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A Survey of Artificial Intelligence Techniques for Modeling and Control in Wind-PV-Battery Hybrid Distributed Energy Systems

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Abstract: - Distributed generation (DG) systems use wind and solar PV for sustainability and decentralised energy production. Hybrid wind-PV-battery systems have complementing generation profiles and energy storage potential. Renewable resource unpredictability makes modelling and controls difficult, limiting performance. AI outperforms traditional forecasting optimization and control methods. This critical review study examines AI-based modelling and control solutions for small-scale wind-PV-battery distributed generating systems.This paper objectively evaluates AI approaches' strengths and weaknesses and discusses their practical applications in renewable resource variability management and energy flow optimization. Its advice is needed by AI solution implementers and researchers researching advances. It shows how AI transforms distributed energy system efficiency, dependability, and sustainability.

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

I. INTRODUCTION

In contrast to the conventional paradigm of large-scale power plants, characterised by a centralised structure, distributed generation (DG) refers to energy production in a more localised manner, close to the point of consumption [1]. The reduction of transmission losses, the reinforcement of energy security, and the urgency to counteract climate change have all contributed to the enormous development distributed generation has seen [2]. Incorporating renewable energy sources, particularly wind and solar photovoltaic (PV), has been a crucial driver of this rise. The advantages they offer to the environment, reduced costs, and technological developments have all contributed to this change [3, 4]. The tremendous contributions that you, as electrical engineers, researchers, and academics, provide to this subject are one of the most important factors in ensuring the sustained success of DG systems.

While offering numerous advantages, the integration of wind and solar PV into DG systems presents significant complexities due to their inherent variability and unpredictable power output [5]. The fluctuations in wind speed and solar irradiance, driven by weather patterns, profoundly impact system stability, making accurate power forecasting a critical necessity [1, 5]. For reliable system operation, short-term and medium-term forecasts of both generation (wind/solar) and load are essential [2]. Furthermore, integrating these renewable sources necessitates sophisticated energy management strategies to balance costs, reliability, and system longevity. These strategies must optimise energy dispatch between sources, battery storage, and the variable load demand [3, 5].

Artificial intelligence (AI), particularly machine learning techniques, has emerged as a powerful tool to tackle the complexities of renewable energy integration. AI excels at modelling complex nonlinear systems with inherent uncertainty, characteristics abundantly present in wind-PV-battery systems [6]. By learning from historical data, AI models can adapt to changing weather conditions and system dynamics, significantly improving forecasting accuracy compared to traditional methods [6, 7]. Moreover, AI's ability to handle complex optimisation problems enables superior energy management and control, enhancing system performance and cost reductions [8]. AI thus shows great promise in revolutionising DG systems driven by variable renewable sources.

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A comprehensive study on the modelling and controlling a photovoltaic-wind hybrid microgrid system utilising a Genetic Algorithm-Adaptive Neuro-Fuzzy Inference System (GA-ANFIS) for voltage regulation amid power generation variations [9]. The research introduces two microgrid models: a Simulink Case Study Model derived from mathematical equations and a Transfer Function model based on nested voltage-current loops [10]. The GA-ANFIS controller is employed as a Maximum Power Point Tracking (MPPT) algorithm to optimise converter outputs, demonstrating superior performance over traditional SSR-P&O and PID controllers in simulation tests [11].

This paper's significance lies in its contribution to addressing the intermittency challenges of wind and solar photovoltaic power sources, proposing an advanced control system that could potentially enhance the stability and efficiency of microgrids [12]. Future work may explore replacing the GA-ANFIS control system with a hybrid artificial intelligence algorithms controller for further improvements. The document underscores the importance of accurate modelling and intelligent control systems in advancing the field of renewable energy microgrids[13].

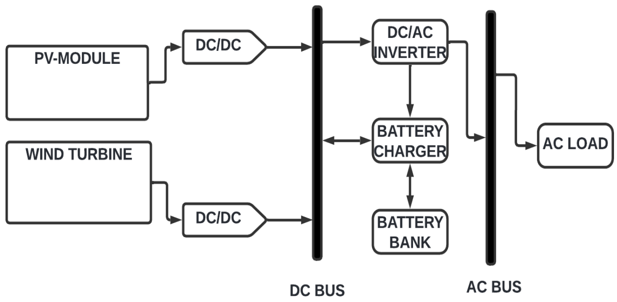

Fig. 1 A simple schematic of a wind-PV-battery system

II. AI-BASED MODELLING TECHNIQUES

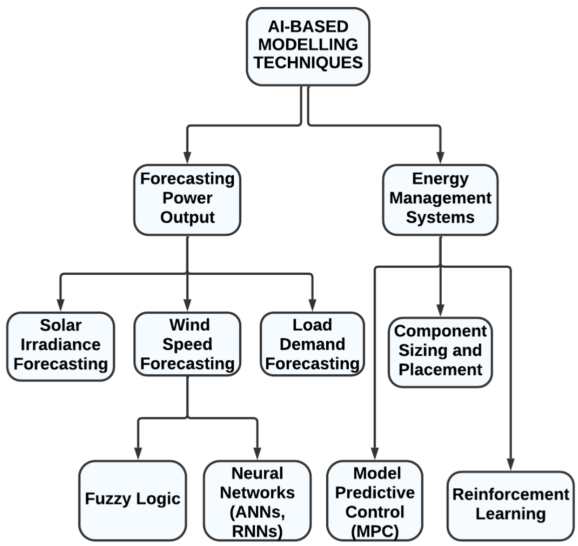

Fig.2 Illustration of AI-Based Modelling Techniques

1) Forecasting Power Output

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

(a) Wind Speed Forecasting:
(i) Neural Networks (ANNs, RNNs)

Predict wind speed at varying time horizons using past wind data, weather patterns, and potentially numerical weather prediction (NWP) data.

(ii) Fuzzy Logic:

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

(b) Solar Irradiance Forecasting
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.

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.
(c) Load Demand Forecasting
ANNs and LSTMs predict energy demand patterns considering historical consumption, time of day, day of week, and other influencing factors.

2) Energy Management Systems (EMS)
(i) 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.

(ii) Model Predictive Control (MPC)

Handle short-term forecasting and control, adapting the system to changing power demand and generation conditions.

(iii) 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.

III. SYSTEM OPTIMIZATION

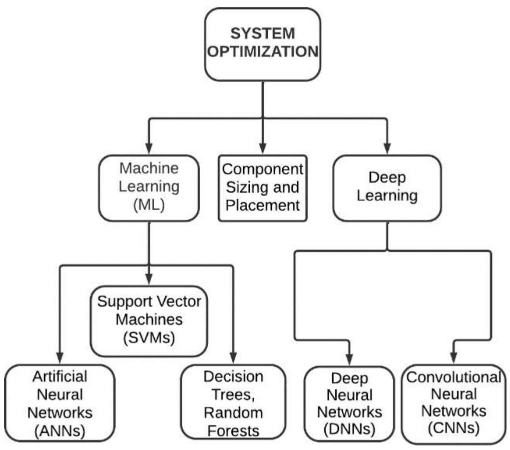

Fig.3. Illustration of System Optimization

(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].

1) Artificial Neural Networks (ANNs)

ANNs, inspired by the structure of biological brains, excel at capturing complex, nonlinear relationships within data. This makes them invaluable in weather and power systems, where phenomena are often highly dynamic and unpredictable.

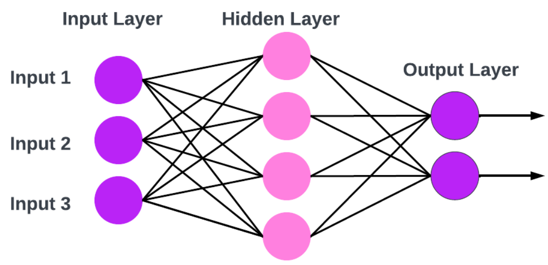

Fig. 4 Artificial Neural Networks

In weather forecasting, ANNs can model the chaotic interplay of temperature, pressure, and humidity to predict patterns that traditional linear models struggle to represent. Similarly, in power systems, ANNs handle the nonlinearities of load demand, generator behaviour, and the influence of renewable sources on grid stability.

Their ability to learn from data without explicit mathematical formulas makes ANNs a powerful tool for modelling and improving our understanding and management of these complex and ever-changing systems. [17].

2) *Support Vector Machines (SVMs)*

Effective on Smaller Datasets and High-Dimensional Data, SVMs are renowned for performing well even with smaller datasets. They find decision boundaries (hyperplanes) that maximise the separation between data classes. This makes them less prone to overfitting, a common issue with limited training data.

Additionally, SVMs can efficiently handle high-dimensional data where the number of features is extensive. Using clever mathematical techniques called "kernels", they can implicitly project data into higher dimensions to find optimal separating boundaries. This strength makes SVMs valuable for applications with numerous input variables, such as those often encountered in weather and power systems analysis. [12].

3) *Decision Trees, Random Forests*

Decision trees offer inherent interpretability by building models resembling flowcharts. They split data into subsets based on hierarchical questions about its features. This structure visually reveals the decision-making process, making the reasoning behind a classification or prediction easy to understand.

There is a degree of interpretability that is maintained by random forests, which are ensembles of decision trees. Even though they are more complicated than individual trees, they offer insights on the relevance of features, which are the variables that contribute the most to the decisions that the model makes. In situations when decisions have real-world repercussions, this interpretability is especially significant since it helps in comprehending the logic of the model and makes it easier to have faith in the results it produces [18].

(b) *Deep Learning*

The field of wind-photovoltaic-battery systems has seen substantial advancements in predicting because to deep learning (DL), a specialised subset of machine learning. The ability to automatically extract complicated and informative characteristics directly from raw time-series data is the primary strength of this particular system. This covers historical weather patterns (such as wind speed and temperature swings), power 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].

1) Deep Neural Networks (DNNs)

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

3) *Convolutional Neural Networks (CNNs)*

These 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].

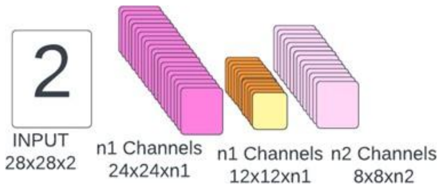

Fig.5 Convolutional Neural Network

3) Recurrent Neural Networks (RNNs)

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

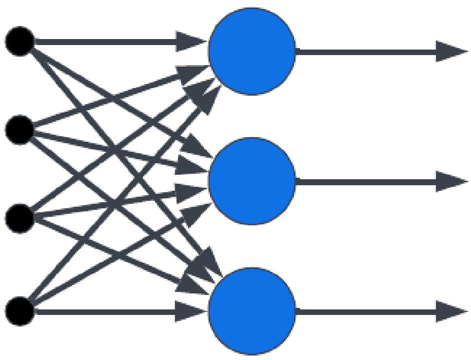

Fig.6 Feed-forward Neural Network

(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.

IV. 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.

1) Energy Management and Optimization

(a) Reinforcement Learning (RL):

In 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].

(b) Model Predictive Control (MPC)

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.

2. Grid Stability and Power Quality Control

(a) Fuzzy Logic:

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

(b) 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].

3. Advanced Techniques and Future Directions

(a) 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.

(b) Metaheuristic Optimization

Evolutionary algorithms, such as Genetic Algorithms, can optimise AI models' controller parameters and hyper parameters to improve system performance.

(c) Distributed Control Architectures

As distributed generation systems scale, hierarchical and decentralised control strategies utilising AI for local and system-wide coordination become essential.

V. 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:

1) Data Availability and Quality

The 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].

2) Computational Complexity and Real-Time Implementation

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.

3) 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.

4) 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.

5) 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.

VI. CONCLUSION

We highlight artificial intelligence's transformative potential in enhancing modelling. ANNs, SVMs, and deep learning are some of the primary artificial intelligence approaches discussed in this research. The paper also discusses these techniques' advantages, such as better prediction accuracy and optimised resource management regions. It expresses optimism that current research will further increase the capabilities of distributed generating systems powered by artificial intelligence and improve systems' reliability.

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