Moreover, flexible control approaches help manage uncertainty and adjust operational settings based on real-time conditions in hybrid systems combining sources like solar and wind; synthetic data generation is being used to fill gaps in historical records, especially in remote areas, which strengthens forecasting and planning across renewable energy networks; and dynamic decision-making tools have improved the operation of energy storage systems by adapting to changing prices and consumption patterns, increasing economic efficiency.

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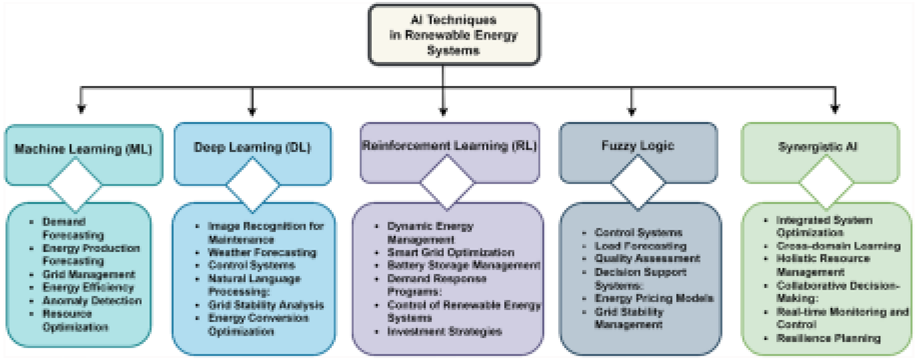

Fig (3): key AI techniques in RES overview

The integration of artificial intelligence (AI) technologies into renewable energy systems enables greater flexibility, efficiency, and adaptability. Hybrid approaches—such as combining machine learning (ML) for predictive tasks with reinforcement learning (RL) for dynamic decision-making, or integrating fuzzy logic with ML and DL algorithms to manage uncertainty—have proven especially effective. These techniques address some of the key challenges in the renewable energy sector, such as production variability and real-time adaptation. As a consequence, the energy system gets smarter and more reliable and more efficient and global infection against lasting power. Table 1 presents a table of observations of the most used AI algorithm, its advantages, disadvantages as well as areas where renewable energy applications can be improved. The choice of the algorithm depends mainly on the difficulty of the problem, the calculation resources and the amount of interpretation required. We observe clear trade-offs between interpretability, the computational cost, and the prediction performance in these different methodologies. Traditional models like Linear Regression (1) and Decision Trees (2) are quick and easy to apply but they have difficulty in handling non-linear relationships and might over fit. Advanced models such as Support Vector Machines (3) and Random Forests (4) generalize better at the expense of computational cost. Gradient Boosting (5) produces high accuracy while vulnerable to overfitting. Non-purposes to non-pausing techniques as the best neighbors (6) are very flexible, but problems with scalability. Deep Learning Models - Artificial Neural Network (7), Conversional Neural Networks (CNNS) and recurrent nervous networks (RNNS) (RNNS) (8) -Excel involve capturing complex patterns in The Excel, although they require large dataset and often lack lacking lacks. Long short -term memory (LSTM) network (9) reduces the disappearance problems, but calculated requirements. Strengthening learning (10) is powerful for dynamic adaptation, but requires extensive training, while unclear logic (11) is effective for dealing with limited uncertainty in scalability.

Development of AI in electrical systems:

With the promotion of data analysis and data processing options, and with the growing requirement for permanent energy solutions, the electrical power system has made a significant change in their control and control methods. Originally, these systems depended on traditional adaptation and control techniques, often based on certain rules and lack the ability to handle the complexity of the modern network. With a transition to renewable energy sources in the late 1990s and early 2000s, large -scale data began to be collected, including operating indicators, consumption patterns and weather conditions, which enables better web handling, strain forecasts and defective diagnosis. Progress in sensors, smart meters and the Internet of things have also improved the increase in grid efficiency, reforms such as wind and sun performance, and has enabled effective integration with the current network. In recent years, smart grids have provided unprecedented flexibility and efficiency through real-time monitoring and control of energy flow, supporting decentralized energy systems, such as local energy exchange platforms, distributed storage, and micro grids, to enhance efficiency and energy access in local communities. As the global shift toward sustainability and reduced emissions continues, developments in the management and operation of electric power systems are expected to continue to accelerate.

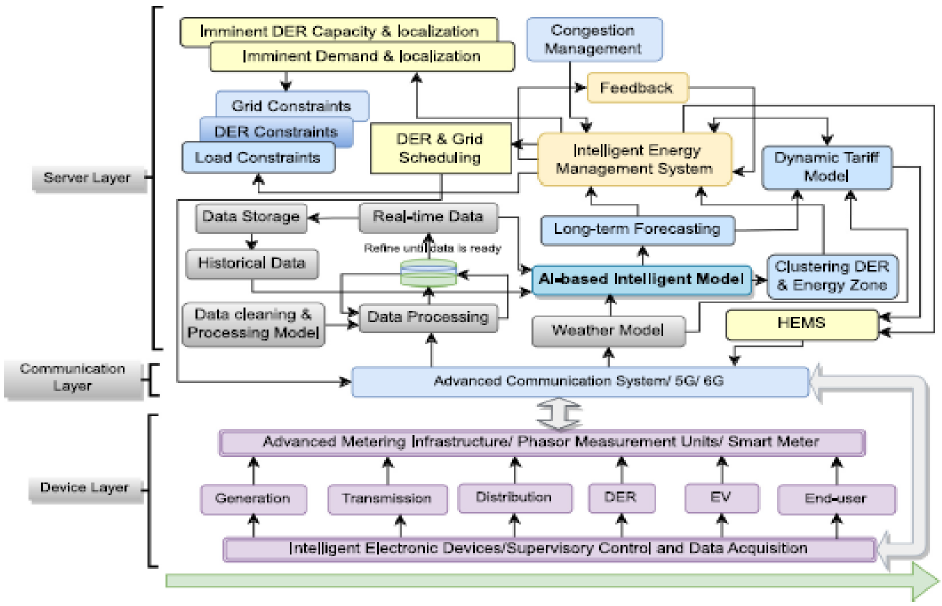

Fig (4): Artificial Intelligent-based intelligent management system

Basic AI techniques for energy management:

Prior to the introduction of advanced analytics, renewable energy technologies such as solar, wind, hydro, and bio thermal were well-established and well-developed, but they faced limitations in efficiency and responsiveness due to the lack of advanced analytical tools. These limitations made it difficult to optimize system performance, reduce costs, and protect the environment, while energy demand increased due to population, economic, and industrial growth. Research responded by developing energy management techniques to enhance efficiency and reduce waste, with a focus on integrating multi-energy systems and improving the integration of renewable sources within comprehensive strategies such as MESI. The goals of environmental policy and rules, such as emissions in the UK, have also played a role in promoting technological innovation and investment in research and development and development of renewable energy. Studies have shown the importance of using a permanent and integrated approach that combines economic and technical efficiency to protect the environment and achieve the transition to more sustainable energy systems.

Current uses of AI in renewable energy systems:

Wind energy:

AI techniques have become indispensable in the optimization of wind energy systems. They are applied across a wide range of areas, including improving the accuracy of very short-term power forecasts, determining the optimal sizing of solar–wind–battery hybrid systems, and designing renewable-powered desalination units. AI is also used to enhance wind power forecasting, maximize wind energy utilization, predict wind speeds more reliably, and optimize both the layout and yaw control of wind farms. AI-powered predictive maintenance makes it possible to identify possible turbine breakdowns early, which drastically lowers maintenance expenses and downtime. In order to predict breakdowns and plan timely maintenance interventions, machine learning algorithms examine past operational data. Additionally, by combining previous performance measurements with real-time meteorological data, AI improves wind power forecasts, increasing prediction accuracy and enabling a more seamless integration into the electrical grid. Supply and demand must be balanced, and this optimization is crucial as RE sources proliferate in current infrastructures.

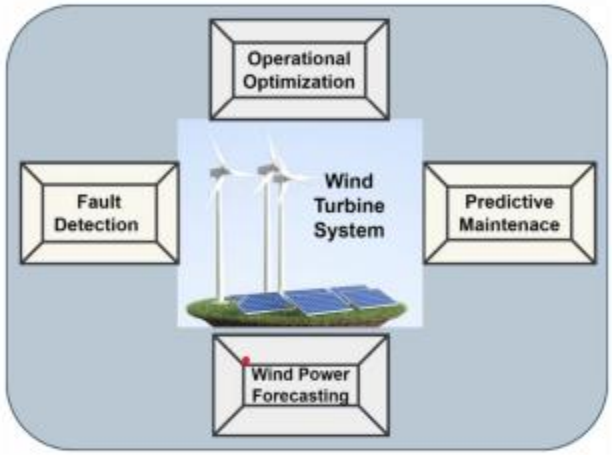

Fig (5): Using AI to Optimize Wind Energy

Because wind speed is inherently random and changeable, wind energy plants operating within sophisticated control systems have difficulty analytically characterizing their transfer functions. The nonlinear features of wind speed data, however, are efficiently analyzed by AI algorithms, producing forecasts of energy output that are more accurate. Forecasting wind speed and power generation, as well as problem detection for gearboxes, bearings, generators, and rotor blades, are important uses of AI in wind energy. AI also optimizes farm and turbine operations by managing variables like speed, pitch angle, maximum power tracking, and inverter reactive power. AI also helps with classification and approximation jobs, which improves wind energy systems' uncertainty analysis. Accurate forecasting is still necessary to ensure safe wind power integration and the successful completion of related projects because wind speed estimates are complicated and influenced by a number of meteorological factors.

Solar Power:

Solar energy systems are essential to the transition to sustainable energy, reducing dependence on fossil fuels and converting sunlight into clean electricity. Given the variable nature of solar energy, accurate solar radiation forecasting is essential for optimizing energy production and reducing losses. It also contributes to fault detection, improving system performance, and reducing maintenance costs. Accurate production forecasting facilitates energy distribution, load balancing, and grid stability, while simulation provides effective alternatives to field design, even in areas where live data is lacking. Energy storage systems contribute to improving grid performance and efficiency by managing charging and discharging and predicting battery health, increasing energy reliability and reducing costs. Smart networks and demand management also help to adapt to real consumption changes, increase the integration of renewable energy sources and improve online stability. In hybrid systems that combine sun, air and storage, improve real -time monitoring and control efficiency, increase flexibility and ensure continuity of supply. Major challenges include the requirement for accurate data, integration of different systems and optimization models under different regional conditions.

Limitations and difficulties:

Many obstacles prevent renewable energy systems to prevent widespread adoption and improvement in efficiency. The absence of accurate and complete data, the challenge to integrate modern systems with inheritance systems, and high financial costs are the most remarkable for these problems. The extension is made more difficult from some established players than vague rules and opposition. In order to support a permanent and fair energy infection, infrastructure is required to modernize, better data collection and clear guidelines. In some areas, effective implementation of these systems is limited by a lack of resources and qualified personnel.

Prospects for the fields future and research

AI for renewable energy systems in the future:

AI is expected to revolutionize Res in the future, especially in state -of -the -art technologies such as space -based solar and floating wind farm. As the demand for cleaner and more efficient energy solutions increases, AI provides the necessary opportunities for adapting the design, operation and integration of the next generation of energy systems. Analysis of oceanographic and environmental data to indicate that the best places are needed to improve the range of floating wind farms. Reducing faults and improving energy efficiency are further benefits of ongoing maintenance and monitoring. Satellite placement and energy conversion and transmission technologies can be enhanced for space solar power to guarantee supply continuity and effective integration with terrestrial networks, while lowering the requirement for human intervention in challenging or dangerous tasks. A cleaner, more sustainable, and more resilient energy future can be achieved by improving data gathering, promoting cooperation among specialized specialists, and creating better forecasting and performance improvement models in order to fully benefit from these cutting-edge technologies.

Renewable energy and artificial intelligence for low-income areas:

The development of renewable energy sources in low-income areas is hampered by factors like poor infrastructure, limited funding, and geographic location. Reliable and reasonably priced energy solutions can be made available to these communities by increasing the efficiency of nearby energy sources like solar and wind turbines and distributing electricity properly. Sustainable energy solutions can be made more cheap for these regions by improving financing and investment models to draw in capital and make pay-per-use services like solar energy easier to acquire.

Fig. (6): The sustainable operation of renewable energy systems (RES) in low-income areas will rely heavily on continued advancements in AI-driven predictive maintenance and real-time monitoring technologies.

4. Discussion:

By evaluating sensor data from renewable energy (RE) infrastructure, AI can help identify potential issues before they develop into critical failures, minimizing downtime and ensuring a more consistent energy supply. This is particularly valuable in regions where technical expertise is limited. Future research should also consider ways of strengthening local capacity-for example, through AI-recognized training programs, which enable local communities to manage and maintain their renewable energy systems independently. Tackling these challenges will allow AI to play an important role in supporting low -income societies on a route to more fair, inclusive and sustainable energy infections. In addition, AI can increase the understanding and management of energy production and storage, can adapt to network operations and facilitated integration of variable renewable sources into the web, as well as to adapt the solution of local communities and to guarantee that everything, change in renewable energy sources requires collaboration of experts in engineering science, environment and economics. Politics producers can improve the distribution of resources and network stability, develop accurate and optimal strategies and evaluate the effects of guidelines for investment, consumption and emissions by promoting market data, weather and consumption patterns. Efficiency, adaptability and stability of energy systems are improved by participation in public, companies and academic fields. This partnership enables renewable energy infection and only worldwide infections.

5. Conclusion:

AI-powered Future Analytics is a powerful tool to ensure that the smooth and effective operation of the renewable energy infrastructure. By identifying the possibility of potential errors and recurrent patterns, it not only prevents disruptions, but also provides valuable insights to improve the continuous system. Accepting this approach to renewable energy projects is capable of more sustainable operations through date -driven maintenance by using this approach. The repair can be determined correctly where the AI algorithm indicates weak points or potential error mode so that operators can continuously function. It reduces unexpected shutdowns, reduces unnecessary interventions and eventually saves both time and resources. Finally, artificial intelligence (AI) has considerable potential to revolutionize the industry for renewable energy, but its full capacity requires coordinated efforts in improving infrastructure, regulatory structure and technology development. AI has the opportunity to use advanced equipment, promote innovation and promote collaborative efforts against more efficient, flexible and permanent energy ecosystem.

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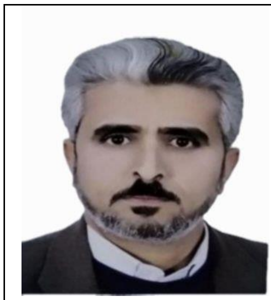
BIOGRAPHIES OF AUTHORS

The recommended number of authors is at least 2. One of them as a corresponding author.
Please attach clear photo (3x4 cm) and vita. Example of biographies of authors:

	Eng. Haider Karim Salman Al-Janabi, received his Diploma from Karbala Technical Institute (2003–2004), B.Sc. from the Technical College – Musayyib (2007), and M.Sc. in Electrical Engineering from Azad University of Science and Research – Tehran. He has been working at the Karbala Sewage Directorate since 2010, holding several positions such as Head of Al-Saddah Sewage Center, Resident Engineer for Al-Har Treatment Unit, Head of Repair Committees for Al-Hussainiya Sewage Branch, and Head of Stations for Al-Hussainiya Branch. He possesses technical skills in MS Office, Photoshop, and AutoCAD, along with personal skills in communication, problem-solving, time management, teamwork, and leadership. He is proficient in both Arabic and English (very good level). He can be contacted at: Haider.eng.jood@gmail.com.