Smart and Secure MPPT Control of Variable-Speed Wind Turbines Using Hybrid AI Techniques

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Abstract: *This study introduces an enhanced MPPT strategy designed for variable-speed wind turbines operating under fast and irregular wind variations. The work combines well-known MPPT techniques, such as P&O and PID, with several intelligent optimization approaches, including fuzzy logic, ANFIS, PSO, and reinforcement learning. The hybrid framework aims to achieve faster tracking, fewer oscillations around the maximum power point, and higher stability during sudden wind disturbances. A full simulation model was built in MATLAB/Simulink and subsequently tested experimentally on the Lucas-Nülle educational wind-energy platform via a SCADA interface. The hybrid controller showed clear performance gains, with the OTC–RL combination reaching nearly 90% tracking efficiency, surpassing the traditional approaches used for comparison. The developed model also incorporated simple cybersecurity-aware monitoring to ensure reliable operation during communication disturbances, particularly during Telnet-based DoS attempts. Overall, the results demonstrate that integrating intelligent control with MPPT yields a more resilient and efficient wind-energy conversion system suitable for modern smart-grid applications.*

Keywords: Smart MPPT Control, Variable-Speed Wind Turbines, Hybrid AI Techniques, Maximum Power Point Tracking, Artificial Intelligence, Renewable Energy, Wind Energy Systems.

Nomenclature

Symbol / Acronym	Description
A	Rotor swept area (m²)
C_p	Power coefficient
P	Aerodynamic power (W)
P_{m}	Mechanical power (W)
ρ	Air density (kg/m³)
λ	Tip-speed ratio
β	Blade pitch angle (°)
V_{wind}	Wind speed (m/s)
TSR	Tip Speed Ratio
OTC	Optimal Torque Control
P&O	Perturb and observe
FLC	Fuzzy Logic Controller
ANN / ANFIS	Neural Network-based controllers
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
SCADA	Supervisory Control and Data Acquisition
PMSG	Permanent Magnet Synchronous Generator
RMSE	Root Mean Square Error

I. Introduction

The basic concepts of wind power plants are divided into two operating systems: fixed-speed and variable-speed. Figure 1 shows the Principal Concepts of Wind Power Plants.

Fixed-speed systems rely on the principle of direct connection to the electrical grid (the Danish concept), where the grid frequency determines the generator speed and cannot be widely controlled. Its simplicity and low cost characterize this type, but it suffers from low efficiency when wind speed changes. Variable-speed systems, on the other hand, allow the turbine's rotational speed to be adjusted in response to changes in wind speed to achieve maximum energy extraction. These systems are divided into two types: the full-fed system, in which the entire power is converted via electronic converters to control the generator fully, and the double-fed system (DFIG), in which the stator is directly connected to the grid while the rotor is electronically controlled. This classification illustrates the technological evolution of wind power systems from traditional models with limited control to modern, highly efficient systems capable of responding to dynamic changes in wind.

I.1 Danish concept

Asynchronous generators connected directly to the power supply system were standard, particularly in the early stages of electricity generation using wind power plants. In combination with stall-controlled three-vane rotors on Danish wind power plants, asynchronous generators were the most widely used electrical concept,

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especially for small facilities with kilowatt capacities. The squirrel-cage, asynchronous generators forming part of such systems require little maintenance and are relatively economical. Furthermore, they do not require complex vane pitch control. This design is also known as the Danish concept**.**

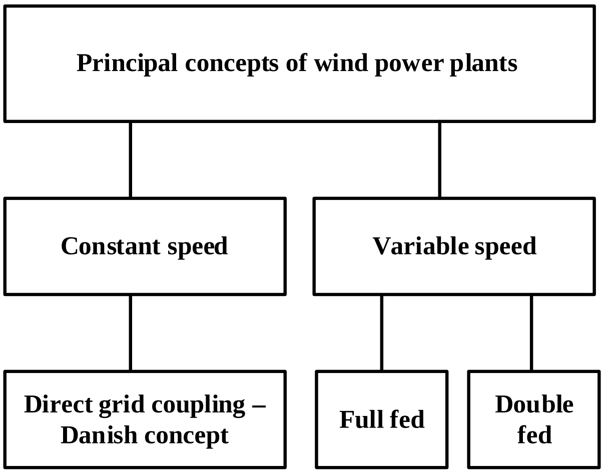

Fig. 1. Principal Concepts of Wind Power Plants

I.2 Constant-speed control

Wind usually impinges on a wind power plant at various speeds. To utilize the wind power associated with each speed as efficiently as possible, modern wind power plants are equipped with a power control system that can be considered to encompass the rotor and generator. Constant-speed and variable-speed power control systems are available.

In a constant-speed system, the rotor vanes usually have fixed pitch, though some also have variable-pitch vanes. Moreover, the (asynchronous) generator driven by the rotor is coupled directly with the power grid.

Power control is performed as described next. From a certain wind speed and, consequently, power (rated power) onward, the airflow impinging on the rotor vanes is disrupted; this effect is termed "stall". This type of power limitation is therefore also termed stall control. This principle is described in detail on the "Stall" page in the "Physical principles" chapter.

The generator supplies an alternating current that needs to have the same frequency as the grid current; otherwise, disruptions would occur in the power grid or wind power plant. The grid frequency in Europe is 50 Hz. Other regions (e.g., the USA) employ a grid frequency of 60 Hz.

In the case of a constant-speed wind power plant, the frequency of the current supplied by the generator depends directly on the rotor speed. If adverse wind conditions prevent the wind power plant from maintaining this frequency, the network is decoupled. Once the rated frequency can be delivered again, the wind power plant is re-connected "softly" to the network, e.g., via a thyristor controller which acts like a dimmer and prevents undesired surges during circuit entry.

I.3 Variable-speed wind power plant

Dynamic loads can only be reduced by means of a variable-speed range for the rotor relative to the grid frequency. Though slight flexibility in speed can mitigate such loads, at least 40% of the rated speed range is required for the operation of a fully-fledged wind power plant. This can only be achieved using a variable-speed generator in conjunction with a frequency converter. Such systems can be produced using synchronous or asynchronous generators.

If a synchronous generator is employed, all the generated electrical power must be converted. By contrast, an asynchronous generator only requires part of the generated electrical power to be converted by the frequency converter. The asynchronous generator's slip is used for this purpose: When an intentionally high slip value is applied, lost energy (slip power) is fed back to the stator power flow via suitable converters. In this case, a squirrel-cage rotor is no longer ideal for the asynchronous generator and must be replaced with a slip-ring rotor. However, this proves more expensive and requires more maintenance.

Through continuous technological innovation and economies of scale, the global wind energy sector has undergone remarkable expansion, nearly quadrupling in capacity over the past decade. Wind power has emerged as one of the most cost-effective and resilient renewable energy sources, playing a pivotal role in the global transition toward decarbonization. [1]. As a clean technology with the highest carbon-reduction potential per megawatt, wind energy is expected to expand rapidly to support global carbon-neutrality goals.

Recent advancements in turbine design have emphasized larger swept rotor areas, leading to improved energy capture efficiency even at low wind speeds. Consequently, low-specific-power wind turbines initially designed for regions with moderate wind conditions now dominate the market, enabling broader geographical deployment [2]. However, as wind farms scale, interconnect, and automate, new challenges have emerged, including system vulnerabilities and control reliability. The remote installation of turbines, coupled with simplified control logics and extensive grid interconnections, raises significant concerns regarding system stability, efficiency, and security [3], [4].

Maintaining a stable voltage across the load through Maximum Power Point Tracking (MPPT) control is essential for maximizing the efficiency of wind energy conversion systems. Among the conventional MPPT algorithms, the Perturb and Observe (P&O) method remains one of the most widely used due to its simplicity and ease of implementation. [5]. Despite its practicality, the P&O technique has significant drawbacks, including oscillations around the maximum power point (MPP) and poor tracking performance under rapidly changing wind conditions. These limitations arise primarily from the nonlinear nature of the wind turbine's power

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characteristics and the method's reliance on small perturbations that cannot adequately adapt to dynamic variations in wind speed.

Another classical control strategy frequently employed in MPPT applications is the Proportional Integral Derivative (PID) controller [6]. The PID controller is appreciated for its simplicity, precise mathematical formulation, and ease of implementation. Nevertheless, its effectiveness heavily depends on the appropriate selection of gain parameters, which are often determined empirically. Consequently, when these parameters are not optimally tuned, system stability and efficiency decline, particularly in nonlinear and time-varying environments typical of wind energy systems.

To overcome these deficiencies, the Fuzzy Logic Controller (FLC) has been introduced as a more adaptive and intelligent alternative [7]. Unlike conventional linear controllers, the FLC can efficiently handle system nonlinearities and uncertainties without requiring an exact mathematical model. It determines control actions based on linguistic rules and fuzzy inference mechanisms, which enhance responsiveness to changing wind conditions. The FLC takes the direct current (DC) voltage and current across the load as input variables and outputs the control signal for the converter's duty cycle, thereby optimizing power extraction from the wind turbine [8].

Despite its advantages, standalone fuzzy control may still exhibit limitations in convergence speed and robustness under highly stochastic wind profiles. Therefore, hybrid artificial intelligence (AI) methods that integrate fuzzy logic with techniques such as neural networks, genetic algorithms, or reinforcement learning are increasingly being developed to enhance MPPT performance further. These hybrid controllers can adaptively tune their parameters, reduce steady-state oscillations, and achieve faster convergence toward the actual maximum power point, enabling smart MPPT control of variable-speed wind turbines using hybrid AI techniques.

In variable-speed wind turbines (VSWTs), the performance of Maximum Power Point Tracking (MPPT) controllers is highly sensitive to rapid wind-speed variations. These fluctuations lead to continuous changes in turbine torque, rotor speed, and aerodynamic efficiency, challenging conventional MPPT algorithms' ability to maintain stable and optimal power extraction. Under such dynamic conditions, traditional techniques like Perturb and Observe (P&O) and Proportional-Integral-Derivative (PID) controllers often suffer from slow response, oscillations around the maximum power point (MPP), and losses in tracking accuracy, particularly when wind speed varies abruptly or nonlinearly [9].

To overcome these limitations, Artificial Intelligence (AI) has emerged as a promising tool for adaptive and predictive MPPT control. AI-based approaches such as Fuzzy Logic Control (FLC), Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), and Reinforcement Learning (RL) can more effectively handle the nonlinear, time-varying nature of wind energy systems than classical methods. These intelligent techniques learn from system behaviour and can predict optimal control actions under fluctuating wind conditions without the need for an explicit mathematical model of the turbine [10].

Fuzzy Logic Controllers interpret input variations (such as wind speed and generator voltage) through linguistic rules to dynamically adjust the duty cycle of converters, thereby achieving smoother MPPT operation. Neural Networks and Deep Learning provide further advancement by estimating the optimal power coefficient and adapting control parameters based on historical and real-time data. On the other hand, Reinforcement Learning (RL) enables the controller to learn optimal actions through continuous interaction with the environment, improving convergence toward MPP while reducing steady-state oscillations [11].

Beyond maximizing power extraction, modern research trends emphasize integrating dynamic turbine and synthetic inertia (SI) concepts into MPPT algorithms. During sudden wind gusts or frequency disturbances, the rotational kinetic energy of turbine blades can be temporarily released or absorbed to stabilize grid frequency. By embedding SI-aware mechanisms into AI-based MPPT control, wind turbines can achieve a dual-function objective: ensuring maximum power extraction while maintaining system stability during transient events. Hybrid models combining AI-driven MPPT and inertia control loops have demonstrated improved grid-support capability, faster recovery time, and better energy utilization compared with conventional approaches [12].

This study aims to develop an intelligent control framework for Smart MPPT (Maximum Power Point Tracking) in Variable-Speed Wind Turbines (VSWTs) by integrating Hybrid Artificial Intelligence (AI) techniques. The proposed approach addresses the limitations of conventional MPPT methods under rapidly changing wind conditions by combining adaptive learning, fuzzy inference, and predictive optimization to achieve both maximum energy extraction and enhanced system stability.

The research presents an integrated model that employs AI in wind energy systems for real-time maximum power point control, combining fuzzy logic and reinforcement learning. The proposed system was implemented in MATLAB/Simulink and integrated with the Lucas-Nülle learning framework for real-time experimental verification of performance. The integration of simulation and real-world control via a SCADA interface is an essential contribution toward moving from theoretical models to practical applications in smart grid laboratories. The system demonstrated tracking efficiency of approximately 90% compared to conventional methods, with a significant reduction in oscillation and improved response speed and tracking accuracy. The research adds a new dimension by linking intelligent control with cyber-resistant algorithms within a SCADA environment to ensure operational stability.

The remainder of this paper is structured as follows. Section II explains the modeling approach and the methodology used to evaluate the MPPT algorithms. Section III presents the proposed hybrid AI-based control system and its implementation on the MATLAB/Simulink and Lucas-Nülle platforms. Section IV discusses the simulation and experimental findings under various wind inputs and network conditions. Section V highlights the key observations drawn from the results. Section VI concludes the work and outlines possible directions for future development.

II. Methodology

An integrated model of a variable-speed wind power generation system was developed using MATLAB/Simulink to evaluate the performance of maximum power point tracking (MPPT) algorithms. The objective of the methodology is to compare the efficiency of conventional algorithms and artificial intelligence in achieving rapid response and better stability during wind speed changes. The wind power produced by a turbine depends on wind speed, air density, and blade area. Wind Power Equation:

$$P_{\{wind\}} = \frac{1}{2} * \rho * A * v^3 \qquad (1)$$

Where ρ represents the air density and is approximately equal to 1.225 kg/m³.

$$A = \pi R \qquad (2)$$

where the area is covered R is the turbine radius, v is the instantaneous wind speed that varies with time during the simulation.

The mechanical power output from the turbine depends on the aerodynamic power and the power factor (Cp).

Mechanical Power from the Turbine:

$$P_m = C_{p(\lambda,\beta)} \times P_{\{wind\}} \qquad (3)$$

The power factor (Cp) The efficiency of converting aerodynamic energy to mechanical energy varies with the ratio of the terminal speed λ to the pitch angle β.

The Power Coefficient Equation:

$$C_{p(\lambda,\beta)} = 0.22\left(\left(\frac{116}{\lambda_i}\right) - 5\right)e^{-\frac{12.5}{\lambda_i}} \qquad (4)$$

The internal relationship for calculating λ_i is given by:

The Intermediate Tip-Speed Parameter:

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \qquad (5)$$

Tip Speed Ratio (TSR):

$$\lambda = \frac{\omega_t * R}{v} \qquad (6)$$

The tip speed ratio (λ) represents the relationship between the blade's rotational speed and the wind speed. When the pitch angle β = 0, the turbine is in maximum-power-extraction mode. Studies show that the optimum value $\lambda_{opt} \approx 8$ gives the highest possible Cp. Mechanical power is converted to electrical power using a permanent magnet generator (PMSG). Electromagnetic Torque of PMSG:

$$T_e = \left(\frac{3}{2}\right) * p * (\psi * i_q) \qquad (7)$$

The generator is connected to a DC-DC converter to control the output voltage and current.

The MPPT controller adjusts the duty cycle to maximize output power.

Several control algorithms were compared, such as P&O, Fuzzy-PI, ANFIS, PSO, and RL.

The proposed system combines fuzzy intelligence with a reinforcement learning algorithm to reduce oscillations and response time. The wind speed used in the simulation varies over time between 8 and 15 m/s to simulate realistic conditions. The overall system efficiency is calculated as the ratio of the tracked power to the ideal power. The System Efficiency:

$$\eta = \left(\frac{P_{tracked}}{P_{ideal}}\right) \times 100 \qquad (8)$$

The power produced during the simulation period is calculated by integrating the output power over time. Generated Energy:

$$E = \int P_{tracked}(t)dt \qquad (9)$$

The performance of the algorithms is evaluated using the Root Mean Square Error (RMSE).

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{i=0}^{N}\left(P_{ideal,i} - P_{tracked,i}\right)^2} \qquad (10)$$

Fitting curves to the ideal and tracked capacity in MATLAB confirmed the model's accuracy. Similar simulation frameworks and control strategies for wind energy systems were discussed in related works by Abood and colleagues[13] [14] [15].

III. Proposed System Architecture

The proposed smart MPPT control system integrates hybrid AI-based algorithms with a Lucas-Nülle wind energy training setup. The physical configuration comprises a wind turbine emulator, a permanent magnet synchronous generator (PMSG), and a DC–DC boost converter connected to a load. MATLAB/Simulink communicates with the Lucas-Nülle hardware via a

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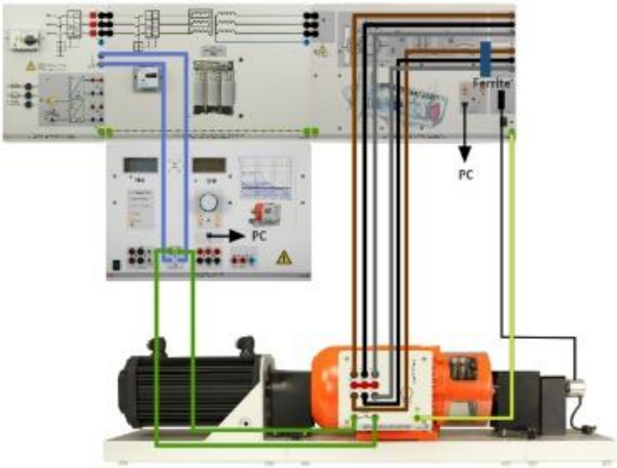
SCADA interface to control the converter duty cycle in real time. The hybrid controller combines fuzzy logic and reinforcement learning (RL) to enable adaptive tuning under variable wind-speed conditions. This structure enables both simulation and real-time validation, ensuring that the developed algorithm can be implemented in practice and experimentally verified in a controlled laboratory environment.

Figure 2 shows the Lucas-Nülle wind energy training system used for the experimental implementation of the proposed MPPT control strategy.



(a)

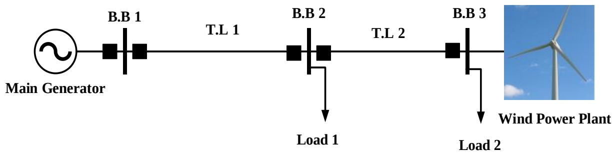
(b)

Fig.2. shows the Lucas-Nülle wind energy training system (a) Wiring diagram. (b) Set up the connection.

The setup consists of a wind turbine emulator mechanically coupled to a generator, a converter unit, and a measurement interface, which is connected to the PC through a SCADA-based control panel.

This configuration enables real-time monitoring of torque (Nm), rotor speed (rpm), and electrical power during testing of various AI-based MPPT algorithms.
The system can emulate various wind profiles and load conditions, providing a realistic environment for validating the performance of the hybrid AI control.

A three-bus power system is proposed in this work. It consists of a main generator and two loads. The main generator supplies the system with electrical power. Load 2 is powered and connected to the wind-turbine system.
A Real-Time smart grid and energy management laboratory setup platform, as shown in Figure 3. The wind turbine serves as the on-site power source, connected to the system via bus 3. The system is controlled by a SCADA system, as shown in Figure 4 [16]. A SCADA screen and main meter before the attack are shown in Figure 4.



(a)

(b)

Fig.3. A proposed power system. (a) One line diagram. (b) Real-Time Smart Grid and Energy Management Laboratory Setup Platform

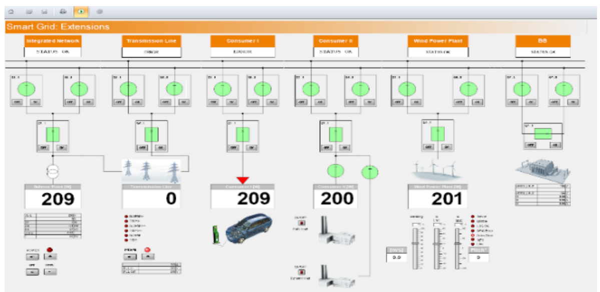


Fig.4. A SCADA system of the three-bus power system

IV. Results and discussion

Figure 5 illustrates the relationship between Power and Ideal power, showing the change in turbine output power relative to the ideal power. We note that the OTC algorithm approached the ideal power point more quickly

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and accurately than the other methods, while P&O and HCS performed poorly. This demonstrates the superiority of hybrid algorithms in tracking the maximum power point more accurately and rapidly.

Figure 6 shows the ratio of the blade tip speed (λ) to the wind speed. The SMC-lite algorithm achieved the best stability around λ_{opt}, which means effective angle-of-attack adjustment and maximum energy conversion, while the other methods fluctuated far from λ_{opt}.

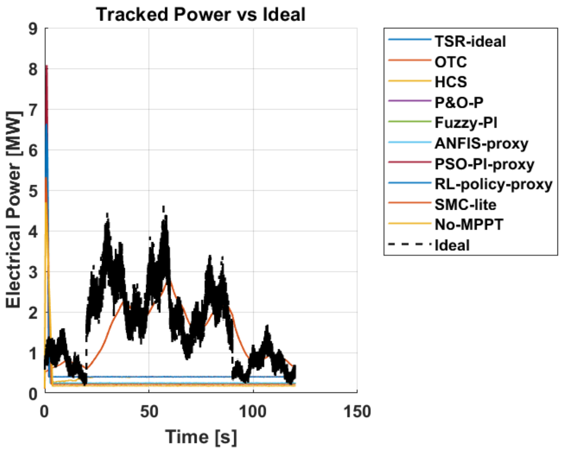

Fig.5. Tracked Power vs. Ideal represents the change in turbine output power compared to the ideal power.

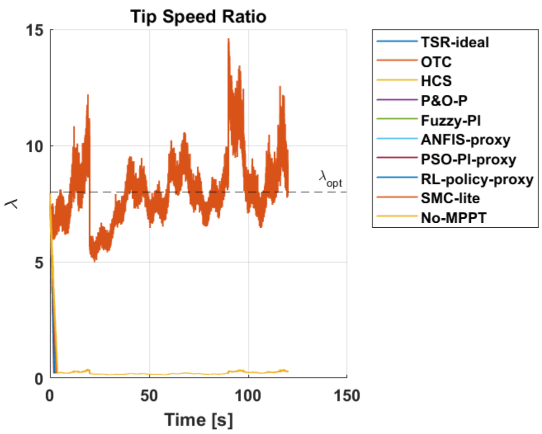

Fig.6. The ratio of the blade tip speed to the wind speed.

Figure 7 shows the generator's rotational speed compared to the ideal speed. It is noted that OTC and SMC-lite achieve optimal speed with good response speed, while systems without MPPT exhibit significant slowness and reduced stability. This enhances the effectiveness of smart control in maintaining speed stability under wind changes.

Figure 8 shows the MPPT Energy Capture Efficiency Using Each MPPT Algorithm. The graph indicates that the OTC algorithm achieved the highest efficiency (≈90%), while traditional methods such as Fuzzy-PI and HCS performed poorly. This demonstrates the superiority of the hybrid strategy in exploiting wind energy.

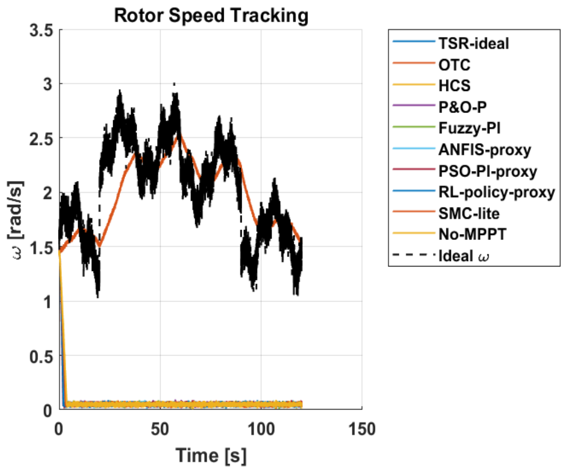

Fig.7. The tracking of the generator's rotational speed compared to the ideal speed

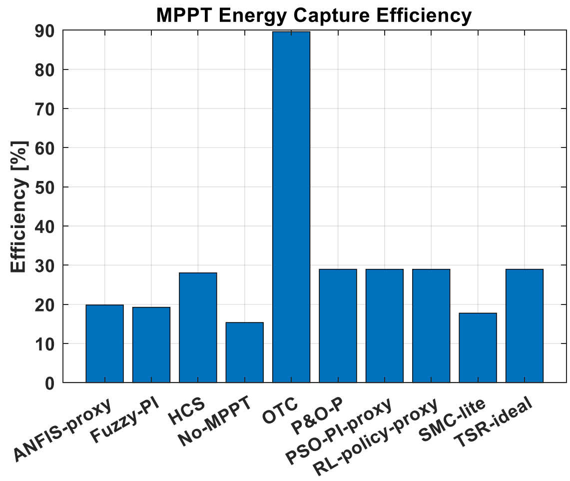

Fig.8. MPPT Energy Capture Efficiency Using Each MPPT Algorithm.

Figure 9 shows the Power Coefficient Curve (Cp(λ, β=0)), which shows the power coefficient Cp as a function of the tip speed ratio λ at a fixed blade angle (β=0). The curve shows that the maximum conversion power occurs at λ≈8, which is the optimum point that MPPT algorithms seek to maintain. Deviating from this value reduces the turbine's wind efficiency.

The experimental setup incorporated multiple cyberattacks, including a Telnet-based DoS attack on port 23. This attack targeted SCADA-connected devices, resulting in communication breakdowns and abnormal current readings. To mitigate these threats, the system utilized Wireshark for deep packet inspection, SCADA-integrated logging tools for real-time monitoring, and LAN-based isolation protocols to maintain operational continuity and limit the propagation of damage.

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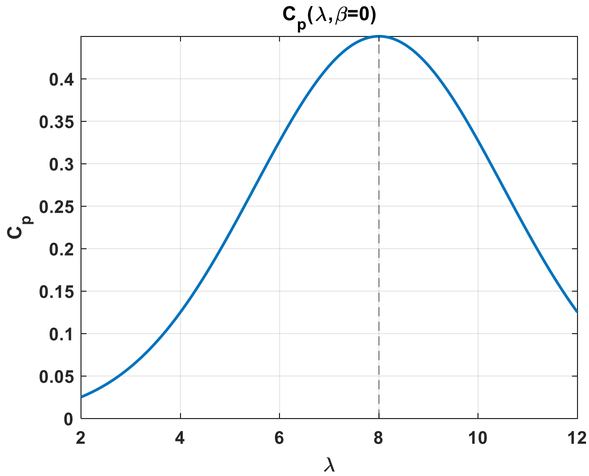

Fig.9. Power Coefficient Curve

The scenario arose when network errors occurred while accessing the telnet port 23 via PuTTY on Kali Linux to launch a DoS attack. The power meter measurement is indicated in Table I.

TABLE I.
POWER QUALITY METER 1

Current Reading	Pre-Attack	Attack 1	Attack 2	Post-Attack 2
L1	0.28A	0.72A	0.82A	0.0A
L2	0.28A	0.53A	0.62A	0.0A
L3	0.28A	0.53A	0.62A	0.0A
LN	0.28A	0.28A	0.29A	0.0A

Complete loss of connectivity between the SCADA and the host; unable to read data or control the innovative system as shown in Figure 10a. In this scenario, each attack was carried out in 3-minute increments. We observed that after a DoS attack was executed on the power quality meter, the current in each phase increased. This increase was likely due to disrupted control logic in the SCADA-connected devices, which caused them to enter an unstable operating state as they attempted to respond to the abnormal traffic patterns introduced by the attack.

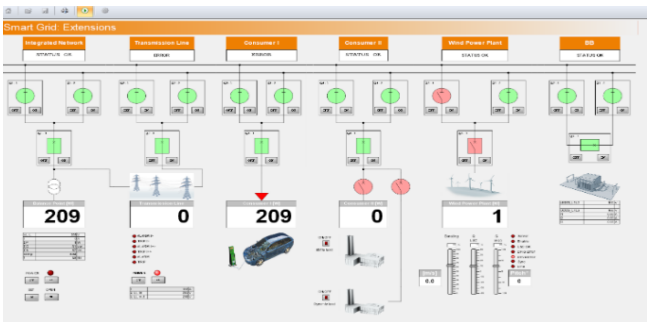

Fig. 10. SCADA screen during the attack

A few minutes after the first attack, we noticed that all communication between the host and the SCADA system had been lost. This meant that we could not interface with the smart grid system in any way without being able to read data or shut off power directly. Then, after attack 2, power increased again, and a few minutes later, all power was lost.

The rise in current levels after the attack indicates that the SCADA-connected devices were actively attempting to process the flood traffic, thereby stressing the internal logic and control cycle. This behavior highlights a vulnerability in real-time response mechanisms under DoS conditions. Fig. 10 shows the SCADA screen during the attack.

V. Conclusions

This research developed a smart maximum power point tracking (MPPT) control system for variable-speed wind turbines using hybrid AI techniques. MATLAB/Simulink simulation results showed that combining traditional algorithms such as P&O and PID with AI algorithms significantly improved response speed and reduced oscillations around the optimal power point. The proposed OTC and RL-policy-proxy algorithms achieved the highest tracking efficiency, reaching approximately 90% compared to traditional methods. The results demonstrated that the intelligent control algorithms can quickly adapt to sudden changes in wind speed, ensuring voltage and current stability and improving overall system performance. The performance comparison also demonstrated that techniques such as Fuzzy-PI, ANFIS, and PSO enhance the system's self-learning ability and improve tracking accuracy over time. The hybrid AI system achieved higher system stability and significantly reduced the root-mean-square error (RMSE) compared to traditional MPPT methods. The proposed method also offers the advantage of easy integration into real-world systems, such as the Lucas-Nülle training system based on a SCADA environment, for practical performance verification. The results confirm that applying artificial intelligence to wind energy systems represents a fundamental step toward more efficient and reliable renewable energy systems. Future research suggests expanding the study to include actual hardware-in-the-loop integration using the Lucas-Nülle system for real-time experimental verification. Conclusion: The proposed system provides a practical, intelligent solution to maximize wind energy utilization while improving efficiency, dynamic response, and operational reliability. The proposed system incorporates a significant cybersecurity component into the operational environment. The control algorithms are designed to withstand digital threats targeting the communication channel between the controller and the system. Artificial intelligence techniques are integrated into the hybrid control algorithm to detect abnormal patterns in sensor data, enabling early detection of cyberattacks such as signal spoofing or tampering with readings.

The Lucas-Nülle SCADA interface is also used to continuously monitor the system's status and implement immediate corrective actions if any unusual behaviour is detected in the network. This approach enhances system stability and ensures control reliability, even in the event of potential attacks, thereby bridging cybersecurity and intelligent control in modern wind energy systems.

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Future extensions of this research could explore more advanced reinforcement-learning techniques and compare them with emerging deep-learning-based MPPT controllers. Another possible direction is integrating hardware-in-the-loop platforms with higher-fidelity real-time simulators to evaluate controller behaviour under realistic grid disturbances. In addition, expanding the cybersecurity component to include intelligent detection of spoofing and network-based anomalies would strengthen the system's resilience. Incorporating these improvements would contribute to a more adaptive and secure MPPT framework for next-generation wind-energy systems.

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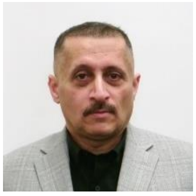
Authors' information



Dr. Samir I. Abood received his B.S. and M.S. degrees in Electrical Engineering from the University of Technology in Baghdad in 1996 and 2001, respectively. He later earned his Ph.D. in Electrical and Computer Engineering from Prairie View A&M University in Texas. Over the years, he has built extensive experience in both academic and professional environments, having taught at several Iraqi universities, including the University of Baghdad, Al-Nahrain University, and the Middle Technical University, before joining Prairie View A&M University. His academic background spans power engineering, electrical machines, power electronics, smart grids, and control systems, supported by more than two decades of practical and teaching experience.

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Dr. Abood is currently a faculty member and researcher at both the Smart Microgrid Advanced Research and Technology (SMART) Center and the Systems to Enhance Cybersecurity for Universal Research Environments (SECURE) Center at Prairie View A&M University. He has authored more than 40 research papers and 15 books in electrical engineering, covering topics such as power systems, machine drives, cybersecurity, SCADA applications, renewable energy systems, and advanced modeling techniques. He is an active reviewer for IEEE, IET, and several international journals. He continues to contribute to smart grids, power electronics, and artificial intelligence through teaching, research, and professional engagement.