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OPTIMIZATION-BASED PID CONTROLLER DESIGN FOR DC-DC BOOST CONVERTERS IN HYBRID RENEWABLE ENERGY SYSTEMS

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Abstract: The increasing awareness of the need for renewable and clean energy sources has become a significant agenda item, especially as global energy demand continues to rise. Studies on renewable energy systems, which provide healthier conditions for current and future generations while meeting energy demand, are becoming increasingly widespread both locally and globally. Hybrid energy systems, formed by combining multiple energy sources, have recently introduced innovative solutions for the integration and management of various energy types. However, the voltage levels obtained from these systems are often low, making it necessary to boost the voltage for storage and household use.To address this, DC-DC boost converters are used to increase the voltage generated by solar panels, wind turbines, or hybrid energy systems. PID (Proportional-Integral-Derivative) controllers are typically required for converter control. However, conventional constant-gain PID controllers and classical PID tuning methods are often ineffective, as they rely on mathematical formulations or experimental system response analyses. To overcome this challenge, meta-heuristic optimization algorithms provide a viable alternative, offering a more stable and faster system response. In this study, a hybrid energy system consisting of a Proton Exchange Membrane (PEM) fuel cell, PV panel, and wind turbine was modeled in the Matlab/Simulink environment. A DC-DC boost converter was designed to elevate the system's output voltage to the desired reference level, enhancing system stability. Three different optimization methods—Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and Artificial Bee Colony (ABC) algorithms—were employed to adjust the parameters of the PID controller used for converter control. The PID coefficients obtained through these optimization algorithms are presented and compared. The performance of the tuned PID controller was evaluated through system response analysis under variable load conditions and by calculating the Root Mean Square Error (RMSE) between the output voltage and the specified reference value. Additionally, the controller performance was analyzed based on overshoot, settling time, and rise time values as shown in the resulting graphs.

Keywords: Renewable energy, Proton exchange membrane, DC-DC boost convertor, Partial swarm optimization, Grey wolf optimization, Artificial bee colony

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1. Introduction

In the contemporary world, the diversity and accessibility of energy resources for electricity generation hold significant importance on a global scale. This issue is closely associated with the increasing energy demand driven by population growth, industrialization, and technological advancements (Long and Liu, 2024). In particular, environmental concerns and the increasing awareness of climate change have intensified interest in renewable energy sources. Renewable sources such as wind, solar, hydroelectric, geothermal, and biomass hold significant potential for clean and sustainable electricity generation (Paraschiv, 2023). Moreover, the use of renewable energy sources contributes to energy supply security by diversifying energy resources. In this context, the effective and efficient utilization of various energy sources for electricity generation is crucial in meeting global energy needs (Hassan et al., 2024).

Hybrid energy systems combine different energy sources to enable more efficient and sustainable energy production. These systems typically integrate fossil-based fuels, referred to as primary energy sources, with renewable energy sources such as wind, solar, and hydrogen. Additionally, some hybrid systems are formed by the combination of two or more renewable energy sources (Krishna and Kumar, 2015). The main challenge with renewable energy sources is their dependence on environmental conditions, such as wind speed and solar irradiance, which limits their ability to provide consistent and high-power output (Paliwal et al., 2014). Therefore, using renewable sources like wind, solar, hydro, biogas, and fuel cells within a hybrid system can help mitigate environmental dependency, ensure energy continuity, and increase power output. For example, a hybrid energy system that combines wind turbines and solar panels can continue generating electricity using wind energy even when sunlight is unavailable. The goal of such systems is to enhance energy efficiency, reduce power outages, and promote energy sustainability.

Significant research is currently being conducted on hybrid systems and their applications. Various configurations, systems, and their effects are well-documented in the literature (Olatomiwa et al., 2016). In particular, a general review of the literature on rural electrification shows that renewable energy sources are among the most effective solutions for providing electricity to rural areas that are located far from the electrical grid (Ma et al., 2013; Mekhilef et al., 2012; Harish and Kumar, 2014).

2. Materials and Methods

In this study, a hybrid energy system model has been developed by combining three separate renewable energy systems, namely PV panel, wind turbine, and PEM fuel cell. The objective of this study is to obtain continuous and uninterrupted voltage from each of these three energy systems, each influenced by specific conditions and environmental factors. Additionally, when operating in pairs or trios, the aim is to achieve a high voltage level. The study is prepared in a simulation environment using Matlab/Simulink. The block diagram of the developed model is given in Figure 1.

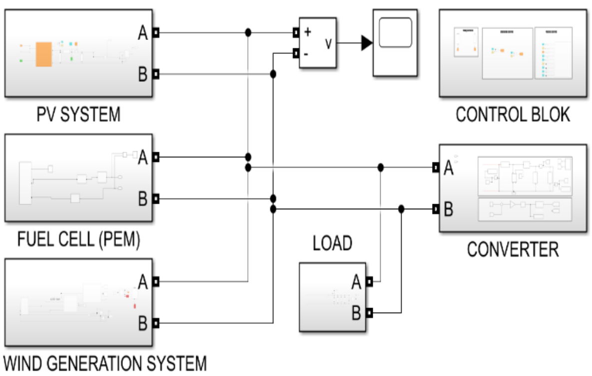

Figure 1. Block diagram of PV panel, fuel cell (PEM) and wind turbine-based hybrid power generation system.

The total voltage obtained from the hybrid system is transferred as an input value to a DC-DC boost converter. In the block diagram, the control unit is responsible for adjusting the converter to raise the incoming voltage to the desired level. Upon closer examination of these blocks and their functions:

2.1. DC-DC Boost Converter

A boost converter is a type of DC-DC power converter that increases the input voltage to a higher output voltage. It operates on the principle of storing energy in an inductor and then releasing that stored energy to the output at a higher voltage level (Liu and Wu, 2023). Boost converters are widely used in various applications where a higher voltage is required from a lower voltage source, such as in battery-powered devices, renewable energy systems, and electric vehicles (Mirzaei et al., 2012).

The primary function of the boost converter is to regulate the charge and discharge cycles between the inductor and capacitor through a control signal that adjusts the voltage level (Paul et al., 2024). In this process, the control signal manages the switching operations of the converter, balancing the storage and release of energy. The circuit of the boost converter used in this study, modelled in the Matlab/Simulink environment, is shown in Figure 2.

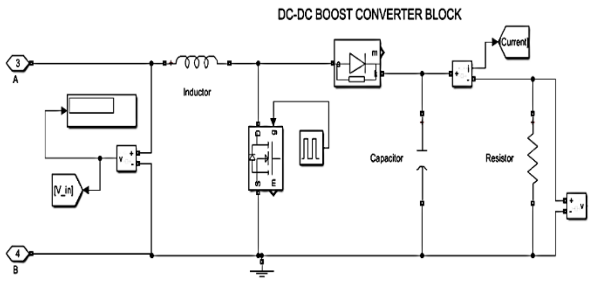

Figure 2. Matlab model of the DC-DC boost converter.

A DC-DC boost converter fundamentally consists of a switching element, a capacitor, an inductor, and a load. The values of these components are calculated based on the system's input voltage and the desired output voltage. Based on this ratio, the duty cycle of the switching element is determined. Since the converter's parameters affect its performance, efficiency, and reliability, they must be selected carefully (Solaiman et al., 2015; Sakly et al., 2017). The key parameters of the boost converter circuit used in this study are provided in Table 1.

Table 1. Parameters of DC-DC boost converter

Parameter	Rated Value
Input Voltage (V_in)	~ 250 V
Output (Reference) Voltage (V_out)	400 V
Inductor (L)	20.50 μH
Capacitor (C)	40 μF
Load (R)	40 Ω
Duty Cycle (D)	0.6

2.2. PID Controller

A PID controller (Proportional-Integral-Derivative controller) is a widely used feedback mechanism in industrial control systems. It continuously calculates the error as the difference between the desired setpoint and the measured process variable, then applies a correction based on proportional, integral, and derivative terms (Ozdemir and Erdem, 2018). Figure 3 presents the PID control algorithm.

The PID control algorithm consists of three fundamental components. The Proportional (P) term generates a control signal that is proportional to the instantaneous error value. This term adjusts the control signal based on the magnitude of the current error, thereby correcting it (Daraz et al., 2023). The Integral (I) term addresses any persistent errors in the system by accumulating the error signal over time. This enhances the long-term stability of the system and helps to balance slow changes.

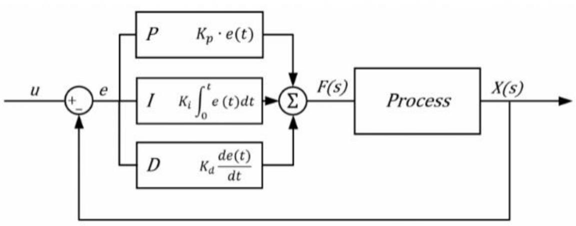

Figure 3. PID control algoritm.

The Derivative (D) term evaluates the rate of change of the error signal over time, thereby controlling the system's response speed. This allows for a quicker response to sudden changes and reduces overshooting, thereby enhancing system stability (Mitra and Swain, 2014). Figure 4 shows the PID control block as prepared in Matlab/Simulink.

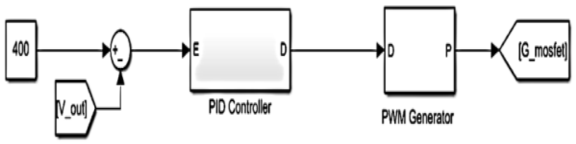

Figure 4. PID control block in Matlab

2.3. Optimization Algorithms for PID Control

Various methods exist for adjusting the parameters of PID controllers, ranging from classical approaches that involve mathematical modeling and system response analysis (Harish and Kumar, 2014) to techniques based on metaheuristic optimization algorithms for determining optimal parameter values (Pareek et al., 2014).

In this study, the PID controller for a DC-DC boost converter connected to a hybrid energy system was tuned using metaheuristic methods. The selected algorithms were Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Artificial Bee Colony (ABC).

The performance of the tuned PID controller was evaluated through system response analysis under variable load conditions, as well as by calculating the Root Mean Square Error (RMSE) between the output voltage and the specified reference value. Additionally, the controller's performance was assessed with a focus on overshoot, settling time, and rise time values, as depicted in the obtained graphs.

2.3.1. Particle swarm optimization (PSO) algoritm

The Particle Swarm Optimization (PSO) algorithm is an optimization technique inspired by the behavior of swarms of fish and insects in nature (Kennedy and Eberhart, 1995). In PSO, the problem is divided into segments, each represented by candidate solutions, referred to as 'particles' within the algorithm (Xiao et al., 2024). These particles navigate the search space, proposing solutions to identify the optimal one.

The PSO algorithm consists of the following stages: Initialization, Evaluation, Updating Particle Velocity and Position, Updating Personal and Global Best Positions, and Termination. These stages are illustrated in Fig. 5 (Yousef et al., 2020). The algorithm is widely preferred in fields such as engineering, economics, and data science due to its simplicity, ability to handle complex problems, and efficiency (Le et al., 2019).

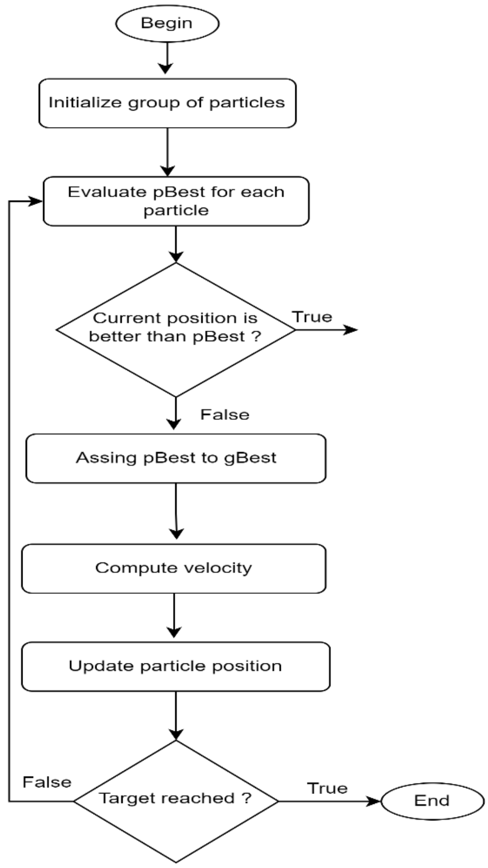

Figure 5. Flow chart of the PSO algorithm (Le et al., 2019).

2.3.2. Grey wolf optimizer (GWO) algoritm

The Grey Wolf Optimizer (GWO) algorithm is inspired by the hunting behaviours of grey wolves (canis lupus), one of nature's most impressive predators (Mirjalili et al., 2014). Wolves, which move in packs, exhibit a strong social hierarchy. This hierarchy includes the alpha (α) wolf, which assumes the leadership role, followed by beta (β) wolves, then delta (δ) wolves, and finally omega (ω) wolves. The algorithm is based on the hunting process of wolf packs, which follows a three-stage strategy: encircling, hunting, and attacking prey to find their target (Prasad et al., 2024). These unique hunting strategies enable the GWO algorithm to achieve successful results in optimization problems. Figure 6 illustrates the GWO algorithm.

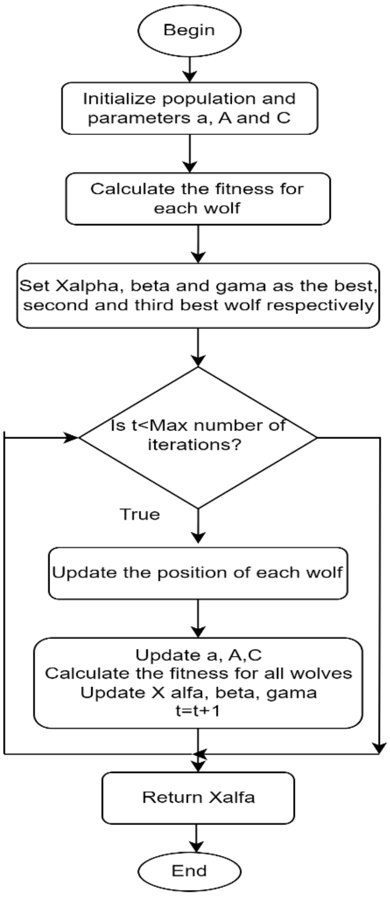

Figure 6. Flow chart of the GWO algorithm (Amirsadri et al., 2018).

Due to its simplicity and ease of implementation, requiring few parameter adjustments, high efficiency, and parallel applicability, Grey Wolf Optimizer (GWO) is recognized as a powerful and innovative tool for solving optimization problems.

2.3.3. Artifical bee colony (ABC) algoritm

The Artificial Bee Colony (ABC) Optimization algorithm is a nature-inspired optimization method based on the foraging strategy of bees (Karaboga, 2005). ABC mimics the foraging behaviour of honeybees as they search for food sources and share information within the colony. In this algorithm, each bee represents a candidate solution and works to optimize a fitness function that evaluates the quality of the solution (Sönmez et al., 2017). The bee colony is composed of employed bees, onlooker bees, and scout bees.

In ABC, the behavior of bees is modeled based on certain assumptions. One key assumption is that only one employed bee is responsible for extracting nectar from each food source. Consequently, the number of food sources in the algorithm is equal to the number of employed bees. Another assumption is that the number of employed bees matches the number of scout bees. However, in practice, if a worker bee returns to a depleted food source, it may transform into a scout bee. The fitness value of a food source is directly proportional to the quality of the food it provides.

The ABC algorithm is highly adaptable to various problem domains and optimization challenges, making it a versatile tool for a wide range of industrial and academic applications. Figure 7 illustrates the ABC algorithm.

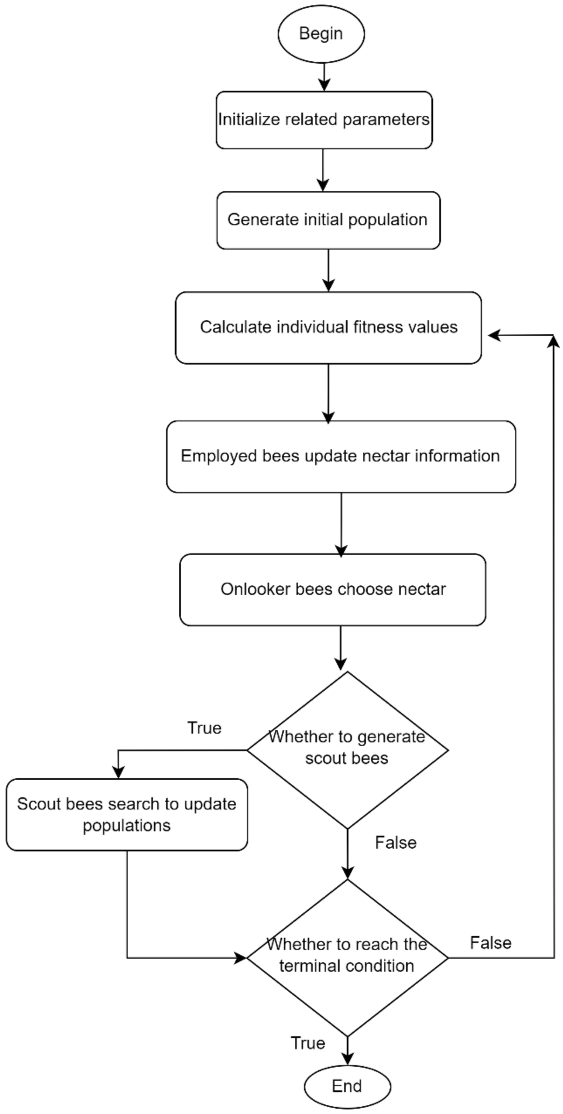

Figure 7. Flow chart of the ABC algorithm (Wang et al., 2019).

3. Simulation and Results

This study focuses on the optimization of PID parameters using PSO, GWO, and ABC algorithms. The selection of appropriate initial values is critically important for effectively tuning the PID parameters and managing the optimization process. These values can significantly influence the success and outcomes of the optimization process. The initial values for the algorithms, each executed over 30 iterations, are provided in Table 2.

After conducting system simulations and optimization using the PSO, GWO, and ABC algorithms, the PID controller gain values were obtained for each scenario. The gain parameters of the PID controller and the RMSE values from the optimization are presented in Table 3.

Table 2. PSO, GWO and ABC Algorithms initial values

Algorithm	Parameters İnitial Values	
	Description	Value
PSO	Number of particles	20
	Number of iterations	30
	Self-adjustment weight	0.9
	Social-adjustment weight	1.2
GWO	Number of Wolves	10
	Number of Iterations	30
ABC	Number of Bees	15
	Number of Iterations	30
	Dimension of problem	3

These results provide a comparative analysis of the performance of the different algorithms and how closely each system achieved the targeted performance. In other words, they demonstrate each algorithm's ability to optimize the PID parameters and its impact on system performance. Table 3 summarizes the optimized parameters and the obtained RMSE values.

Table 3. Optimized parameters and obtained RMSE values

Parameter	Algorithms		
	PSO	GWO	ABC
Kp	5.2307	3.1072	2.2106
Ki	5.5473	6.0041	8.8505
Kd	4.6979	7.8168	1.2033
RMSE	1.8261	2.7458	2.4495

When comparing the results based on RMSE values, it is evident that the PSO algorithm delivers the best performance. PSO achieved the lowest error with an RMSE value of 1.8261, making it the most successful algorithm by a significant margin. The ABC algorithm, with an RMSE value of 2.4495, ranked second, demonstrating approximately 15% lower performance compared to PSO. The GWO algorithm exhibited the lowest performance, with an RMSE value of 2.7458, showing approximately 20% lower performance than PSO. These findings highlight the superior capability of the PSO algorithm in optimizing PID parameters and its significantly greater impact on system performance compared to the other algorithms. The exceptional success of PSO strongly supports its preference in optimization processes.

The output voltages obtained when the PID parameters, determined through the optimization process, were applied to the system are shown in Fig. 8. As illustrated in the figure, the output voltage achieved using the PSO algorithm demonstrates significant success compared to the results from the other algorithms. This success is reflected not only in its low error (RMSE) values but also in its superior dynamic performance metrics, such as overshoot, settling time, and rise time. Specifically, the output signal obtained with the PSO algorithm exhibited minimal overshoot and the fastest settling time to the desired values. These findings clearly demonstrate the effectiveness of the PSO algorithm in optimizing PID parameters and its positive impact on system performance.

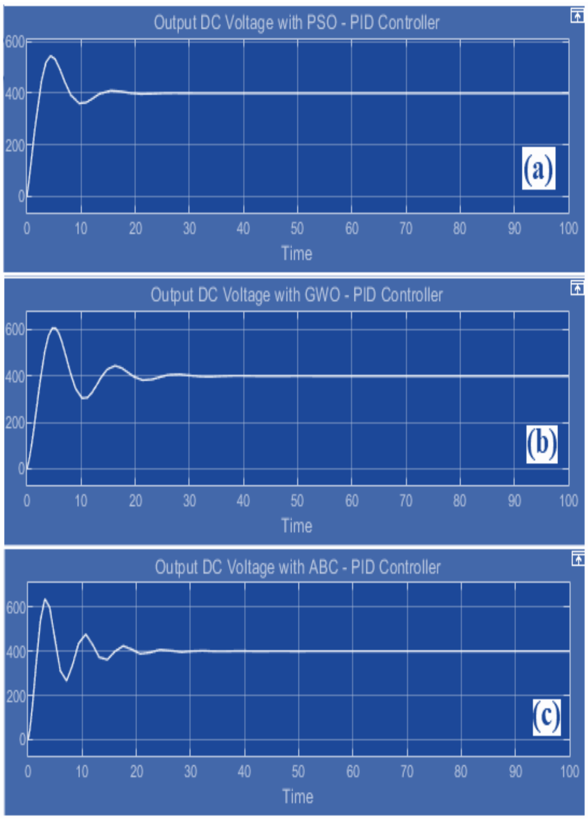

Figure. 8. System response comparison for the PID controller tuned by (a) PSO, (b) GWO and (c) ABC algorithms under output voltage changes.

4. Discussion

With the increasing demand for energy today, the utilization of renewable energy sources is becoming more crucial. In this context, a study was conducted to model a hybrid energy system integrating three different renewable energy sources—PV panels, wind turbines, and PEM fuel cells—using the Matlab/Simulink simulation environment. The system is managed with an optimized control strategy that accounts for the characteristics of each energy source. This control strategy employs a PID controller, which was tuned using various optimization techniques. Specifically, the coordinated operation of these three energy sources depends on solar irradiance for PV panels, wind speed for wind turbines, and the fuel source for fuel cells.

The parameters of the DC-DC boost converter modelled in the Matlab/Simulink environment are critical components that directly influence the system's performance. The PID controller is used to adjust the output voltage of the DC-DC boost converter to approach the desired reference value. In this study, metaheuristic algorithms such as PSO, GWO, and ABC were employed to optimize the PID controller. The simulations and optimization studies revealed that the PSO algorithm demonstrated the best performance, achieving the lowest RMSE value of 1.8261 and effectively reaching the desired output voltage in the system.

This study demonstrates the effectiveness of metaheuristic optimization methods in optimizing renewable energy systems and enhancing energy efficiency. It makes a significant contribution to the literature by providing a comparative analysis of the impacts of different optimization algorithms on PID controller settings. The results represent a crucial step towards the integration of renewable energy systems, as hybrid systems combining various energy sources offer a potentially effective solution for balancing fluctuations in energy production and ensuring a continuous energy supply.

The study contributes to the development of sustainable and efficient energy production methods to meet future energy demands. It also provides valuable guidance for researchers and industry professionals in the design and optimization of hybrid systems.

In the next stage of the study, the optimization methods will be expanded, and the performances of different hybrid optimization techniques will be evaluated. The study will be further developed by detailing the training and execution times of the algorithms, as well as the validation approaches, to present an original and innovative contribution to the literature.

Author Contributions

The percentages of the authors' contributions are presented below. All authors reviewed and approved the final version of the manuscript.

	M.G.	F.D.
C	50	50
D	50	50
S	50	50
DCP	50	50
DAI	50	50
L	50	50
W	50	50
CR	50	50
SR	50	50
PM	50	50
FA	50	50

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

References

Amirsadri S, Seyed Jalaleddin M, Hossein E-K. 2018. A Levy flight-based grey wolf optimizer combined with back-propagation algorithm for neural network training. Neural Comput Appl, 30(12): 3707–3720. https://doi.org/10.1007/s00521-017-2952-5

Daraz A, Basit A, Zhang G. 2023. Performance analysis of pid controller and fuzzy logic controller for dc-dc boost converter. Plos One, 18(10): e0281122. https://doi.org/10.1371/journal.pone.0281122

Harish VSKV, Kumar A. 2014. Demand side management in ındia: action plan, policies and regulations. Renew Sust Ener Rev, 33: 613-624. https://doi.org/10.1016/j.rser.2014.02.021

Hassan Q, Victor P, Al-Musawi TJ, Ali BM, Algburi S, Alzoubi HM, Khudhair AAJ, Sameen AZ, Salman HM, Jaszczur M. 2024. The renewable energy role in the global energy transformations. Renew Ener Focus, 48: 100545. https://doi.org/10.1016/j.ref.2024.100545

Hossam F, Aljarah I, Al-Betar MA, Mirjalili S. 2018. Grey wolf optimizer: a review of recent variants and applications. Neural Comput Appl, 30(2): 413-435. https://doi.org/10.1007/s00521-017-3272-5

Karaboga D. 2005. An idea based on honey bee swarm for numerical optimization. Erciyes University Engineering Faculty, Computer Engineering Department Technical Report, Kayseri, Türkiye, pp: 1-10.

Kennedy J, Eberhart R. 1995. Particle swarm optimization. In Proceedings of ICNN'95-International Conference on Neural Networks, November 27, Perth, Australia, 4: 1942-1948. https://doi.org/10.1109/ICNN.1995.488968

Krishna KS, Kumar KS. 2015. A review on hybrid renewable energy systems. Renew Sust Ener Rev, 52: 907-916. https://doi.org/10.1016/j.rser.2015.07.187

Le LM, Ly HB, Pham BT, Le VM, Pham TA, Nguyen DH, Tran XT, Le TT. 2019. Hybrid artificial intelligence approaches for predicting buckling damage of steel columns under axial compression. Materials, 12(10): 1670. https://doi.org/10.3390/ma12101670

Liu X, Wu X. 2023. A two-stage bidirectional dc-dc converter system and its control strategy. Energy, 266: 126462. https://doi.org/10.1016/j.energy.2022.126462.

Long Y, Liu X. 2024. Optimal green investment strategy for grid-connected microgrid considering the impact of renewable energy source endowment and incentive policy. Energy, 295: 131073. https://doi.org/10.1016/j.energy.2024.131073

Ma T, Yang H, Lu L. 2013. Performance evaluation of a stand-alone photovoltaic system on an isolated island in Hong Kong. App Ener 112: 663-672. https://doi.org/10.1016/j.apenergy.2012.12.004

Mekhilef S, Saidur R, Kamalisarvestani M. 2012. Effect of dust, humidity and air velocity on efficiency of photovoltaic cells. Renew Sust Ener Rev, 16(5): 2920-2925. https://doi.org/10.1016/j.rser.2012.02.012

Mirjalili S, Mirjalili SM, Lewis A. 2014. Grey wolf optimizer. Adv Eng Software, 69: 46-61. https://doi.org/10.1016/j.advengsoft.2013.12.007

Mirzaei A, Awang J, Zainal S. 2012. Design and implementation of high efficiency non-isolated bidirectional zero voltage transition pulse width modulated dc-dc converters, Energy, 47(1): 358-369. https://doi.org/10.1016/j.energy.2012.09.035

Mitra L, Swain N. 2014. Closed loop control of solar powered boost converter with pid controller. IEEE International Conference On Power Electronics, Drives And Energy Systems, Decenber 16-19, Mumbai, India, pp: 1-5. https://doi.org/10.1109/pedes.2014.7041973

Olatomiwa l, Mekhilef S, Ismail MS, Moghavvemi M. 2016. Energy management strategies in hybrid renewable energy systems: A review. Renew Sust Ener Rev, 62: 821-835. https://doi.org/ 10.1016/j.rser.2016.05.040

Ozdemir A, Erdem Z. 2018. Double-loop pi controller design of the dc-dc boost converter with a proposed approach for calculation of the controller parameters. J Syst Control Eng, 232(2): 137-148.

Paliwal P, Patidar NP, Nema RK. 2014. Planning of grid integrated distributed generators: a review of technology, objectives and techniques. Renew Sust Ener Rev, 40: 557–570. https://doi.org/10.1016/j.rser.2014.07.200

Paraschiv S. 2023. Analysis of the variability of low-carbon energy sources, nuclear technology and renewable energy sources, in meeting electricity demand. Ener Rep, 9(s11): 276–283. https://doi.org/10.1016/j.egyr.2023.09.008

Pareek S, Kishnani M, Gupta R. 2014. Optimal tuning of pid controller using meta heuristic algorithms. International Conference on Advances in Engineering and Technology Research, August 1-2, Kanpur, India, pp: 1–5. https://doi.org/10.1109/ıcaetr.2014.7012816

Paul AK, Ram BS, Kulkarni SV. 2024. Review of coupled inductors in power electronics: from concept to practice. E-Prime Adv Electr Eng Electron Ener, 8: 100501. https://doi.org/10.1016/j.prime.2024.100501

Prasad T, Raj S, Kundu D. 2024. Artificial neural network framework for the selection of deep eutectic solvents promoted enhanced oil recovery by interfacial tension reduction mechanism. Energy, 307: 132602. https://doi.org/10.1016/j.energy.2024.132602

Sakly J, Abdelghani ABB, Slama-Belkhodja I, Sammoud H. 2017. Reconfigurable dc/dc converter for efficiency and reliability optimization. IEEE J Emerg Selected Topics Power Electron, 5(3): 1216–1224. https://doi.org/10.1109/jestpe.2017.2676027

Solaiman HM, Hasan MM, Mohammad A, Kawsar SR, Hassan MA. 2015. Performance analysis of dc to dc boost converter using different control methods. IEEE International Conference on Electrical, Computer and Communication Technologies (ICECC), March 5-7, Tamilnadu, India, pp: 1–5.

Sonmez M, Akgüngör MA, Bektaş S. 2017. Estimating transportation energy demand in Turkey using the artificial bee colony algorithm. Energy, 122(2017): 301–310. https://doi.org/10.1016/j.energy.2017.01.074

Wang S, Liu H, Gao K, Zhang J. 2019. A multi-species artificial bee colony algorithm and its application for crowd simulation. IEEE Access, 7: 2549–2558.

Xiao X, Zhang X, Song M, Liu X, Huang G. 2024. Npp accident prevention: integrated neural network for coupled multivariate time series prediction based on pso and its application under uncertainty analysis for npp data. Energy, 305: 132374. https://doi.org/10.1016/j.energy.2024.132374

Yousef AM, Ebeed M, Abo-Elyousr FK, Elnozohy A, Mohamed M, Abdelwahab SAM. 2020. Optimization of pid controller for hybrid renewable energy system using adaptive sine cosine algorithm. Int J Renew Ener Res, 10(2): 669–677. https://doi.org/10.20508/ijrer.v10i2.10685.g7938