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Enhancing Hybrid Power System Performance with GWO-Tuned Fuzzy-PID Controllers: A Comparative Study

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ABSTRACT

This study explores the implementation of a novel control strategy within hybrid power systems, leveraging a Grey Wolf Optimization (GWO)-tuned Fuzzy Proportional-Integral-Derivative (Fuzzy-PID.) controller to enhance the integration of renewable energy sources. By addressing the critical challenge of grid frequency deviations, this approach significantly bolsters the stability and efficiency of power flow, ensuring a more reliable electricity supply. Employing MATLAB simulations, the research underscores the superior performance of the GWO-tuned Fuzzy-PID. controller, which necessitates fewer control interventions and yields lower oscillation frequencies than its conventional PID. and Fuzzy-PID. counterparts. The robustness of this optimized controller is further validated through extensive tests, demonstrating its resilience across a spectrum of parameter adjustments and operational scenarios, including the hypothetical removal of system components. The findings reveal that this advanced control method markedly surpasses traditional solutions in maintaining stable electricity flow and enhancing the system's overall resilience and adaptability to the variable nature of renewable energy. Thus, the GWO-tuned Fuzzy-PID. controller emerges as a significant innovation in hybrid power system management, heralding a new era of optimization and efficiency in renewable energy integration.

1. Introduction

The pressing need for sustainable and environmentally friendly energy solutions has never been more critical than in our current era. As the detrimental effects of traditional fossil fuels on the environment become increasingly apparent, the search for alternative, renewable energy sources has intensified [1]. The PID controller, recognized for its extensive application, is widely utilized in various control systems [2]. Despite the higher costs and pollution associated with fossil fuels, the global energy sector continues to rely heavily on these diminishing and environmentally harmful resources to meet the world's growing electricity demands [3]. This reliance underscores a significant challenge in transitioning toward greener energy solutions, highlighting the inherent trade-offs between economic costs, energy security, and environmental sustainability. PID controllers are preferred in industries for their simplicity and reliability in regulating DC motor speed, resulting in faster response times, decreased error, and minimized overshoot [4].

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Renewable energy sources, including solar, wind, geothermal, and tidal power, offer promising pathways to address these challenges [5]-[15]. These technologies harness natural processes to produce clean, abundant, and sustainable energy, presenting viable alternatives to fossil fuels. However, the adoption of renewable energy is not without its challenges. One of the primary obstacles is the inherent variability of these energy sources. The output from solar panels and wind turbines, for example, can fluctuate significantly due to changing weather conditions, posing challenges for integrating these sources into the existing power grid reliably [16].

To mitigate the impacts of this variability, advanced energy storage technologies such as ultracapacitors, flywheels, and batteries have been developed [5], [17]-[20]. These systems play a crucial role in stabilizing the power grid by storing excess energy generated during peak production times and releasing it during periods of high demand or low production. The integration of these storage solutions into hybrid power systems, which combine multiple renewable energy sources, represents a critical advancement in efforts to enhance grid stability and ensure a consistent energy supply [21].

The complexity of managing the dynamic interactions between various renewable energy sources and storage systems in hybrid power systems necessitates sophisticated control strategies. Traditional control methods, such as Proportional-Integral-Derivative (PID.) controllers, have been widely used across various industries for their simplicity and effectiveness. However, the unique challenges posed by hybrid power systems, characterized by non-linear dynamics and unpredictable fluctuations in energy production and demand, require more adaptable and resilient control solutions [21].

Recent advancements in control strategies for hybrid power systems have focused on enhancing performance and stability through various innovative approaches. Among these, the Grey Wolf Optimizer-tuned Fuzzy Proportional-Integral-Derivative controllers stand out as a promising solution to meet the dynamic demands of modern power systems. The integration of intelligent control mechanisms, such as fuzzy logic and hybrid models, has shown significant improvements over conventional control techniques in stabilizing the net frequency against load variations and improving control performance.

Doan et al. explored a novel fuzzy logic-based load frequency control method for multi-control-area interconnected power systems. Their research demonstrated the potential of intelligent control methods to outperform traditional controllers, such as Integral, PI, and PID controllers, in stabilizing frequency variations [22]. Similarly, [23] compared the effectiveness of Adaptive Neuro Fuzzy Inference System (ANFIS) controllers with conventional PID and Fuzzy logic controllers in managing load frequency control of a three-area interconnected power system. Their findings highlighted the comparative advantages of ANFIS controllers in enhancing system performance.

In the domain of robust and fuzzy controllers, Falkner and Heck identified that these controllers exhibited superior overall behavior in enhancing the power system performance [24]. This study provides a foundational understanding of the potential of robust and fuzzy logic controllers in power system applications. De Carvalho Neto [25] furthered this research by applying a hybrid control method to a DC-DC boost converter, aiming to maintain a constant output voltage and ensure high power quality. Their approach combined signals from robust and fuzzy controllers based on operational conditions, offering an effective solution for power quality improvement.

Giri and Sinha [26] introduced a Hybrid Neuro-Fuzzy (HNF) controller for load frequency control in a four-area interconnected power system. Their work demonstrated the HNF controller's superior speed and effectiveness in managing nonlinearities compared to traditional controllers such as fuzzy, artificial neural network (ANN), and conventional PI controllers. Complementing this, Mishra in [27] implemented a robust trapezoidal membership function-based type-II fuzzy PID controller for automatic generation control (AGC) in multi-area power systems, showcasing the benefits of intelligent controllers in power generation monitoring.

These studies collectively underline the shift towards integrating fuzzy logic and hybrid intelligent control systems in power system management. The emphasis on such innovative approaches stems from their ability to efficiently address system nonlinearities, disturbances, and load variations, which are crucial for the development of more reliable and efficient power systems.

The optimization of controller parameters is a critical aspect of deploying effective control strategies in hybrid power systems. Among the various optimization techniques explored in recent studies, Grey Wolf Optimization has emerged as a particularly effective method for tuning the parameters of Fuzzy-PID. controllers. Inspired by the social hierarchy and hunting behavior of grey wolves, G.W.O. is a meta-heuristic optimization algorithm that has demonstrated superior performance in identifying optimal solutions for complex, multi-dimensional optimization problems. In the realm of VLSI integration for low power applications, the quest for enhancing hybrid power system performance takes center stage [28]-[30].

Despite the advances in control strategies and optimization techniques, several research gaps remain, particularly regarding the comparative effectiveness of different control approaches under varying operational conditions and parameter uncertainties. This study aims to fill these gaps by conducting a comprehensive analysis of Fuzzy-PID. controllers optimized with G.W.O. in hybrid power systems. Through a detailed examination of the performance of these controllers in managing the variability of renewable energy sources and ensuring grid stability, this research seeks to contribute to the ongoing efforts to develop more resilient, efficient, and sustainable energy systems.

As the world continues to grapple with the challenges of transitioning to a sustainable energy future, the findings of this study hold significant implications for the design and management of hybrid power systems. By providing insights into the effectiveness of optimized control strategies in enhancing the reliability and performance of these systems, this research contributes to the broader goal of achieving a sustainable, reliable, and clean energy supply for future generations.

2. Renewable Energy Sources and Hybrid Power Systems

The quest for sustainable, reliable, and clean energy sources has directed substantial scholarly attention towards renewable energy technologies and their integration into power systems. This section delves into the expansive body of literature on renewable energy sources and hybrid power systems, underlining the significance of these discussions in the context of global energy transformation.

The global shift towards sustainable development has significantly increased the focus on renewable energy sources and hybrid power systems as vital components in achieving energy security and environmental sustainability. Renewable energy sources, such as solar, wind, geothermal, and tidal energy, are pivotal in the transition from conventional fossil-fuel-based power systems to more sustainable alternatives due to their low environmental impact and potential to provide clean, abundant, and sustainable energy [1]. These sources represent the cornerstone of a green energy future, offering the promise of reducing greenhouse gas emissions and mitigating the adverse effects of climate change.

Hybrid power systems, which integrate multiple renewable energy sources with conventional power generators and energy storage technologies, emerge as a compelling solution to address the intermittency and unpredictability of renewable energy sources. By combining various energy sources and storage systems, hybrid power systems can offer more reliable and stable energy supply, enhancing grid stability and reducing dependency on fossil fuels [4]. The integration of energy storage technologies, such as batteries, flywheels, and ultracapacitors, into hybrid systems plays a critical role in balancing energy supply and demand, storing excess energy during peak production periods, and releasing it during high demand or low production periods [27].

The management of these complex systems requires advanced control strategies to optimize the dynamic interactions between the different components of hybrid power systems. Traditional control methods like Proportional-Integral-Derivative (PID.) controllers, while widely used for their simplicity and effectiveness in various applications, often fall short in addressing the unique challenges presented by the nonlinear dynamics and variable nature of hybrid power systems. As such, there is a growing research interest in developing more sophisticated and adaptive control strategies that can better handle the complexities of hybrid power systems, ensuring efficient operation and maximizing the utilization of renewable energy sources.

Renewable energy sources and hybrid power systems represent critical elements in the global transition towards a more sustainable energy future. The continuous development and integration of these systems hold the potential to significantly reduce reliance on fossil fuels, decrease carbon emissions, and provide a resilient and sustainable energy supply. However, the effective management and optimization of hybrid power systems necessitate innovative control strategies that can accommodate the inherent variability of renewable energy sources and ensure the reliable and efficient operation of these complex systems.

2.1. Challenges in Hybrid Power System Control

The control of hybrid power systems, which integrate renewable energy sources with conventional power generation and energy storage, is fraught with challenges. These systems' inherent variability, complexity, and the need for reliability present significant hurdles. Recent research has aimed to address these issues, offering insights and solutions to optimize hybrid power system control. One of the primary challenges is managing the intermittent nature of renewable energy sources. Espina in [31] have investigated the use of predictive control strategies to mitigate the impacts of solar and wind energy variability. Their study emphasizes the importance of forecasting tools in predicting renewable outputs, enabling more responsive and adaptive control strategies.

Energy storage is critical in compensating for renewable energy's fluctuating nature, yet its integration poses operational challenges. A study by [32] on battery management systems has highlighted the necessity of sophisticated algorithms to manage the charging and discharging of batteries effectively, ensuring energy availability during demand peaks and minimizing storage costs. The complexity of coordinating multiple energy sources and storage technologies within hybrid systems calls for advanced control frameworks. [33] proposed a modular control architecture that facilitates the integration and scalable expansion of hybrid systems, ensuring efficient operation across diverse configurations.

Economic operation and optimization are vital for the viability of hybrid power systems. Research by Zhao [34] on economic dispatch models has shown how real-time pricing and demand forecasts can optimize the use of renewable energies and storage, reducing reliance on fossil fuels and lowering operational costs. Integrating hybrid systems into the existing grid infrastructure without compromising stability is a significant concern. Studies by [35] have explored solutions for voltage regulation and frequency stabilization in grids with high renewable penetration, highlighting the role of hybrid systems in enhancing grid resilience.

2.2. Previous Approaches in Control Strategies

The evolution of control strategies for hybrid power systems has been marked by significant advancements and research efforts aimed at optimizing the performance and reliability of these complex systems. Over the years, several approaches have been explored, each addressing specific challenges associated with the integration of renewable energy sources, conventional power generation units, and energy storage systems. This literature review delves into the key developments and methodologies that have shaped the landscape of control strategies for hybrid power systems.

Early control strategies predominantly relied on Proportional-Integral-Derivative controllers due to their simplicity and proven effectiveness in various industrial applications. However, the intricacies of hybrid power systems, characterized by non-linear dynamics and unpredictable renewable energy outputs, quickly highlighted the limitations of PID controllers. In Camacho's [36] comparative study, the performance of PID controllers in hybrid systems, identifying the need for more adaptive and robust control solutions to handle system complexities and variability were evaluated.

The recognition of these limitations led researchers to explore advanced control strategies, such as Model Predictive Control (MPC) and Adaptive Control. MPC emerged as a powerful tool for managing the dynamic interactions within hybrid power systems, offering the ability to predict future system states and make informed control decisions. A seminal work by [37] demonstrated the efficacy of MPC in optimizing energy management and distribution in hybrid systems, underscoring its potential to enhance system efficiency and stability.

Adaptive control strategies further expanded the capabilities of hybrid system management by introducing mechanisms that adjust control parameters in real-time based on system performance and environmental conditions. Pao and Johnson in [38] explored the application of adaptive control in wind energy conversion systems, showcasing its advantages in accommodating the variability of wind speeds and improving energy capture efficiency.

In addition to these technical approaches, optimization-based control strategies have also gained prominence, focusing on the economic operation of hybrid power systems. Optimization techniques aim to minimize operational costs while maximizing the utilization of renewable energy sources. A pivotal study by Connolly [39] employed genetic algorithms to optimize the energy mix in hybrid systems, achieving significant improvements in cost-effectiveness and renewable energy penetration.

More recently, the integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques into control strategies has opened new avenues for enhancing the performance and adaptability of hybrid power systems. AI-based approaches enable sophisticated data analysis and decision-making processes, facilitating the real-time optimization of system operations. Chang [40] highlighted the potential of AI and ML in predicting renewable energy outputs and optimizing storage management, marking a significant advancement in control strategy development.

2.3. Optimization Techniques in Control Parameter Tuning

The intricate dynamics of hybrid power systems, characterized by their integration of renewable energy sources, conventional generators, and energy storage technologies, necessitate precise and adaptive control strategies. A pivotal aspect of these strategies is the tuning of control parameters to achieve optimal system performance. Recent advancements in optimization techniques have significantly contributed to the refinement of control parameter tuning, enhancing the efficiency, reliability, and economic viability of hybrid power systems. This literature review encapsulates key developments and applications of optimization techniques in the context of control parameter tuning for hybrid power systems.

One of the cornerstone methodologies in this domain is the application of Genetic Algorithms (GAs). GAs have been widely recognized for their ability to solve complex optimization problems by simulating the process of natural selection. A seminal contribution by [41] introduced the concept of Particle Swarm Optimization (PSO), a GA variant, which has since been applied to various aspects of hybrid power system control, including parameter tuning. The versatility and efficacy of PSO in navigating multi-dimensional optimization landscapes have made it a preferred choice for optimizing control parameters in these complex systems.

Model Predictive Control (MPC) strategies, another critical area of optimization, rely on the accurate prediction of future system states to make informed control decisions. The work by [42] highlights the integration of MPC with optimization techniques to dynamically adjust control parameters in response to predicted changes in system conditions, thereby ensuring optimal performance under varying operational scenarios.

Recent years have seen a surge in the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques for optimization in hybrid power systems. AI and ML offer sophisticated tools for analyzing vast amounts of data, learning system behaviors, and identifying optimal control parameters. A notable study by [43] demonstrates the use of Reinforcement Learning (RL), a subset of ML, for optimizing control strategies in energy systems. RL algorithms iteratively learn the best actions to take in different states of the system, enabling the fine-tuning of control parameters to minimize energy consumption and operational costs.

Furthermore, the integration of Big Data analytics with optimization algorithms has opened new avenues for enhancing the precision of control parameter tuning. Big Data technologies enable the processing and analysis of large datasets generated by hybrid power systems, providing deep insights into system dynamics and performance. Zhang [44] explored the use of Big Data analytics in conjunction with optimization algorithms to develop predictive models for system performance, facilitating the real-time adjustment of control parameters for optimal operation.

3. Components of Hybrid Power System

Hybrid power systems represent a cutting-edge integration of energy storage and power generation components, designed to harness and optimize the use of renewable energy. These systems synergize the strengths of various energy sources to ensure a stable, reliable, and sustainable power supply. Fig. 1 illustrates the comprehensive layout of a hybrid power system, highlighting its complexity and the interconnectivity of its components.

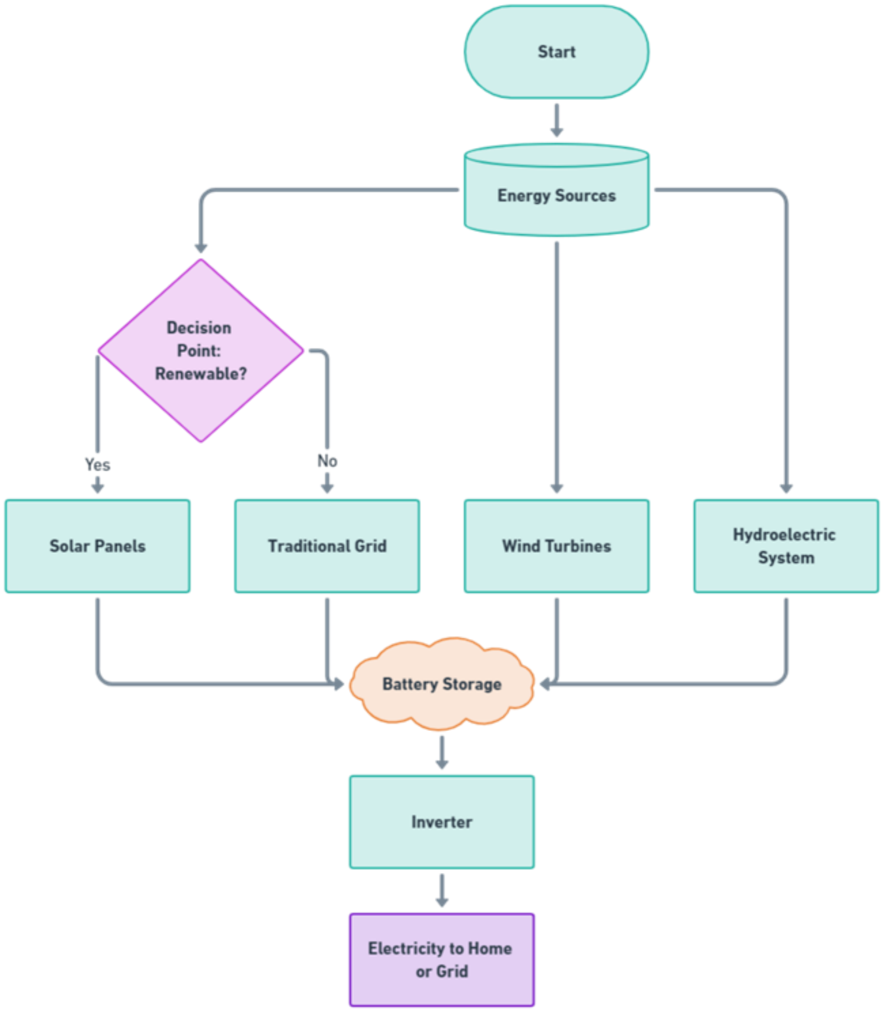

Fig. 1. Simulation diagram of complete hybrid power system

3.1. Modelling of the Power Generation Station

At the core of any hybrid power plant are its power generation units, each contributing unique characteristics to the system's overall performance and efficiency. Predominantly, a hybrid power plant encompasses wind turbine generators (WTGs), solar photovoltaic cells, and diesel engine generators (DEGs), among others. The modeling of these components is crucial for understanding their behavior within the system and optimizing their operation and were obtained by [45] given by:

- Wind Turbine Generators (WTGs): The WTG model captures the conversion of kinetic wind energy into electrical power. The dynamic response of a WTG can be represented by a first-order transfer function, where $G_{WTG}(\mathrm{S})$ is given by Eq. (1).

$$G_{WTG}(\mathrm{S}) = \frac{\mathrm{K_{WTG}}}{1 + (\mathrm{S} * \mathrm{T_{WTG}})} = \frac{\Delta \mathrm{P_{WTG}}}{\Delta \mathrm{P_W}} \tag{1}$$

Here, $\mathrm{K_{WTG}}$ and $\mathrm{T_{WTG}}$ denote the system gain and time constant, respectively, characterizing the WTG's efficiency and response time to wind speed variations.

- Solar Photovoltaic Cells: Solar cells convert sunlight directly into electricity. The model for solar thermal power generators (STPGs) involves a transfer function that accounts for the solar irradiance's impact on power output. It is given by Eq. (2).

$$G_{STPG}(\mathrm{S}) = \frac{\mathrm{K_S}}{1 + (\mathrm{S} * \mathrm{T_S})} * \frac{\mathrm{K_T}}{1 + (\mathrm{S} * \mathrm{T_T})} = \frac{\Delta \mathrm{P_{STPG}}}{\Delta \mathrm{P_{Sol}}} \tag{2}$$

where $\mathrm{K_S}$ and $\mathrm{K_T}$, along with $\mathrm{T_S}$ and $\mathrm{T_T}$, represent the gains and time constants associated with solar energy conversion and thermal storage dynamics.

- Diesel Engine Generators (DEGs): DEGs serve as a reliable backup, ensuring power supply continuity during periods of low renewable energy generation. Their behavior is modeled by Eq. (3).

$$G_{DEG}(\mathrm{S}) = \frac{\mathrm{K_{DEG}}}{1 + (\mathrm{S} * \mathrm{T_{DEG}})} = \frac{\Delta \mathrm{P_{DEG}}}{\Delta \mathrm{u}} \tag{3}$$

with $\mathrm{K_{DEG}}$ and $\mathrm{T_{DEG}}$ indicating the generator's efficiency and responsiveness to control inputs.

- Fuel Cells (FCs): Fuel cells offer a clean, efficient way to produce electricity from chemical energy stored in fuels. The transfer function for a fuel cell, $G_{FCk}(\mathrm{S})$ is given by Eq. (4).

$$G_{FCk}(\mathrm{S}) = \frac{K_{FC}}{1 + (\mathrm{S} * \mathrm{T_{FC}})} = \frac{\Delta \mathrm{P_{FCk}}}{\Delta \mathrm{P_{AE}}} \tag{4}$$

Reflects its power output relative to the input energy, with K_{FC} and $\mathrm{T_{FC}}$ encapsulating the conversion efficiency and dynamic response characteristics. The parameters outlined in these models, detailed in Table 1, provide a foundational framework for simulating and analyzing the performance of hybrid power systems. Through these models, engineers and researchers can predict system behavior under various operational scenarios, enabling the optimization of power generation and the strategic management of energy resources within the hybrid system.

3.2. Implementation of Different Energy Storage Components

Energy storage plays a pivotal role in hybrid power systems, providing a buffer that mitigates the variability of renewable energy sources and ensures a steady and reliable power supply. This section delves into the functionality and modeling of key energy storage components employed within these systems, including fuel cells, battery systems, ultra-capacitors, and aqua electrolyzers. Each component's unique characteristics contribute to the overall efficiency and resilience of the power system.

- Flywheel System: The flywheel system operates on the principle of kinetic energy storage, where energy is stored in the form of rotational energy. The system accelerates a rotor to high speeds, and this rotational energy is converted back into electrical energy when needed. The dynamic behavior of a flywheel system can be represented by the transfer function as given in Eq. (5):

$$G_{FS}(S) = \frac{K_{Fs}}{1 + (S * T_{Fs})} \tag{5}$$

Where $G_{Fs}(S)$ is the transfer function, K_{Fs} denotes the system gain, T_{Fs} is the time constant. This model captures the efficiency of energy conversion and the response time of the flywheel system to changes in energy demand.

- Ultra-capacitor (UC): Ultra-capacitors excel in energy storage density and charging speed, storing significantly more energy per unit volume or mass than conventional electrolytic capacitors. They support numerous charge and discharge cycles without degradation, making them ideal for rapid energy transfer applications. The transfer function for an ultra-capacitor is given by Eq. (6):

$$G_{UC}(s) = \frac{K_{UC}}{1+(s*T_{UC})} \tag{6}$$

Where $G_{UC}(s)$ is the transfer function, K_{UC} is the capacitor gain, T_{UC} is the time constant for UC system.

- Battery System (BS): Battery systems are integral for long-term energy storage, offering a balance between energy density and charge cycles. They play a crucial role in maintaining the structural integrity, safety, performance, and lifespan of the hybrid power system. The behavior of a battery system can be modeled as given in Eq. (7):

$$G_{BS}(s) = \frac{K_{Fs}}{1 + (S * T_{Fs})} \tag{7}$$

Where $G_{Fs}(S)$ = Transfer function, K_{Fs} is the gain, T_{Fs} are the time constant for Battery system respectively.

- Modelling of the Aqua Electrolyzer: Aqua electrolyzers utilize clean energy sources to electrolyze water into hydrogen, which can then be stored or used directly by fuel cells to produce electricity. This technology bridges renewable energy production with hydrogen economy, offering a sustainable pathway for energy storage and utilization. The operation of an aqua electrolyzer is described by the transfer function as given in Eq. (8):

$$\mathrm{AE} = K_{AE}/1 + sT_{AE} \tag{8}$$

- Transfer Function Modelling for Power System: The essence of managing a hybrid power system lies in its ability to maintain stability and efficiency despite the fluctuations in power generation and demand. A fundamental tool in achieving this stability is through the development of a transfer function that models the system's response to changes. The transfer function, represented as $G_{\mathrm{SYSTEM}}(\mathrm{s})$, encapsulates the dynamics of the power system, particularly focusing on how it reacts to deviations in power and load demand. The transfer function for the power system is expressed as:

$$G_{\mathrm{SYSTEM}}(\mathrm{s}) = \Delta f/\Delta P_e = 1/D + I_s \tag{9}$$

In this equation, Δf denotes the fluctuation in frequency deviation within the power system, an indicator of the system's stability in response to changes. ΔP_e represents the error between the power generated and the power demanded, a critical factor in ensuring the balance between supply and demand. The denominator combines two pivotal constants: the damping constant (D) and the inertia constant (I_s).

- Modelling of Solar, Wind, and Demand Load Power: The dynamic interplay between power generation from renewable sources and the demand load presents a complex challenge for hybrid power systems. To navigate this challenge, a mathematical model has been developed to simulate the variations in wind and solar power generation, as well as fluctuations in demand load. This model is pivotal for understanding how these variables impact the overall power system and for designing effective strategies to maintain balance and reliability. The model encapsulates the power generation and demand dynamics through the following equation:

$$\mathrm{P} = \xi * \varphi\sqrt{\eta}\,(1 - \mathrm{G(s)}) + \eta) * \frac{\beta}{\eta} * ¥ \tag{10}$$

In this context, load power is represented by P, indiscriminate power element is represented by ξ, average power is represented by η, and time-based signal switching with gain that controls the sudden change in mean output of power is represented by ¥. The low pass transfer-function is denoted by $G(s)$ and constants (φ and β) are utilized to standardize powers of ξ to achieve per unit level coordination.

Parameters of the equation for generation of solar power is given by Eq. (11):

$$\xi \sim U\ (-1,\ 1);\ \varphi=0.7;\ \eta=2;\ \beta=0.1;\ ¥=1.1111H(t)-0.5555H(t-40);$$

$$G(s) = \frac{1}{10^4 s + 1} \tag{11}$$

Parameters of the equation for generation of demand load is given by Eq. (12):

$$\xi \sim U\ (-1,\ 1);\ \varphi=0.8;\ \eta=100,\ \beta=0.1,\ ¥ = H(t) - \frac{0.8}{\xi} H(t-40);$$

$$G(s) = \frac{300}{(300 * s) + 1} - \frac{1}{(1800 * s) + 1} \tag{12}$$

Equation for the parameters used for the generation of wind power is given by Eq. (13):

$$\xi \sim U\ (-1,\ 1),\ \varphi=0.8,\ \eta=2,\ \beta=10,$$

$$G(s) = \frac{1}{10^4 s + 1} \tag{13}$$

where H(t) is Heaviside step function.

Table 1. Parameters of different components in a hybrid power system

Component	Gain (K)	Time Constant (T)
Solar Power (STPG)	K S = 1.80, KT = 1	TS = 1.80, TT = 0.30
Wind Power (WTG)	K WP = 1	T WP = 1.50
Diesel Engine Generator (DEG)	K DEG = 0.0030	T DEG = 2
Flywheel System	K FS = −0.010	T FS = 0.10
Battery System	K BS = −0.0030	T BS = 0.10
Ultra Capacitor	K UC = −0.70	T UC = 0.90
Aqua Electrolyzer	K AE = 0.0020	T AE = 0.50
Fuel Cell	K FC = 0.010	TFC = 4

Fig. 2 illustrates the open-loop response of the system, showcasing the interactions between generated powers (P_{SOL} and P_W), demand load (P_L), and the total power reaching the grid (P_t). The model highlights the stochastic nature of renewable energy sources and demand, underscored by abrupt changes at random intervals. This variability necessitates robust control mechanisms capable of minimizing frequency deviations and ensuring a consistent supply of electricity to meet the demand.

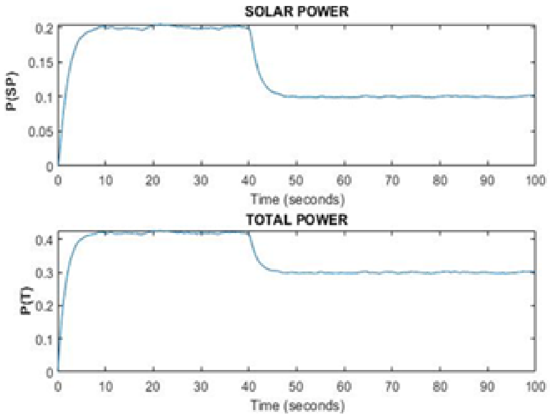

Fig. 2. Open loop response of system

4. Design of Controller

The PID controllers use controls based on the derivative, proportional, and integral of the system. Integral can improve steady-state by integrating available error, and derivative can improve transient response by deriving error. Error is directly proportional to the proportional part. The proportional component determines error. Error is equal to part of proportion. Here e(t) is error signal which is difference between reference frequency (F_{ref}) and frequency obtained at the output f(t). Fig. 3 demonstrates demand power and renewable power realization.

$$e(t) = f_{ref}(t) - f(t) \tag{14}$$

The output of controller is denoted by $y(t)$ in time domain such that, K_p= the proportional gain, K_d =derivative gain, K_I *is* integral gain. In this study, the parameters were optimized using the GreyWolf Optimization software (GWO).

5. Results and Discussions

The study's objective to enhance the operation of hybrid power systems through advanced control strategies has led to a comprehensive simulation analysis. Utilizing MATLAB, the hybrid power system's behavior was meticulously simulated over a duration of 100 seconds, incorporating a range of controller tuning configurations to closely mimic real-world operational scenarios. The simulation accounted for environmental variables such as weather changes, which significantly affect renewable energy inputs, and demand load fluctuations that occur cyclically every one minute and eighty seconds.

Initial simulations employed traditional Proportional-Integral-Derivative and Fuzzy-PID controllers as benchmarks. These controllers, while effective in many standard control applications, showed limitations in handling the dynamic and unpredictable nature of hybrid power systems, particularly under varying weather conditions and load demands. The application of the GWO algorithm to optimize the Fuzzy-PID controller parameters marked a significant advancement in the control strategy. The optimization process focused on refining the controller's ability to maintain system stability and respond efficiently to fluctuations in power generation and demand. The controller parameters are listed in Table 2. Because control signals initialize mechanical parts like DEG, BS, and FS, this fuzzy-PID tuned GWO variation is very important. As a result, the oscillations' intensity is reduced.

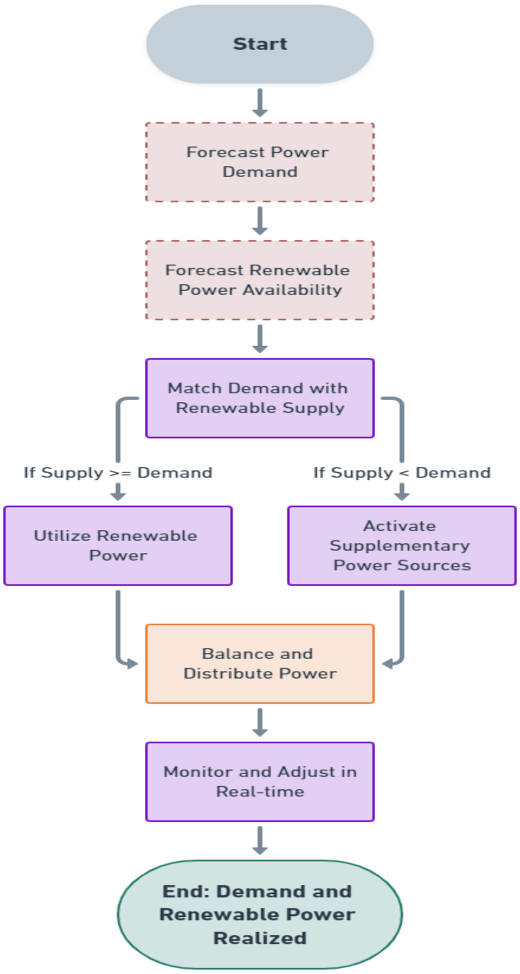

Fig. 3. Demand power and renewable power realization

Table 2. Controller constraints

Controller	K_P	K_I	K_D	K_{PI}
PID	0.9548	1.8324	0.0273	--
Fuzzy-PID	2.2347	0.8123	0.0524	10.3779
GWO tuned Fuzzy-PID	2.2347	0.8123	0.0524	10.3779

5.1. Robustness Test

Variations in parameters of Ultra capacitor (UC): In assessing the robustness of the hybrid power system under the influence of varying energy storage parameters, particular attention was given to the UC due to its significant role in fast energy transfer within the system. Modifications in the UC parameters, including a 30% increase in time constant and a 50% reduction in gain, were explored to simulate potential variances in energy storage behavior and its impact on the system's stability and efficiency. For each possible set of UC parameters, the ISE is shown in Table 3. Compared to other controller structures the values of ISE are less for Fuzzy PID tuned with GWO controller. The ISE value for Fuzzy PID with GWO is 1.24, when time constant, gain of Ultra Capacitor is reduced by 30%, it is greater when compared with PID and fuzzy PID without GWO. But in maximum cases, say in case of a Fuzzy PID with GWO controller, ISE value is least.

Fig. 4 shows representation in graphical form of Integral Square of Error (ISE) values for various controllers while varying parameters of UC. In Fig. 4, ‘blue’ color shows the ‘PID’, ‘red’ shows ‘Fuzzy-PID’ and ‘green’ shows ‘Fuzzy PID with GWO’.

Table 3. Variation of parameter of ultra-capacitor for robustness tst

Conditions	ISE		
	PID	Fuzzy-PID	GWO tuned Fuzzy-PID
NORMAL	1.5163	1.3252	1.1527
30% INCREAMENT	1.9257	1.3538	1.2089
30% DECREAMENT	1.1924	1.3624	1.2441
50% INCREAMENT	2.3021	1.4216	1.2112
50% DECREAMENT	1.3779	0.9046	0.7648

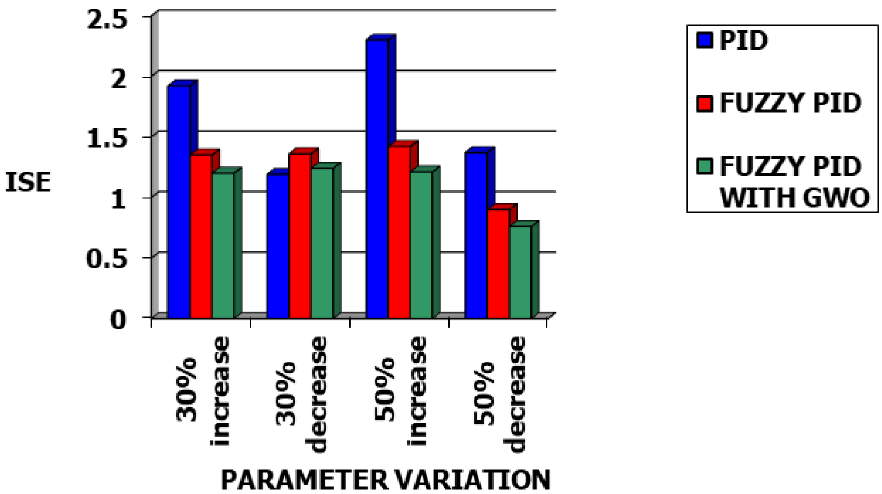

Fig. 4. Graphical presentation of ISE values for various controllers against ultra capacitor parameter variation

5.2. Robustness Test After Disconnecting Various Energy Storage Elements

We were able to confirm the parameter values of the simulated controller by removing various hybrid system components. The disconnects of the FS, BS, and DEG occur under three different conditions. Depending on the situation, the removal of these components may cause the system's functionality to either improve or degrade. The GWO-tuned Fuzzy-PID controller can lessen both frequency deviation and controller effect, as shown in Table 4. In exploring the dynamics of hybrid power system control, a suite of figures helps illustrate the nuances of frequency regulation and the effectiveness of optimization algorithms. Fig. 5 presents a comparison of frequency deviations resulting from various parameter variations in ultra-capacitors, highlighting the sensitivity of system response to changes in UC parameters. It is evident from the data that careful calibration of these parameters is crucial for maintaining system stability.

Table 4. Testing for robustness by disconnecting different energy storage components

Controller	Removed Component	ISE
PID	Battery Storage System	1.7125
	Energy Gen-set (Diesel)	1.7434
	Flywheel System	1.4579
Fuzzy-PID	Battery Storage System	1.4366
	Energy Gen-set (Diesel)	1.3347
	Flywheel System	1.4659
GWO tuned fuzzy-PID	Battery Storage System	1.2671
	Energy Gen-set (Diesel)	1.1739
	Flywheel System	1.2667

Fig. 6 showcases the convergence curve of the Grey Wolf Optimizer when applied to tune a Fuzzy PID controller. The graph illustrates a rapid decline in the 'Alpha cost,' suggesting that the GWO algorithm efficiently minimizes the cost function, leading to an optimized set of control parameters for the Fuzzy PID controller. The swift convergence indicates the potential of GWO as a robust optimization tool in control parameter tuning.

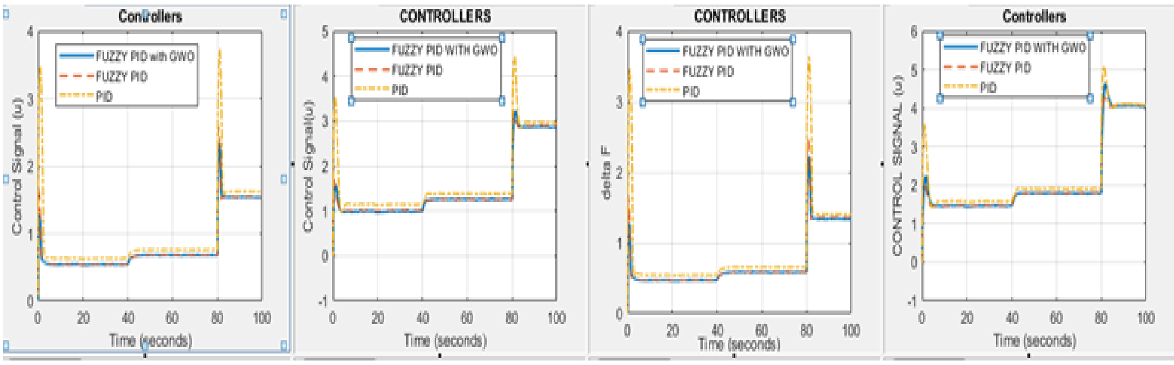

Fig. 5. Frequency deviations for various variations in UC parameters

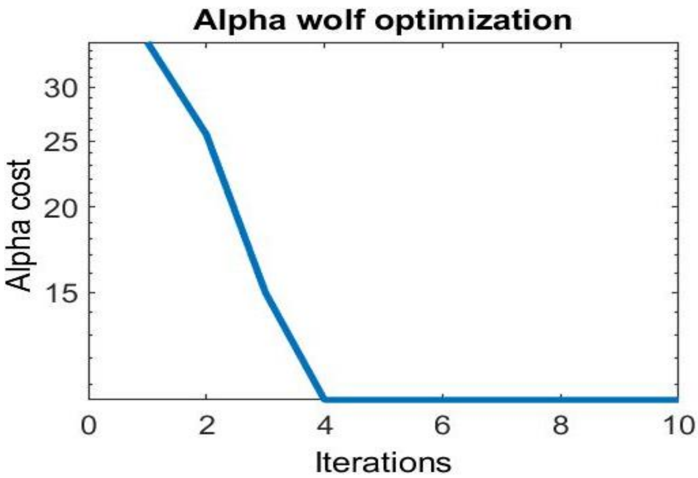

Fig. 6. Convergence plot of GWO for Fuzzy PID

Control strategies are further dissected in Fig. 7, which compares control signal deviations for various controllers. The plot provides insight into the comparative performance of a Fuzzy PID controller with GWO, a standalone Fuzzy PID, and a traditional PID controller. The Fuzzy PID with GWO exhibits a closely aligned response with the standalone Fuzzy PID, suggesting that the addition of GWO does not compromise control signal integrity and might enhance performance.

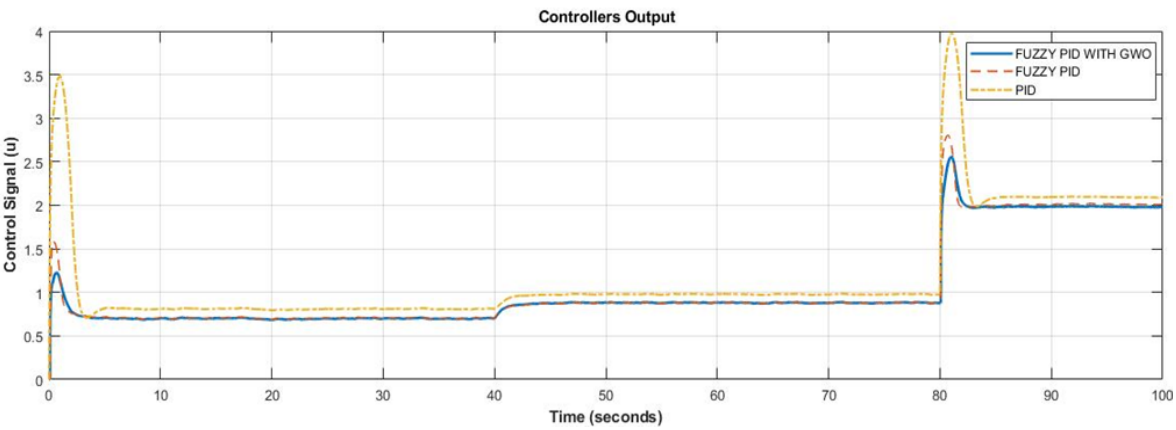

Fig. 7. Variations in control signals across different controllers

The role of these controllers in managing frequency deviation is underscored in Fig. 8. It depicts the frequency deviation for the aforementioned controllers, showing that the Fuzzy PID with GWO combination and the standalone Fuzzy PID both maintain frequency deviations within a tighter range compared to the PID, reflecting the advanced controllers' superior ability to handle system frequency variations.

Finally, Fig. 9 displays the power output of various elements within a hybrid power system, including flywheel energy storage, ultracapacitors, fuel cells, diesel generators, and battery energy storage systems. The responses indicate how different energy components react over time to demand changes, underlining the importance of integrated control strategies that can synchronize the disparate power outputs to ensure a steady net power supply to the grid.

Together, these figures highlight the importance of optimized control parameters and the efficacy of advanced controllers in managing the intricate behaviour of hybrid power systems. The convergence of GWO optimization with Fuzzy PID control strategies exemplifies the potential of intelligent algorithms in enhancing the performance and stability of these complex systems.

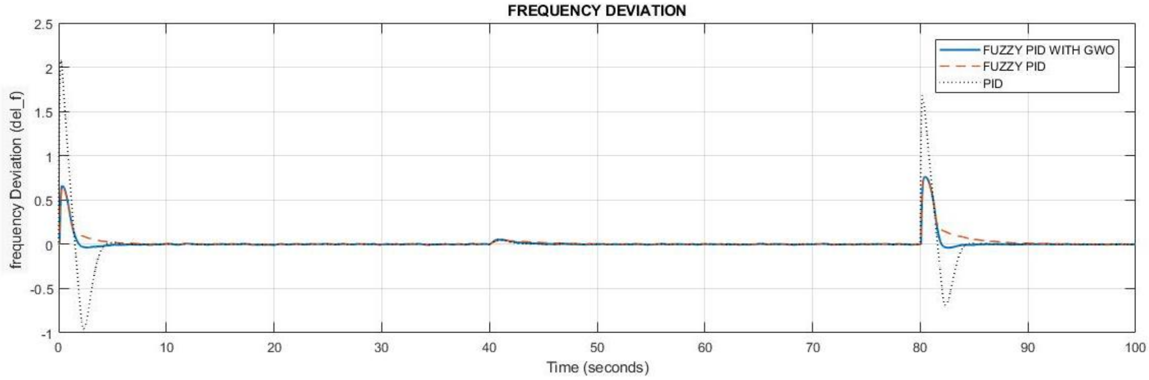

Fig. 8. Frequency variation across different controllers

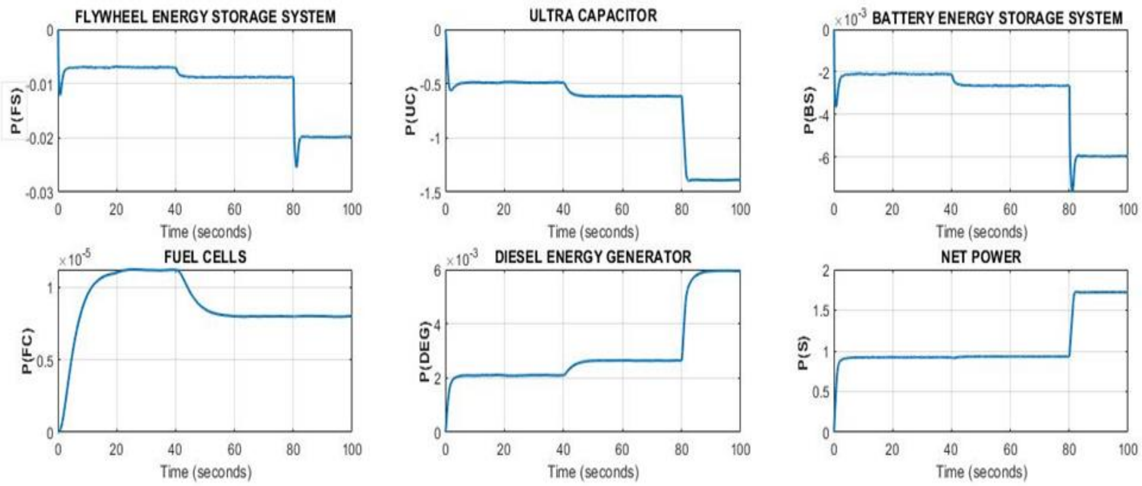

Fig. 9. Output power of various components of hybrid power system

Table 3 and Table 4 data reveal that the GWO-tuned Fuzzy-PID controller consistently has the lowest system effectiveness indicator. The proposed strategy is contrasted with other strategies currently in use in Table 5. The frequency, control signal deviation, and ISE can all be reduced with a GWO-tuned fuzzy- PID Table 5 shows that the GWO-tuned Fuzzy-PID controller performs better even with changes to the parameters and the removal of components.

The robustness tests conducted provide compelling evidence of the GWO-tuned Fuzzy-PID controller's superior performance in managing hybrid power systems. Through rigorous simulation, the controller demonstrated exceptional adaptability to parameter variations and component disconnects, ensuring optimal system operation under diverse conditions. This adaptability, coupled with the controller's ability to maintain lower ISE values, underscores its potential to significantly enhance the stability, efficiency, and reliability of hybrid power systems, marking a substantial improvement over traditional control strategies. These results advocate for the broader adoption of advanced optimization techniques, like GWO, in the design and management of future energy systems, aiming for resilience and sustainability in the face of evolving energy landscapes.

Table 5. Comparison of results

Parameters	GWO-tuned Fuzzy-PID	Literature [45]
Frequency Deviation	0.6372	0.8243
Controller Signals	2.4861	3.0136
ISE	1.1529	1.5598

6. Conclusion

This research embarked on an exploratory journey to harness the capabilities of advanced control strategies within hybrid power systems, aiming to enhance the management of energy flow between generation sources and demand loads. The focal point of this endeavor was the comparative analysis of three distinct control mechanisms: the conventional PID controller, the Fuzzy-PID controller, and the innovative GWO-tuned Fuzzy-PID controller. Through comprehensive simulations and robustness assessments, this study meticulously evaluated each controller's efficacy in stabilizing grid frequency variations, a critical challenge in the integration of renewable energy sources.

The investigation revealed significant insights into the performance dynamics of the examined control strategies. Among the key findings, the GWO-tuned Fuzzy-PID controller emerged as a superior solution, outperforming its counterparts in several critical metrics. Notably, it achieved the lowest values in frequency deviation, control signal deviation, and the Integral Square Error, underscoring its enhanced precision and reliability in managing the power system's stability. This superiority can be attributed to the refined tuning of the controller's parameters through the Grey Wolf Optimization algorithm, which effectively harnessed the nuanced capabilities of fuzzy logic to adaptively respond to the system's fluctuating conditions.

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References

[1] M. Z. Jacobson *et al.*, “100% clean and renewable wind, water, and sunlight all-sector energy roadmaps for 139 countries of the world,” *Joule*, vol. 1, no. 1, pp. 108–121, 2017, https://doi.org/10.1016/j.joule.2017.07.005.

[2] A. Ma’arif, I. Suwarno, E. Nur’aini, and N. M. Raharja, “Altitude Control of UAV Quadrotor Using PID and Integral State Feedback,” *BIO Web of Conferences*, vol. 65, p. 07011, 2023, https://doi.org/10.1051/bioconf/20236507011.

[3] T. Kober, H. W. Schiffer, M. Densing, and E. Panos, “Global energy perspectives to 2060 – WEC’s World Energy Scenarios 2019,” *Energy Strategy Reviews*, vol. 31, p. 100523, 2020, https://doi.org/10.1016/j.esr.2020.100523.

[4] D. Saputra, A. Ma'arif, H. Maghfiroh, P. Chotikunnan, and S. N. Rahmadhia, "Design and Application of PLC-based Speed Control for DC Motor Using PID with Identification System and MATLAB Tuner," *International Journal of Robotics and Control Systems*, vol. 3, no. 2, pp. 233–244, 2023, https://doi.org/10.31763/ijrcs.v3i2.775.

[5] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, and Y. Ding, "Progress in electrical energy storage system: A critical review," *Progress in natural science*, vol. 19, no. 3, pp. 291–312, 2009, https://doi.org/10.1016/j.pnsc.2008.07.014.

[6] S. Ganesan, U. Subramaniam, A. A. Ghodke, R. M. Elavarasan, K. Raju and M. S. Bhaskar, "Investigation on Sizing of Voltage Source for a Battery Energy Storage System in Microgrid With Renewable Energy Sources," *IEEE Access*, vol. 8, pp. 188861-188874, 2020, https://doi.org/10.1109/ACCESS.2020.3030729.

[7] Y. Gu, Y. Huang, Q. Wu, C. Li, H. Zhao and Y. Zhan, "Isolation and Protection of the Motor-Generator Pair System for Fault Ride-Through of Renewable Energy Generation Systems," *IEEE Access*, vol. 8, pp. 13251-13258, 2020, https://doi.org/10.1109/ACCESS.2020.2965773.

[8] N. M. Haegel and S. R. Kurtz, "Global Progress Toward Renewable Electricity: Tracking the Role of Solar (Version 2)," *IEEE Journal of Photovoltaics*, vol. 12, no. 6, pp. 1265-1272, 2022, https://doi.org/10.1109/JPHOTOV.2022.3206532.

[9] A. Qazi *et al*., "Towards Sustainable Energy: A Systematic Review of Renewable Energy Sources, Technologies, and Public Opinions," *IEEE Access*, vol. 7, pp. 63837-63851, 2019, https://doi.org/10.1109/ACCESS.2019.2906402.

[10] R. M. Elavarasan *et al*., "A Comprehensive Review on Renewable Energy Development, Challenges, and Policies of Leading Indian States With an International Perspective," *IEEE Access*, vol. 8, pp. 74432-74457, 2020, https://doi.org/10.1109/ACCESS.2020.2988011.

[11] M. F. Tahir, C. Haoyong, A. Khan, M. S. Javed, N. A. Laraik and K. Mehmood, "Optimizing Size of Variable Renewable Energy Sources by Incorporating Energy Storage and Demand Response," *IEEE Access*, vol. 7, pp. 103115-103126, 2019, https://doi.org/10.1109/ACCESS.2019.2929297.

[12] W. Wang, S. Huang, G. Zhang, J. Liu and Z. Chen, "Optimal Operation of an Integrated Electricity-heat Energy System Considering Flexible Resources Dispatch for Renewable Integration," *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 4, pp. 699-710, 2021, https://doi.org/10.35833/MPCE.2020.000917.

[13] E. C. Mathew, R. Sharma and A. Das, "A Fault Tolerant Scheme for Integration of Remote Renewable Energy Sources With HVDC System," *IEEE Transactions on Power Delivery*, vol. 35, no. 6, pp. 2876-2884, 2020, https://doi.org/10.1109/TPWRD.2020.3015933.

[14] F. R. Albogamy *et al*., "Real-Time Scheduling for Optimal Energy Optimization in Smart Grid Integrated With Renewable Energy Sources," *IEEE Access*, vol. 10, pp. 35498-35520, 2022, https://doi.org/10.1109/ACCESS.2022.3161845.

[15] F. Angizeh, J. Bae, J. Chen, A. Klebnikov and M. A. Jafari, "Impact Assessment Framework for Grid Integration of Energy Storage Systems and Renewable Energy Sources Toward Clean Energy Transition," *IEEE Access*, vol. 11, pp. 134995-135005, 2023, https://doi.org/10.1109/ACCESS.2023.3337133.

[16] Z. Ishrat, S. Vats, K. B. Ali, O. Ahmad Shah and T. Ahmed, "A Comprehensive Study on Conventional HPPT Techniques for Solar PV System," *2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN)*, pp. 315-321, 2023, https://doi.org/10.1109/CICTN57981.2023.10140264.

[17] H. Schiffer, T. Kober, and E. Panos, "World energy council's global energy scenarios to 2060," *Zeitschrift für Energiewirtschaft*, vol. 2, no. 42, pp. 91–102, 2018, https://doi.org/10.1007/s12398-018-0225-3.

[18] M. Edwin, M. S. Nair, and S. Joseph Sekhar, "A comprehensive review for power production and economic feasibility on hybrid energy systems for remote communities," *International Journal of Ambient Energy*, vol. 43, no. 1, pp. 1456–1468, 2022, https://doi.org/10.1080/01430750.2020.1712252.

[19] E. Widya Suseno and A. Ma'arif, "Tuning of PID Controller Parameters with Genetic Algorithm Method on DC Motor," *International Journal of Robotics and Control Systems*, vol. 1, no. 1, pp. 41–53, 2021, https://doi.org/10.31763/ijrcs.v1i1.249.

[20] A. Kumar, P. Chaudhary and O. A. Shah, "Intelligent Controller Based on Artificial Neural Network and INC Based MPPT for Grid Integrated Solar PV System," *International Journal of Robotics & Control System*, vol. 3, no. 4, pp. 839–852, 2023, https://doi.org/10.31763/ijrcs.v3i4.1150.

[21] L. Yao, B. Yang, H. Cui, J. Zhuang, J. Ye, and J. Xue, "Challenges and progresses of energy storage technology and its application in power systems," *Journal of Modern Power Systems and Clean Energy*, vol. 4, pp. 519–528, 2016, https://doi.org/10.1007/s40565-016-0248-x.

[22] D. V. Doan, K. Nguyen, and Q. V. Thai, "A Novel Fuzzy Logic Based Load Frequency Control for Multi-Area Interconnected Power Systems," *Engineering, Technology & Applied Science Research*, vol. 11, no. 4, pp. 7522–7529, 2021, https://doi.org/10.48084/etasr.4320.

[23] R. Patra, P. Chaudhary, and O. A. Shah, "Design and Development of ANFIS based Controller for Three Phase Grid Connected System," *International Journal of Robotics and Control Systems*, vol. 4, no. 1, pp. 125-138, 2024, https://doi.org/10.31763/ijrcs.v4i1.1242.

[24] C. M. Falkner and B. S. Heck, "A comparison of nonlinear controllers on a single generator-infinite bus power system," *Proceedings of 1995 American Control Conference - ACC'95*, vol. 3, pp. 1550-1555, 1995, https://doi.org/10.1109/ACC.1995.529768.

[25] J. T. D. C. Neto, A. O. Salazar, F. M. U. D. Araújo and A. L. d. O. Cavalcanti, "Hybrid fuzzy and robust controller applied to a DC-DC boost converter," *IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society*, pp. 5108-5114, 2014, https://doi.org/10.1109/IECON.2014.7049277.

[26] S. P. Giri and S. K. Sinha, "Four-area load frequency control of an niterconnected power system using neuro-fuzzy hybrid intelligent proportional and integral control approach," *Journal of Intelligent Systems*, vol. 22, no. 2, pp. 131-153, 2013, https://doi.org/10.1515/jisys-2012-0025.

[27] D. Mishra, P. C. Sahu, R. C. Prusty, and S. Panda, "Power Generation Monitoring of a hybrid Power System with I-GWO designed trapezoidal type-II fuzzy Controller," *International Journal of Modelling and Simulation*, vol. 42, no. 5, pp. 797-813, 2022, https://doi.org/10.1080/02286203.2021.1983744.

[28] O. A. Shah, I. Ahmed Khan, G. Nijhawan and I. Garg, "Low Transistor Count Storage Elements and their Performance Comparison," *2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN)*, pp. 801-805, 2018, https://doi.org/10.1109/ICACCCN.2018.8748364.

[29] Rakesh, O. A. Shah and S. Vats, "Floorplanning and Comparative Analysis of 16-bit Synchronous Up/Down Counter in Different CMOS Technology," *2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, pp. 867-871, 2023, https://doi.org/10.1109/CISES58720.2023.10183608.

[30] P. Teotia, and O. A. Shah, "Power and Area Efficient Sense Amplifier Based Flip Flop with Wide Voltage and Temperature Upholding for Portable IoT Applications," *Informacije MIDEM-Journal of Microelectronics, Electronic Components and Material*, vol. 53, no. 1, pp. 39-48, 2023, https://doi.org/10.33180/InfMIDEM2023.104.

[31] E. Espina, J. Llanos, C. Burgos-Mellado, R. Cárdenas-Dobson, M. Martínez-Gómez and D. Sáez, "Distributed Control Strategies for Microgrids: An Overview," *IEEE Access*, vol. 8, pp. 193412-193448, 2020, https://doi.org/10.1109/ACCESS.2020.3032378.

[32] K. Mahmud, G. E. Town, S. Morsalin, and M. J. Hossain, "Integration of electric vehicles and management in the internet of energy," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 4179–4203, 2018, https://doi.org/10.1016/j.rser.2017.11.004.

[33] M. Kumar, S. C. Srivastava and S. N. Singh, "Control Strategies of a DC Microgrid for Grid Connected and Islanded Operations," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1588-1601, 2015, https://doi.org/10.1109/TSG.2015.2394490.

[34] J. Zhao, F. Wen, Z. Y. Dong, Y. Xue and K. P. Wong, "Optimal Dispatch of Electric Vehicles and Wind Power Using Enhanced Particle Swarm Optimization," *IEEE Transactions on Industrial Informatics*, vol. 8, no. 4, pp. 889-899, 2012, https://doi.org/10.1109/TII.2012.2205398.

[35] N. Kumar, P. Besuner, S. Lefton, D. Agan, and D. Hilleman, "Power plant cycling costs," *National Renewable Energy Laboratory*, 2012, https://doi.org/10.2172/1046269.

[36] E. F. Camacho, C. Bordons, "Constrained model predictive control," *Springer*, 2007, https://doi.org/10.1007/978-0-85729-398-5.

[37] D. Acharya, D. K. Das and A. Srivastava, "A New Quantum-Class Topper Optimization Based Fractional Order Proportional Integral Power System Stabilizer Design to Damp Out Low Frequency Oscillations in Power Systems," *2020 IEEE Calcutta Conference (CALCON)*, pp. 45-49, 2020, https://doi.org/10.1109/CALCON49167.2020.9106504.

[38] L. Y. Pao and K. E. Johnson, "Control of Wind Turbines," *IEEE Control Systems Magazine*, vol. 31, no. 2, pp. 44-62, 2011, https://doi.org/10.1109/MCS.2010.939962.

[39] D. Connolly, H. Lund, B. V. Mathiesen, and M. Leahy, "A review of computer tools for analysing the integration of renewable energy into various energy systems," *Applied Energy*, vol. 87, no. 4, pp. 1059–1082, 2010, https://doi.org/10.1016/j.apenergy.2009.09.026.

[40] C. Chang, H. Lee, and C. Liu, "A review of artificial intelligence algorithms used for smart machine tools," *Inventions*, vol. 3, no. 3, p. 41, 2018, https://doi.org/10.3390/inventions3030041.

[41] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proceedings of ICNN'95 - International Conference on Neural Networks*, vol. 4, pp. 1942-1948, 1995, https://doi.org/10.1109/ICNN.1995.488968.

[42] J. Maciejowski, "Model Predictive Control: A New Paradigm for Automatic Control 2002 Presidential Address," *Measurement and Control*, vol. 36, no. 2, pp. 44-47, 2003, https://doi.org/10.1177/002029400303600201.

[43] J. R. Vázquez-Canteli and Z. Nagy, "Reinforcement learning for demand response: A review of algorithms and modeling techniques," *Applied Energy*, vol. 235, pp. 1072–1089, 2019, https://doi.org/10.1016/j.apenergy.2018.11.002.

[44] Y. Zhang, T. Huang, and E. F. Bompard, "Big data analytics in smart grids: a review," *Energy informatics*, vol. 1, no. 1, pp. 1–24, 2018, https://doi.org/10.1186/s42162-018-0007-5.

[45] I. Pan and S. Das, "Fractional order fuzzy control of hybrid power system with renewable generation using chaotic PSO," *ISA Transactions*, vol. 62, pp. 19–29, 2016, https://doi.org/10.1016/j.isatra.2015.03.003.