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Review of AI-Based Modelling and Control Methods for Wind-PV-Battery Distributed Generation

Amit Kumar Panday*, [1], Prabhakar Tiwari*, and D.K. Nishad*

Abstract *–PV and wind electricity are used in distributed generation (DG) systems for sustainability and decentralisation. Wind, solar, and battery systems can provide energy storage and complementary generating profiles. Renewable resources are unpredictable, making modelling and controlling difficult and limiting performance. Traditional prediction, optimisation, and control methods are inferior to AI. This critical analysis examines AI-based modelling and control methods for small scale wind-photovoltaic battery distributed generating systems. This paper objectively evaluates AI approaches strengths and weaknesses and discusses their practical applications in energy flow optimisation and renewable resource variability. Oversight is necessary for those implementing AI solutions and researchers making breakthroughs. The evidence presented here demonstrates that artificial intelligence can potentially improve distributed energy systems' efficiency, dependability, and sustainability.*

Keywords – Distributed Generation, Renewable Energy Integration, Wind-PV-Battery Systems, Artificial Intelligence (AI), AI-Based Modelling and Control.

1. INTRODUCTION

Distributed generation (DG) produces energy locally, near consumers, unlike large-scale power plants [1]. Transmission loss reduction, energy security, and climate change urgency have driven dispersed generation's growth [2]. The spike can be attributed to renewable energy sources such as solar photovoltaics and wind power. This shift is a result of a number of factors, including environmental advantages, decreased costs, and technological advancements [3, 4]. Your contributions, as electrical engineers, researchers, and academics, are absolutely necessary for the development of DG systems. Integrating renewable sources requires sophisticated energy management to balance prices, reliability, and system longevity. Strategies must optimize energy dispatch between sources, battery storage, and variable load demand [3, 5] DG systems are beneficial when wind and solar photovoltaics are used, but their power production fluctuation makes integration difficult [5]. Accurate power forecasting is needed because weather patterns affect solar irradiance and wind speed, which affect system stability [1, 5].

Short-term and medium-term generation (wind and solar) and load projections are needed for system reliability [2]. Renewable energy integration is complicated, but AI, especially machine learning, can help. AI excels in modeling complicated nonlinear systems with uncertainty, which are common in wind-PV-battery systems [6]. AI models can adapt to changing weather and system dynamics by learning from prior data, enhancing forecasting accuracy [6, 7]. AI's capacity to solve complicated optimization issues improves energy management and control, improving system performance and cost [8]. AI has significant potential to transform variable renewable DG systems.

Modelling and controlling a hybrid solar-wind microgrid was extensively studied. It used a Genetic Algorithm-Adaptive Neuro-Fuzzy Inference System (GA-ANFIS) to adjust voltage during power generation variations [9]. A Simulink Case Study Model utilising mathematical equations and a Transfer Function model using layered voltage-current loops are shown [10]. Simulation experiments [11] show that the GA-ANFIS controller optimises converter outputs via MPPT. This approach outperforms SSR-P&O and PID controllers.

This work helps with the intermittency problems associated with wind and solar photovoltaic power sources. Its sophisticated control mechanism may improve the microgrid's stability and efficiency [12]. To achieve better performance, research may replace the GA-ANFIS control system with a hybrid controller incorporating AI algorithms in the future. When it comes to the construction of microgrids for renewable energy, the text places emphasis on precise modelling and intelligent control systems [13].

The Figure 1 shows a schematic diagram of a hybrid wind-PV-battery system. It illustrates the integration of PV modules and wind turbines through DC/DC converters connected to a DC bus, with a DC/AC inverter, battery charger, and battery bank feeding an AC load. The comparative Table 1 presents key features of wind, PV, and battery components in distributed generation systems, highlighting their resource types, weather dependence, power fluctuation characteristics, land use requirements, maintenance needs, costs, technology maturity, optimal applications, and environmental impacts.

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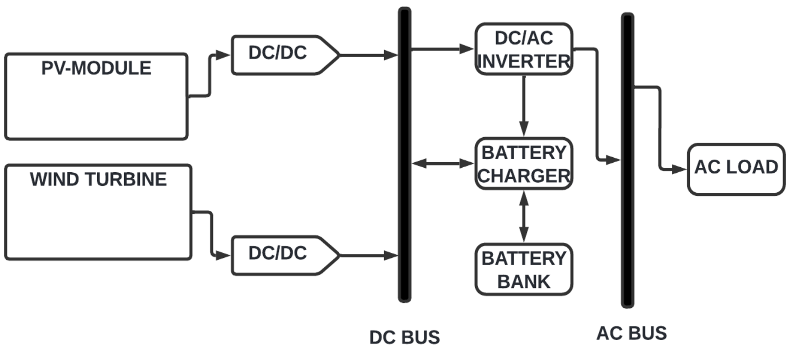

Fig. 1. A simple schematic of a wind-PV-battery system.

Table 1. Comparative chart for wind-PV-battery distributed generation.

Feature	Wind	Photovoltaic (PV)	Battery	References
Resource	Wind speed	Solar radiation	Chemical reaction	[32], [33]
Reliance on Weather	Highly dependent	Highly dependent	Not dependent on weather (releases stored energy)	[34]
Power Fluctuation	High fluctuation	High fluctuation during sunrise/sunset	Steady power output (based on discharge rate)	[35]
Land Use	Requires open space	Requires open space	Relatively compact	[36]
Maintenance	Requires regular maintenance	Requires minimal maintenance	Requires maintenance for longevity	[37],[38]
Cost	Moderate upfront cost	Moderate upfront cost	High upfront cost	[39]
Maturity of Technology	Well-established technology	Well-established technology	Rapidly developing technology	[40]
Best Suited for	Areas with consistent winds	Areas with good solar insolation	Energy storage and peak shaving	[41]
Environmental Impact	Low emissions, some visual impact	Low emissions, minimal land impact	No emissions, potential for recycling concerns	[42]

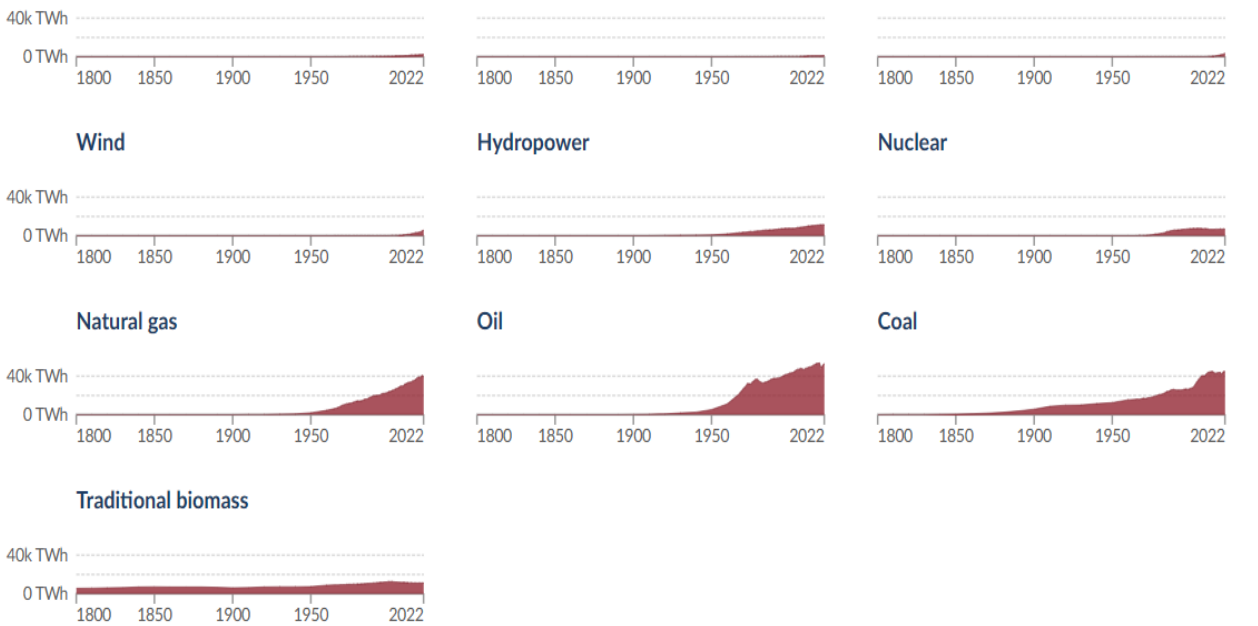

Chart-1 Global Energy Sources Utilization [31].

Table-2. Comparative control techniques for wind-PV-battery distributed generation.

Control Technique	Function	Advantages	Disadvantages	Suitable for	References
Maximum Power Point Tracking (MPPT)	Optimizes power extraction from wind turbine and PV system	Maximises energy harvest from renewable sources	Increased complexity	Wind Turbines (Individual)	[34], [37]
Droop Control	Maintains power sharing and frequency stability	Simple and decentralised control	May not achieve perfect power-sharing under all conditions	Wind and PV integrated systems (grid-connected)	[36]
Proportional-Integral (PI) Control	Regulates DC link voltage and power flow	Robust and widely used	Tuning can be complex	Battery storage	[41]
Fuzzy Logic Control	Adapts to changing system dynamics	Handles non-linear behavior effectively	Requires expertise in fuzzy logic design	Wind and PV integrated systems (grid-connected) with varying weather	[37]
Centralized Control	Provides coordinated control of all distributed energy resources	Optimal system-wide performance	Single point of failure, complex communication	Large Wind-PV-Battery microgrids	[42]
Decentralized Control	Independent control of individual resources with limited communication	Reliable and scalable for large systems	May not achieve optimal overall performance	Wind farms with multiple turbines	[35]

Chart-1 illustrates the historical utilization trends of global energy sources from 1800 to 2022, showing the evolution of wind, hydropower, nuclear, natural gas, oil, coal, and traditional biomass consumption, with fossil fuels demonstrating significant growth in recent decades.

The Table-2 presents various control techniques for wind-PV-battery systems, comparing MPPT, droop control, PI control, fuzzy logic, centralized, and decentralized approaches, detailing their functions, advantages, disadvantages, and suitable applications for distributed generation management.

2. AI BASED MODELLING TECHNIQUES

2.1 Forecasting Power Output

To optimize decision-making for energy management and control within wind-photovoltaic-battery distributed generation systems [14], it is essential to emphasise the vital role that accurate wind and solar power forecasts play. Improved forecasts directly influence elements such as the scheduling of cost-effective resources, the management of batteries, and the grid's stability [15].

For the Wind Speed Forecasting Neural Networks (ANNs, RNNs) Predict wind speed at varying time horizons using past wind data, weather patterns, and potentially numerical weather prediction (NWP) data.

Fuzzy Logic Handle uncertainty and variability in wind speed, especially in complex terrain or rapidly changing weather conditions.

Solar Irradiance Forecasting is a critical area of research, especially in green energy. Scientists aim to predict daily solar irradiance by leveraging deep-learning methodologies and historical solar radiation data. These models extract patterns and relationships from multi-site data, enabling accurate predictions. Bidirectional long-short-term memory (LSTM) and attention-based LSTM models have shown promise in forecasting solar irradiance.

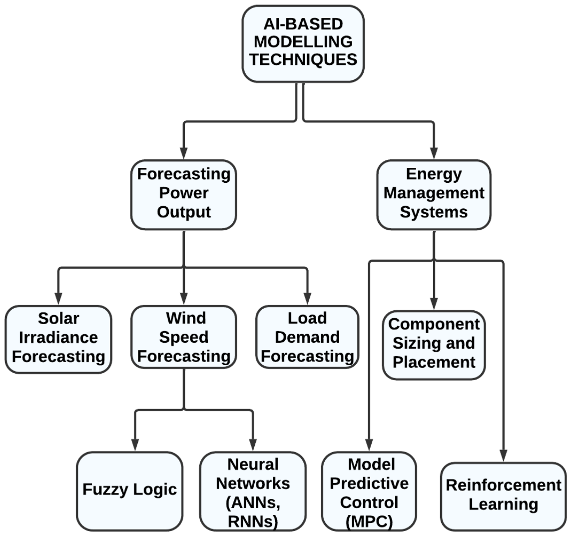

Fig. 2. Illustration of AI-based modelling techniques.

Figure 2 illustrates AI-based modeling techniques for renewable energy systems, categorizing them into forecasting power output and energy management systems. It outlines specific applications like solar irradiance and wind speed forecasting, along with various AI methods including fuzzy logic, neural networks, and reinforcement learning for optimal system control.

ANNs and CNNs Predict solar irradiance based on cloud cover, time of day, and historical weather data.

Image-based forecasting using CNNs can be helpful for cloud pattern analysis.

Load Demand Forecasting by ANNs and LSTMs predicts energy demand patterns considering historical consumption, time of day, day of week, and other influencing factors.

Energy Management Systems (EMS)

Reinforcement Learning Optimise the dispatch of wind and solar power, battery charging/discharging, and power flow to ensure reliable and cost-effective real-time operation.

Model Predictive Control (MPC) Handle short-term forecasting and control, adapting the system to changing power demand and generation conditions.

Component Sizing and Placement Metaheuristics (Genetic Algorithms, Particle Swarm Optimization) help find optimal sizes and locations for wind turbines, solar panels, and batteries to maximise energy output and economic benefits.

2.2 System Optimization

(a) Machine Learning (ML)

Accurate wind and solar power output forecasting is crucial for effective decision-making and stability in distributed generation (DG) systems [9]. Machine learning (ML), especially supervised learning, has emerged as a powerful tool for addressing this challenge. In supervised learning, AI models are trained on historical datasets that include weather variables (wind speed, solar irradiance, temperature, etc.), past power generation patterns, and corresponding load demand. The models analyse this data to discover complex relationships, enabling them to predict future power production [16].

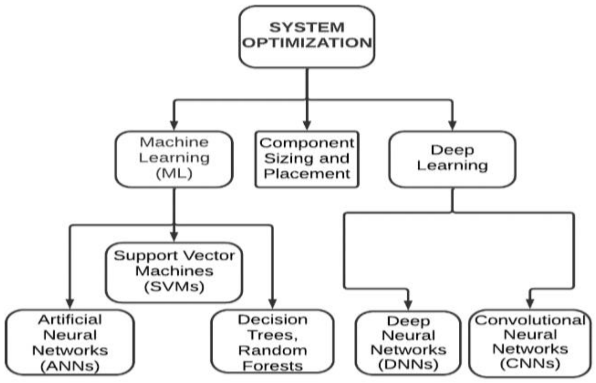

Fig. 3. Illustration of system optimization.

Figure 3 depicts the hierarchical structure of system optimization techniques, branching into three main categories: Machine Learning (ML), Component Sizing and Placement, and Deep Learning. ML further subdivides into SVMs, ANNs, and Decision Trees/Random Forests, while Deep Learning includes DNNs and CNNs.

Artificial neural networks (ANNs) capture complex and nonlinear data correlations well due to their biological brain structure. This makes them valuable in weather and power systems, which are often dynamic and unpredictable. In weather forecasting, artificial neural networks (ANNs) can predict the chaotic interaction of temperature, pressure, and humidity. This helps ANNs predict patterns that linear models struggle with. Power systems use artificial neural networks (ANNs) to control load demand, generator behavior, and renewable source effects on grid stability. Because they can learn from data without mathematical formulas, artificial neural networks (ANNs) can help us model and manage these complex and ever-changing systems [17].

Table 3. Different optimization techniques for wind-PV- battery distributed generation.

Technique	Description	Advantages	Disadvantages
Linear Programming [43]	Solves problems with linear objective functions and constraints.	Efficient for well-defined problems, provides guaranteed optimal	May struggle with complex non-linear problems, limited scalability for large system
Dynamic Programming [44]	Breaks down complex problems into smaller subproblems, solving them sequentially.	Can handle complex problems with time-varying dynamics, guarantees optimal solution.	Computationally expensive for large problems with many stages.
Heuristic Techniques [45]	Use iterative approaches to find good, but not necessarily optimal, solutions.	Fast and efficient, adaptable to complex problems, good for real-time applications.	No guarantee of optimality, solution quality can vary depending on the algorithm.
Machine Learning [46]	Utilizes algorithms that learn from data to make optimization decisions.	Can handle highly non-linear problems, good at adapting to changing system dynamics.	Requires large amounts of training data, computational cost for training models.

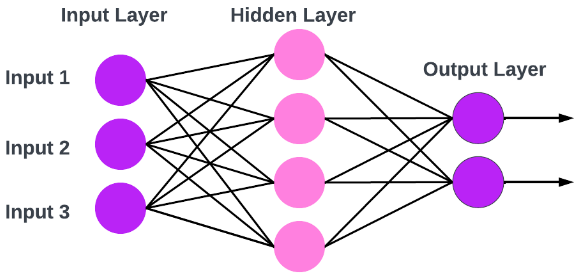

Fig. 4. Artificial neural networks.

Figure 4 depicts a basic neural network architecture with three layers: an input layer containing three nodes, a hidden layer with four nodes, and an output layer with two nodes, all interconnected through weighted connections.

Support Vector Machines SVMs are well-known for their effectiveness on datasets that are both high-dimensional and compact in size. The separation of data classes is improved by decision boundaries, also known as hyperplanes. As a result, overfitting, which is a common problem when there is inadequate training data, is reduced.

SVMs, which stand for support vector machines, are also capable of processing high-dimensional data that has a variety of attributes. Researchers are able to implicitly extend data into higher dimensions by utilizing "kernels," which allows them to locate the most effective separation borders. Because of its ability to process a large number of input variables, Support Vector Machines (SVMs) are an excellent choice for analyzing weather and power systems. Twelve.

Decision Trees, Random Forests decision trees are flowchart-like models that are interpretable. Hierarchical feature questions divided data into subsets. This framework shows the decision-making process, making classification and prediction explanations clear. Random forests, decision tree ensembles, retain interpretability. Even though they are more intricate than individual trees, they reveal the relevance of features, which are the variables that most influence model decisions. Interpretability is especially important when decisions have real-world consequences since it helps understand the model's logic and trust its outcomes [18].

(b) Deep Learning

Deep learning (DL), a subset of machine learning, has improved wind-photovoltaic-battery system prediction. The main feature of this system is its ability to automatically extract complex and useful properties from raw time-series data. This includes historical wind speed and temperature oscillations, electricity generation trends, and load demand variations.

Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs) are examples of deep learning models. These models comprise numerous processing layers that develop hierarchical representations of the data. Automating the process of feature extraction and doing away with laborious manual engineering are two primary benefits. Identifies complex nonlinear patterns that are present inside time-series documents. Compared to established forecasting models, it frequently performs better [19].

Deep Neural Networks (DNNs) Inspired by the structure of the human brain, DNNs use layers of interconnected "neurons" to learn complex patterns within data.

Convolutional Neural Networks (CNNs) are specialised for image processing. They extract features from images using filters and are highly successful in computer vision tasks. CNNs use 'filters' that slide over the input data (e.g., a weather map), identifying local patterns and spatial relationships [20].

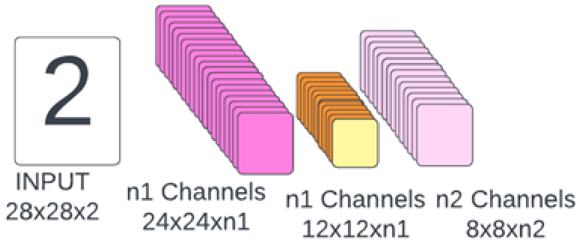

Fig. 5. Convolutional neural network

Recurrent Neural Networks (RNNs) are designed to process sequential data (e.g., text, time series). RNNs have a "memory" element, allowing them to use information from previous inputs.

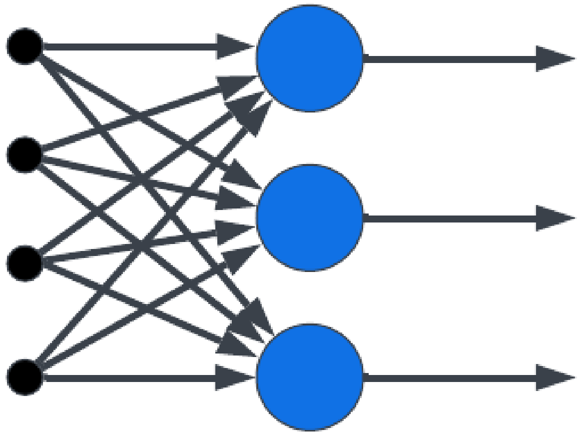

Fig. 6. Feed-forward neural network.

(c) Component Sizing and Placement

Metaheuristics (Genetic Algorithms, Particle Swarm Optimization) help find optimal sizes and locations for wind turbines, solar panels, and batteries to maximise energy output and economic benefits.

3. AI-BASED CONTROL STRATEGIES

The inherent variability of wind and solar power and fluctuating load demands necessitate intelligent control strategies to ensure a distributed generation system's reliable and efficient operation. AI-based techniques offer adaptability, self-learning capabilities, and optimisation potential to address these challenges.

Energy Management and Optimization by reinforcement Learning (RL) agents interact with the power system environment and learn from rewards to optimise long-term energy dispatch and battery management decision-making. Studies have demonstrated the effectiveness of RL for optimising battery charging/discharging schedules and overall energy flow in microgrids [21, 22].

Model Predictive Control (MPC) leverages short-term forecasts of renewable generation and load demand to proactively optimise control actions over a receding horizon [23]. It is particularly suitable for systems with nonlinearities and operational constraints.

Grid Stability and Power Quality Control of Fuzzy logic controllers effectively handle uncertainties and nonlinearities associated with renewable energy integration, maintaining voltage and frequency stability within allowable limits [24].

Neural Network-based Controllers (ANNs) can learn complex relationships between system variables, facilitating adaptive control of power converters and compensation equipment to improve power quality under varying conditions [25].

4. ADVANCED TECHNIQUES AND FUTURE DIRECTIONS

Hybrid AI Models combining the strengths of different AI techniques (e.g., fuzzy logic for uncertainty and neural networks for forecasting) can lead to more robust control strategies. Metaheuristic Optimization is evolutionary algorithms, such as Genetic Algorithms, can optimise AI models' controller and hyper parameters to improve system performance. Distributed control architectures as distributed generation systems scale, hierarchical and decentralised control strategies utilising AI for local and system-wide coordination become essential.

Table 4. Estimated global energy losses.

Energy Sources	Optimization Loss (%)	Nonlinear load loss (%)	Total Loss (%)
Fossil Fuels	8	4	12
Hydropower	3	2	5
Nuclear	5	1	6
Solar	9	6	15
Wind	12	5	17

5. CHALLENGES AND FUTURE DIRECTIONS

While AI-based techniques offer significant promise for optimising renewable energy systems, several challenges and potential areas for future research remain:

Data availability and quality success of AI models heavily depends on access to large amounts of diverse, high-quality data encompassing weather patterns, power output, load demand, and system component behaviour [26]. Real-world datasets may contain noise, missing values, and inconsistencies. Collaboration within the industry can facilitate the creation of larger, more comprehensive datasets. Techniques like GANs can generate realistic scenarios to supplement limited real-world data [27].

Computational Complexity and Real-Time Implementation In advanced deep learning models and optimisation algorithms can be computationally demanding [28]. Balancing model accuracy and complexity is crucial for real-time control. Reducing model size for faster inference without sacrificing performance. Distributing intelligence closer to where data is generated can reduce computational burden and latency.

Explainability and Trust Black-box AI models may lack transparency in their decision-making processes, hindering trust in critical power system operations [29]. Methods to understand the reasoning behind AI model predictions and control actions are being developed. Expert knowledge and oversight are being incorporated in conjunction with AI-based systems for safer operation.

Resilience to Cyberattacks AI models can be susceptible to attacks by adversaries, which could result in system instability. Model robustness can be improved by training on instances intended to trick artificial intelligence systems [30]. Using artificial intelligence-based control in conjunction with effective cybersecurity measures to protect the infrastructure of power systems.

Scaling and Coordination in Large-Scale Microgrids Implementing scalable and coordinated control algorithms is necessary for distributed generation systems involving a large number of energy sources, storage units, and loads. Investigate hierarchical control architectures that allow artificial intelligence agents to optimize at both the local and system-wide scales. To accomplish the objectives of global optimization, it is necessary to investigate cooperative learning strategies for various AI controllers.

After finalising this survey, we have found some research gap and these are as:

❖ In a real-world implementation, no research addresses data quality and hardware limits when transitioning AI models from simulation to large-scale grids.

❖ Uncertainty modelling reviews could underline the necessity for AI methods that explicitly handle renewable energy sources' uncertainty and variability.

❖ Hybrid AI approaches combining AI methods like fuzzy logic and neural networks may improve accuracy and robustness.

❖ Cybersecurity AI-controlled systems' cybersecurity threats are neglected, making dispersed power grids vulnerable.

6. CONCLUSION

This research emphasises the revolutionary potential of artificial intelligence (AI) in improving the modelling and control of distributed generation systems, particularly those that use wind, photovoltaic (PV), and battery storage. This article discusses the merits of artificial intelligence approaches such as artificial neural networks (ANNs), support vector machines (SVMs), and deep learning for the purpose of improving prediction accuracy and optimizing resource management efficiency. In the publication, the authors express optimism that ongoing research will further develop distributed generating systems powered by artificial intelligence, boosting the systems dependability and efficiency.

REFERENCES

[1] M. S. Mahmoud and M.S.A. Moteleb, "Distributed generation: concepts, benefits, technologies, and challenges," in Distributed Generation Systems, 2018.

[2] T. Ackermann, G. Andersson, and L. Söder, "Distributed generation: a definition," Elect. Power Syst. Res., vol. 57, no. 3, pp. 195-204, 2001.

[3] International Renewable Energy Agency (IRENA), Renewable Power Generation Costs in 2021, Abu Dhabi, 2022.

[4] R. Belfkira, C. Zhang, and G. Barakat, "Optimal sizing study of hybrid wind/PV/diesel power generation unit," Sol. Energy, vol. 85, no. 1, pp. 100-110, 2011.

[5] Khalid, M., "Smart grids and renewable energy systems: Perspectives and grid integration challenges," Energy Strategy Rev., vol. 51, p. 101299, 2024.

[6] S. S. Refaat, H. Abu-Rub, M. S. Saad, and M. Abdel-Fadil, "Artificial intelligence techniques in power systems: A review," in Proc. 13th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON), 2021.

[7] A. M. Abd Elaziz and A. M. Ramadan, "Artificial Intelligence techniques in the electric power sector: A comprehensive review," Ain Shams Eng. J., 2023.

[8] Z. Zhang, D. Zhang, and R. C. Qiu, "Deep reinforcement learning for power systems: A Comprehensive Survey," IEEE Access, vol. 8, 2020.

[9] E. N. Odonkor, P. M. Moses, and A. O. Akumu, "Intelligent ANFIS-Based Distributed Generators Energy Control and Power Dispatch of Grid-Connected Microgrids Integrated into Distribution Network."

[10] Nishad, D.K., Tiwari, A.N., Khalid, S. et al. AI based UPQC control technique for power quality optimization of railway transportation systems. Sci Rep 14, 17935 (2024). https://doi.org/10.1038/s41598-024-68575-5

[11] L. A. Aloo, P. K. Kihato, S. I. Kamau, and R. S. Orenge, "Modeling and control of a photovoltaic-wind hybrid microgrid system using GA-ANFIS," Heliyon, vol. 9, no. 4, 2023.

[12] S. Ahmad, M. Shafiullah, C. B. Ahmed, and M. Alowaifeer, "A review of microgrid energy management and control strategies," IEEE Access, vol. 11, pp. 21729-21757, 2023.

[13] A. R. Taylor, "Performance Analysis Of Hybrid Ai-Based Technique For Maximum Power Point Tracking In Solar Energy System Applications," 2023.

[14] X. Kong et al., "Multi-scale, hierarchical and distributed coordination mechanisms for future grid resilience: a review," CPSS Trans. Power Electron. Appl., vol. 5, no. 4, pp. 308-321, 2020.

[15] A. Tascikaraoglu, O. Erdinc, M. Uzunoglu, and A. Y. Karakas, "An adaptive load dispatching and forecasting strategy for a virtual power plant including renewable energy conversion units," Appl. Energy, vol. 119, pp. 445–453, 2014.

[16] M. S. Mahmoud and M.S.A. Moteleb, "Distributed generation: concepts, benefits, technologies, and challenges," in Distributed Generation Systems, 2018.

[17] Q. Wang et al., "Short-term photovoltaic power generation interval prediction method based on support vector machine," Prot. Control Mod. Power Syst., vol. 6, no. 1, 2021.

[18] J. R. Quinlan, "Induction of decision trees," Mach. Learn., vol. 1, no. 1, pp. 81–106, 1986.

[19] Y. Wang et al., "Multi-spatial-scale deep learning for wind speed forecasting," IEEE Trans. Sustain. Energy, 2022.

[20] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to Forget: Continual Prediction with LSTM," Neural Comput., vol. 12, no. 10, pp. 2451–2471, 2000.

[21] Z. Zhang, D. Zhang, and R. C. Qiu, "Deep reinforcement learning for power system applications: An overview," CSEE J. Power Energy Syst., vol. 7, no. 1, pp. 213-225, 2021.

[22] V. François-Lavet, P. Henderson, R. Islam, M. G. Bellemare, and J. Pineau, "An introduction to deep reinforcement learning," Found. Trends Mach. Learn., vol. 11, no. 3-4, pp. 219–354, 2016.

[23] E. F. Camacho and C. Bordons, Model predictive control. Springer Science & Business Media, 2007.

[24] P. K. Dash, M. Padhee, and S. K. Bhoi, "A hybrid controller for power quality improvement and grid synchronisation of a wind-PV-battery-based distributed system," Eng. Sci. Technol. Int. J., vol. 21, no. 6, pp. 1183–1196, 2018.

[25] L. Yin, T. Yu, B. Yang, and X. Zhang, "A new radial basis function neural network control with load fluctuation suppression for shipboard power systems," Trans. Inst. Meas. Control, vol. 39, no. 7, pp. 1013–1025, 2017.

[26] Y. Zhou, S. Zheng, and G. Zhang, "Artificial intelligence-based intelligent control and energy management for complex energy systems: A literature review," Front. Energy Res., vol. 10, p. 1013885, 2022.

[27] K. Wang et al., "Generative adversarial networks: introduction and outlook," IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 25, no. 6, pp. 1118-1135, 2017.

[28] Z. Zhang, D. Zhang, and R. C. Qiu, "Deep reinforcement learning for power system applications: An overview," CSEE J. Power Energy Syst., vol. 7, no. 1, pp. 213-225, 2021.

[29] A. B. Arrieta et al., "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," Inf. Fusion, vol. 58, pp. 82-115, 2020.

[30] Demontis et al., "Yes, machine learning can be more secure! A case study on android malware detection," IEEE Trans. Dependable Secure Comput., vol. 16, no. 4, pp. 711-724, 2019.

[31] H. Ritchie, P. Rosado, and M. Roser, "Energy Production and Consumption," Our World in Data, Feb. 26, 2024. [Online]. Available: https://ourworldindata.org/energy-production-consumption

[32] S. A. Kalogirou, Solar energy engineering: processes and systems. Elsevier, 2023.

[33] Nishad, D.K., Tiwari, A.N., Khalid, S. et al. Power quality solutions for rail transport using AI-based unified power quality conditioners. Discov Appl Sci 6, 651 (2024). https://doi.org/10.1007/s42452-024-06372-5.

[34] Y. Yang, S. Bremner, C. Menictas, and M. Kay, "Battery energy storage system size determination in renewable energy systems: A review," Renew. Sustain. Energy Rev., vol. 91, pp. 109-125, 2018.

[35] H. Shi et al., "Long-Term Solar Power Time-Series Data Generation Method Based on Generative Adversarial Networks and Sunrise–Sunset Time Correction," Sustainability, vol. 15, no. 20, p. 14920, 2023.

[36] E. O'Shaughnessy, R. Wiser, B. Hoen, J. Rand, and S. Elmallah, "Drivers and energy justice implications of renewable energy project siting in the United States," J. Environ. Policy Plan., vol. 25, no. 3, pp. 258-272, 2023.

[37] S. Sheng and R. O'Connor, "Reliability of wind turbines," in Wind Energy Engineering, Academic Press, 2023, pp. 195-211.

[38] E. Singh, S. S. Afshari, and X. Liang, "Wind Turbine Optimal Preventive Maintenance Scheduling Using Fibonacci Search and Genetic Algorithm," J. Dyn., Monit. Diagnostics, vol. 2, no. 3, pp. 157-169, 2023.

[39] A. Chatterjee and B. Banerjee, "Cost-Effective Hybrid Wind-Photovoltaic Generation System for Isolated Critical Loads: A Case Study," J. Electron. Electr. Eng., pp. 274-286, 2023.

[40] S. Rehman et al., "A review of energy extraction from wind and ocean: Technologies, merits, efficiencies, and cost," Ocean Eng., vol. 267, p. 113192, 2023.

[41] F. Wu et al., "A comprehensive evaluation of wind-PV-salt cavern-hydrogen energy storage and utilization system: A case study in Qianjiang salt cavern, China," Energy Convers. Manag., vol. 277, p. 116633, 2023.

[42] P. Wang et al., "Peak shaving auxiliary service analysis for the photovoltaic and concentrating solar power hybrid system under the planning-dispatch optimization framework," Energy Convers. Manag., vol. 295, p. 117609, 2023.

[43] Singh, R., Nishad, D.K., Khalid, S. et al. A review of the application of fuzzy mathematical algorithm-based approach in autonomous vehicles and drones. Int J Intell Robot Appl (2024). https://doi.org/10.1007/s41315-024-00385-4

[44] J. Mahmoudimehr and L. Loghmani, "Optimal management of a solar power plant equipped with a thermal energy storage system by using dynamic programming method," Proc. Inst. Mech. Eng. A, J. Power Energy, vol. 230, no. 2, pp. 219-233, 2016.

[45] N. Kirchner-Bossi and F. Porté-Agel, "Wind farm area shape optimization using newly developed multi-objective evolutionary algorithms," Energies, vol. 14, no. 14, p. 4185, 2021.

[46] S. Ozturk, "Forecasting Wind Turbine Failures and Associated Costs: Investigating Failure Causes, Effects and Criticalities, Modeling Reliability and Predicting Time-to-Failure, Time-to-Repair and Cost of Failures for Wind Turbines Using Reliability Methods and Machine Learning Techniques," Ph.D. dissertation, Columbia Univ., 2019.