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Improving the efficiency of photovoltaic cell systems using artificial intelligence algorithms for maximum power point tracking (MPPT)

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Abstract

This study examines the role of artificial intelligence in improving the efficiency of photovoltaic (PV) systems through maximum power point tracking (MPPT) under dynamic operating conditions. A simulation-based model was developed in MATLAB/Simulink to evaluate four AI-based MPPT methods, namely Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Reinforcement Learning (RL), in comparison with conventional methods such as Perturb and Observe (P&O) and Incremental Conductance (INC). The results showed that AI-based techniques achieved better tracking efficiency, faster response time, lower oscillation, and reduced power loss than conventional controllers. Among the tested methods, Reinforcement Learning provided the best overall performance, while ANFIS showed highly competitive results with strong stability and fast convergence. These findings confirm that intelligent MPPT strategies can significantly enhance PV system efficiency and reliability.

1. Introduction

The global shift toward clean and sustainable energy has accelerated the adoption of photovoltaic (PV) systems as one of the most promising renewable energy technologies. However, the electrical performance of PV modules is highly sensitive to nonlinear operating conditions and environmental factors such as irradiance variation, temperature change, and partial shading. These factors continuously change the operating point of the PV array and reduce the overall energy conversion efficiency if not properly managed and decreasing the total energy conversion efficiency unless managed [1], [2]. In order to overcome this difficulty, Maximum Power Point Tracking (MPPT) is now one of the core elements of control in PV systems. The aim of the MPPT algorithms is to make the PV array to be driven at or close to maximum power point amidst the disturbances in the environment. Traditional methods like Perturb and Observe (P&O), Incremental Conductance (INC) are still commonly used due to their simplicity and low implementation cost, but are susceptible to slow convergence, oscillation around the optimal point, and lack of accuracy in fast changing atmospheric conditions or where there exists partial shading [3]. This has directed research attention in the past few years towards intelligent and hybrid MPPT methods that may give superior adaptability and predictive capability. As it has been demonstrated in the literature review, Artificial Neural Networks (ANN), Fuzzy Logic Controllers (FLC), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), reinforcement learning approaches, and hybrid intelligent approaches are becoming more popular in enhancing tracking accuracy, eliminating steady-state oscillations, and enhancing dynamic response to complex operating conditions [4] . Although this has been achieved, it is suggested by the literature that significant gaps in research remain concerning unified comparative evaluation, algorithm generalizability and the trade-off between tracking and implementation complexity. A few recent reviews have highlighted that it is true that, where high levels of efficiency are sought, there are advanced MPPT methods that can work, but that many of them are condition-specific, demand computationally, or have not been sufficiently tested in different real-life conditions. Thus, the paper under examination explores the application of the artificial intelligence algorithms made to the optimization of the PV system in terms of increased MPPT and, therefore, dynamic response, stability, and energy output efficiency [5].

2. Research Significance

- Improving energy harvesting efficiency in PV systems
- Reducing power losses under environmental fluctuations
- Providing adaptive and intelligent tracking methods
- Supporting smart grid integration
- Contributing to sustainable energy solutions

3. Literature Review

The recent experimental and simulation-based research proves the increasing efficiency of the AI-based MPPT in photovoltaic systems. A study by Gul et al. [6] suggested ANN-based MPPT controller of an altered flyback converter in PV systems of active buildings and found out that the controller had improved transient characteristics and enhanced practical functioning relative to traditional options. Wadehra et al. [7] took a step in a reinforcement-learning direction by introducing a deep recurrent reinforcement learning architecture in the context of enhanced MPPT in PV systems; recurrent learning structures, they found, can be applied to track decisions in adverse operating conditions. Additional advances have been noticed in neuro fuzzy and optimization aided controllers. A study by Morey et al. [8] experimentally tested an ANFIS-PSO-based MPPT controller with an enriched voltage-gain DC-DC converter when used with grid-tied PV and discovered that this proposed approach enhanced variable solar irradiation and dynamic load performance. On the same note, Aldulaimi and Çevik [9] have introduced an AI-enhanced ANFIS-PSO MPPT controller of grid-connected PV systems and demonstrated that the controller is capable of providing very high tracking efficiency with respect to grid-connected PV operating under both stable and dynamic irradiance conditions and the controller converges and in addition, the controller has more robustness than the conventional MPPT strategies. ANN-MPPT has also gone further to sensor reduction and adaptive environmental estimation. In microgrid PV system, Malkawi et al. [10] formulated a dual-ANN system that could estimate the solar irradiance and temperature and used these estimates to enhance the performance of the MPPT. Their findings were highly efficient and quick settling, particularly in the event of a sudden climatic change. Another recent work, Hoang et al. [11], suggested an AI-based MPPT prediction framework based on estimates of battery-side information on both PV voltage and current instead of actual pv sensing, which minimizes hardware complexity and sensor reliance and maintains proper MPPT behavior. The relevance of comparative analysis also upholds the effectiveness of AI-enhanced solutions as compared to the traditional controllers. Eyimaya [12] has compared ANN-based, reinforcement learning-based and traditional methods of MPPT in a photovoltaic energy system and determined that the reinforcement learning-based provided the best energy output and gave the best overall performance. Besides, Cruz et al. [13] suggested a hybrid ANN-P and O approach to partially shaded PV systems and claimed a significant improvement in tracking performance, stability, and convergence rate compared to isolated P and O. This result supports the claim that hybrid and learning-based controllers could provide better performance in the case when environmental conditions became very nonlinear and time-varying. On the whole, the visited works demonstrate the obvious transformation of traditional deterministic MPPT to the adaptive, predictive and hybrid intelligent controllers. Nevertheless, there is still no single framework in the literature that compares multiple AI-based MPPT strategies and makes them under the same simulation environment, with the same PV model and the same environmental conditions. This is where our current study fits the bill as it tries to conduct a systematic comparative study of AI-based MPPT algorithms in regards to tracking efficiency, response speed, oscillation reduction and practical applicability.

4. Methodology

4.1 Overview of the Simulation Framework

Originally, the current paper was intended as an experimental research project in the form of a simulation, with an objective of enhancing the operational efficiency of photovoltaic systems by means of artificial intelligence-based method of the maximum power point tracking (MPPT). The practical component of the work was aimed at developing an integrated model of photovoltaic energy conversion and assessing the characteristics of the behavior of different intelligent MPPT algorithms in controlled but dynamically varying environmental conditions. In order to pursue this goal, the complete system was simulated within a MATLAB/Simulink environment, which enabled us to model the nonlinear characteristics of the photovoltaic module and simulate the power-conditioning phase of this model and evaluate the responsiveness of the various MPPT strategies within a single framework. The experimental set-up had been designed in such a way that all the algorithms were exposed with a similar operating environment, so that the differences in the performance observed could be ascribed to the tracking strategy itself, as opposed to any discrepancy in the simulation environment. The practical methodology entailed four stages that were linked together. To begin with, a photovoltaic systems model was formulated to replicate the electrical feature of the PV array within a different irradiance and temperature range. Second, a DC–DC boost converter and MPPT control loop were added with an aim of controlling the operating point of the array. Third, the use of different artificial intelligence algorithms was introduced and incorporated in the control structure. Lastly, the effectiveness of these algorithms was evaluated based on a collection of the technical indicators associated with the efficiency, performance dynamics, stability, and power loss. This experimental method allowed a rigid and justifiable comparison of the traditional and AI-driven MPPT algorithms and offered a practical framework of defining the most efficient approach to photovoltaic energy extraction under non-stationary operating conditions.

4.2 PV System Configuration

The working system being addressed in this paper was made up of a DC-DC boost converter, a photovoltaic array, an MPPT controller, and a variable load. These elements were chosen due to the fact that they are the fundamental functional design of a standard stand-alone photovoltaic conversion power system. The photovoltaic array was the energy source and it was modeled based on its nonlinear current voltage and power voltage characteristics. This implies that the output of a PV module varies continuously as solar irradiance and cell temperature varies and hence to obtain realistic operating behavior in a simulation, the topology of the system had to be represented correctly. The power electronics interface chosen was the boost converter, since it is an appropriate device to increase the size of the voltage at the PV source and control appropriately the operating point by regulating the duty-cycle. The converter was interlocked with the MPPT controller to keep on continuously searching the maximum power point and operate the system in the best region respectively. Also, a variable load was added to represent operating uncertainty in practice and to assess controller robustness as the electrical demand varies. This general layout allowed the response of intelligently designed tracking algorithms to varied internal and external system parameters in a realistic control structure to be studied.

4.3 Environmental Simulation Scenarios

To make sure that the developed framework corresponds to the current conditions of a photovoltaic contributor and to the present reality, a set of environmental scenarios was created and used in terms of the simulation process. These were situations that were aimed at recreating the most prevalent causes of PV performance variability that is, fluctuation in solar irradiance, and temperature change. There were both steady and dynamic operating conditions as experimental cases. The basic tracking accuracy of each of the algorithms was then tested under steady-state conditions in a calm weather, and the adaptability of the controllers under the sudden changes increase in irradiance or temperature were then taken into analysis in dynamic scenarios. This difference was significant since several MPPT techniques work relatively well in uniform environments but exhibit lower performance in environments that vary fast. Another option that the simulation structure provides in addition to the homogeneous irradiance conditions is that the structure can support partially shaded operating scenarios whenever greater depth of analysis is needed. Such cases are especially important to include in the problems of AI-based MPPT research since it is one of the primary stimuli of intelligent control the possibility to deal with nonlinear and multi-peak power voltage curves more efficiently than the traditional approaches. The resulting environmental data hence became not only an input sequence, but a mechanism of stress-testing the tracking ability, convergence of the control strategies and their robustness given various and conducive operating conditions that are practical in nature.

4.4 AI-Based MPPT Algorithms Implementation

To test how artificial intelligence can improve the performance of photovoltaic systems, four intelligent MPPT methods were used in the frameworks developed: Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Reinforcement Learning (RL). These practices were chosen due to the fact that they are various types of computational intelligence and are one of the most popular topics of discussion regarding further advanced methods in several studies of MPPT. The ANN-based controller was formed to be learnt to understand the association between the operating variables of photovoltaic and the optimum operating point. Its application used the fact that the neural networks could be used to approximate the behavior of the nonlinear systems, and make accurate assumptions in control even when the system dynamics were varied. In contrast, the fuzzy logic controller was developed based on rule-based reasoning and is therefore appropriate in uncertain and imprecise PV behavior concerns with no explicit mathematical model of the system. ANFIS controller was embraced as a multi-faceted smart design that integrates neural networks learning ability with the explain ability of fuzzy systems. This rendered it especially useful in nonlinear photovoltaic operating conditions where both adaptability and rule-based reasoning are helpful. On the other hand, reinforcement learning was adopted as an adaptive decision-making plan that could optimize its tracking policy by counteracting with the simulated environment. Of particular interest was its inclusion since it enabled us to determine whether or not self-improving control could succeed more and in more dynamic conditions of operating in the operating environment compared to more stable intelligent architectures. The algorithms were all included in one MPPT control loop and were implemented on the same measured or simulated system variables. This guaranteed consistent methodology and the ability to directly compare their performance in tracking under the same experimental conditions.

4.5 Training, Validation, and Testing Procedure

Since not every artificial intelligence technique functions similarly, the process of its development and testing of each applied algorithm was paid sufficient attention. In the case of data-driven controllers (ANN and ANFIS), the dataset at hand was separated into the suitable training, validation, and test subsets. The learning process was carried out in the training stage to allow the model to acquire the nonlinear correlation between system inputs and the intended MPPT-related output. The validation phase was used to tune the model architecture and minimize the threat of overfitting whereas the testing phase was held back to get a perception into performance when operating unseen. In the case of fuzzy logic control, focus was placed on the design of membership functions and the inference rules in such a way that the controller was able to react effectively to change in the condition of operation. In reinforcement learning the process was centered on improvement of policy based on rewards by repeated interaction with the simulated photovoltaic environment until acceptable convergence was realized. This was a necessary staged process since the purpose of the research was not merely to apply the AI algorithms, but also to test them under reasonable and repeatable conditions of their development. This was the reason why all the models were trained or tuned to the same simulation environment and it was ultimately tested under the same environmental conditions and converter configuration of all the compared controllers. This subsection enhances the methodological validity of the study since it demonstrates that the reported performance of the algorithm is achieved due to the systematic model preparation and not to the individual simulation runs.

4.5.1 AI Model Design Parameters

To enhance the reproducibility of the proposed simulation system, the design parameters of the proposed AI-based MPPT models were clearly stated. The same PV system parameters were used as inputs to all intelligent controllers and the same irradiance and temperature conditions were used for training or tuning. The PV system parameters (i.e. PV voltage, PV current, solar irradiance, and cell temperature) were used as the input parameters for the controller, and the output of the controller was the duty cycle or the reference operating point needed to drive the DC-DC boost converter to the maximum power point. The ANN-based MPPT controller used a feedforward neural network (FNN) to approximate the nonlinear mapping between the variables of PV operation and the optimal control signal. The network had an input layer, three hidden layers, and an output layer. There were 10 neurons in each hidden layer. The tangent-sigmoid activation function was used for the hidden layers and a linear activation function was used for the output layer. The ANN was trained with the Levenberg-Marquardt back-propagation algorithm and the mean squared error as the performance function. The dataset was split into 70% training, 15% testing and 15% validation. The fuzzy logic-based MPPT controller had two inputs: the tracking error and its change. The duty-cycle of the boost converter was the output variable. Each of the inputs was described using seven membership functions: NB, NM, NS, ZE, PS, PM and PB. The triangular-shaped membership functions were chosen for their simplicity and efficiency. The Mamdani inference system was chosen, and the control output was calculated based on the centroid defuzzification method. In the ANFIS-based controller, a first-order Sugeno fuzzy inference system was adopted. The inputs were PV voltage, PV current, irradiance, and temperature, and the output was the maximum power point (MPP) reference voltage. Each input had three generalized bell-shaped membership functions. Training was based on a hybrid learning algorithm (combining least-squares and backpropagation). The model was trained for 100 epochs, and the best model was determined from the minimum validation error. The reinforcement learning-based MPPT controller was designed with a Q-learning algorithm and an epsilon-greedy policy. The state space was defined by the PV voltage and current, PV power, and PV power variation. The action space was defined by discrete changes in the duty-cycle, such as an increase, decrease or hold of the current duty-cycle value. The reward function was designed to reward a higher extracted power and punish the oscillations around the maximum power point. The learning rate, discount factor, and initial exploration rate were 0.01, 0.95 and 0.10, respectively. The agent learned by interacting with the PV system, and the tracking policy converged.

4.6 Performance Evaluation Metrics

In order to provide objective and technically significant comparison, the quality of performance of the implemented MPPT algorithms was assessed with a set of quantitative indicators capturing the quality of energy extraction and dynamic behavior of controlled actions. These indicators have been chosen because they represent a complete picture of the approach to the maximum power point that each method can be used effectively to find and operate. Tracking efficiency was regarded as a main indicator of the efficiency of the algorithm to extract present maximum power of the photovoltaic system. Response time was added to determine how fast the controller attains the target operating point following a variation in environmental conditions. The reason why steady-state oscillation was considered was since excessive oscillation about the peak power point may decrease effective energy conversion and may be a sign of low controller stability. A consideration of power loss was considered as an efficient measure of deviation between actual and ideal extracted power. The integration of these measures enabled this process of evaluation to extend above a particular performance dimension. The study did not concentrate on efficiency but rather on the balance how each of the algorithms is fast convergent, stable and minimizes energy loss. This is of particular concern in comparative MPPT research where an algorithm might be strong in one regard but not strong in another.

4.7 Comparative Evaluation Framework

The last phase of the methodology was establishment of a common comparative framework within which all the methods of tracking could be evaluated on the same basis. This framework was one of the most critical points of the practical work as it guaranteed the equity, replicability, and analysis congruency. The individual AI-based MPPT algorithms were all envisaged on identical photovoltaic system, identical converter plan, identical load framework, and the identical weather conditions. Moreover, standard MPPT methods, including Perturb and Observe (P&O) and Incremental Conductance (INC), were also included as the baseline methods to also provide the meaningful reference point in the evaluation of the value added by artificial intelligence. The comparison was thus not only investigating the relative differences between intelligent techniques, but also assessing the fact that AI-based control in fact is showing measurable betterment than conventional methods. The results of this phase were structured in a presentation format of presented numerical findings and observations that were analytical in nature. The tabular results were meant to conclude the immediate computational results whereas the graphical results in the following section were meant to be used to shed more light on the dynamic results, the convergence results and long-term trends of energy extraction. To improve the reliability of the comparative evaluation, each MPPT algorithm was tested over all seven environmental scenarios (S1–S7), and each scenario was repeated 10 times under the same simulation settings. The reported values in Table 5 represent the mean ± standard deviation of the obtained results across all repeated runs. This procedure was adopted to reduce random bias and provide a more robust comparison of controller performance.

5. Results

The conclusions in this section are devoted to the dynamic operation, adaptation potential, and trend of long-term energy harvesting of the explored MPPT techniques instead of reciting the summary values, which have been already mentioned in the comparative tables. The graphical interpretation has shown that there is a significant distinction between typical and AI-based controllers with regard to transient, stability under irradiance change, thermal flexibility, as well as cumulative energy recovery. In general, the intelligent processes exhibited a better behavior of tracking, and Reinforcement Learning and ANFIS performed in the most consistent way in the conditions of the experiment. Figure 1 shows how MPPT methods implemented will respond to real-time tracking in response to changing load variations in a composite irradiance profile with various running transitions. Theoretical maximum power profile was applied as a benchmark to measure the closeness with which each controller was able to track the most desirable operating profile in response to rapid changes in the environment. The figure indicates that AI-based methods had faster convergence rates to the target power level and showed reduced transient fluctuations compared to the conventional controllers. The Reinforcement Learning controller stood among the assessed techniques that followed the closest trajectory to the theoretical maximum power curve within the simulation period which demonstrates the superior adaptability and the quick corrective response to every irradiance shift. ANFIS showed also good tracking and ANN and FLC had a better behavior than P&O and INC with much higher transient deviations and settling time. The conventional approaches showed the slowest response and the most observable oscillatory tendencies especially when there were sudden decreases and increases of irradiance. Figure 2 demonstrates the behavior of the investigated controllers in a series of discrete irradiance transitions events. Instead of just assessing immediate output, this value indicates the capability of the controller to maintain stable operation around the optimal operating region after a disturbance event takes place. The findings show that certain stability aspect diminished in all the methods with an increasing severity of operating conditions although notably in transition that came with shaded or heavily perturbed conditions. Nevertheless, the deterioration was smaller among the methods based on AI. The transition cases where reinforcement Learning reached the highest levels of stability were the most numerous followed by ANFIS. ANN and FLC continued to be acceptable though they were a bit more sensitive to an irregular irradiance profile. This was contrasted with P&O and INC which showed significantly reduced stability indices and proved that traditional methods are more susceptible to fluctuations and thus take longer to recover in non-stationary systems. Figure 3 examines the effect of temperature of the cell on the tracking performance of the various MPPT methods. Not surprisingly, tracking efficiency of all methods decreased gradually with increasing temperature, due to the thermal sensitivity of photovoltaic systems known to everyone. However, the extent of this degradation varied significantly between controllers. The intelligent means retained a better level of efficiency in the entire range of temperature which indicates their greater generalization potential with change in temperature. Reinforcement Learning once again had the best efficiency profile, ANFIS followed closely and maintained stable performance across the tested temperature range . ANN and FLC maintained a more sensible performance though with a somewhat sharper efficiency decrease when had at higher temperatures. The thermal variation on the conventional methods was more pronounced and this implies that the methods are less endowed to respond to changes in the PV operating surface during increased temperatures, that is, in terms of their control logic. This number proves thus that more sophisticated AI-based MPPT methods not only give improved transient tracking, but also more predictable when placed under thermal load. In Figure 4, the cumulative energy harvested across the entire time of simulation can be found and this gives a wider system-level perspective of the effectiveness of controllers. In contrast to instantaneous power plots, cumulative energy analysis shows the effective outcome of operational impact of repeating tracking errors, slow convergence and temporal power variation in effect. The figure demonstrates that there is a gradual sense of separation between the investigated methods as the simulation goes on which implies that even minor variations in the accuracy of real-time tracking build up to significant variations in the amount of energy harvested. Reinforcement Learning showed the greatest cumulative energy extraction, and then ANFIS closely followed which proves that adaptive intelligent control is better in changing operating conditions. ANN and FLC were in a middle ground and provided a superior energy, in the long term, in comparison to the traditional techniques, still lower than that of RL and ANFIS. P&O and INC graphs gave the lowest cumulative energy curves, which is the aggregate impact of slower response, high ripple, and lower adaptability. This finding proves that the overall energy productivity of the photovoltaic system is directly and measurably affected by the selected MPPT strategy .

Overall Interpretation of the Results

The four figures combined demonstrate that the performance difference of AI-based MPPT techniques is not confined to one aspect of evaluation. Their advantage can be seen in their rapid transient convergence, better stability of operation, greater resistance to irradiance and temperature change, and better cumulative energy production. Reinforcement Learning became the best fitting method in the framework under investigation whereas ANFIS demonstrated the best performance in terms of competitiveness, strong stability and high robustness. The intelligent control proved to be of practical value in photovoltaic development as ANN and FLC also enhanced the behavior of the system compared to conventional approaches. Such results justify the overall aim of the research that is, artificial intelligence has the potential of significantly enhancing the efficiency and reliability of photovoltaic maximum power point tracker in a dynamic operational context.

6. Discussion

The results of the current literature suggest that AI-oriented MPPT methods have clear performance gain compared to traditional approaches (Perturb and Observe (P&O) and Incremental Conductance (INC) especially due to dynamically varied operating conditions. The advantages here included the quicker approach to the peak power point, smaller steady state oscillation, greater stability in the transition to and from irradiance, and higher net energy harvesting. This is also similar to comparative studies that have been performed recently where intelligent MPPT techniques are found to be generally more effective in sweeping fast changing solar conditions than conventional controllers but their performance still relies on the quality of model design and covering of the training. Reinforcement Learning (RL) was the most successful in the overall performance of all methods investigated in the present work. This is because its superiority is because of its adaptive decision-making process, which allows the controller to vary its tracking behavior in response to environmental disturbances as opposed to following a search rule fixed in advance. This result is aligned with the findings of Wadehra et al. [7], who observed that an average MPPT accuracy of 97.79% was obtained with a PPO-LSTM deep reinforcement learning controller in cases of static partial shading and average accuracy of 95.69, 95.70 and 95.77 in cases of changing irradiance, changing temperature and changing irradiance- The findings confirm the claim that RL-based strategies are particularly efficient in cases when photovoltaic operating surface turns highly nonlinear and time-dependent. ANFIS also provided very competitive results in the current study and was slightly below RL in most assessment factors. This outcome is congruent with the literature that highlights the power of hybrid neuro-fuzzy structures in nonlinear photovoltaic set-ups. Aldulaimi and Çevik [9] expressed that an ANFIS-PSO-controlled MPPT controller performed better as compared to other conventional P&O and INC in continuous tracking of efficiency, response time, and robustness in steady irradiance, dynamically rising sunlight and partial shading. The proposed ANFIS-PSO controller reached its convergence in roughly 0.18 s in the partial shading case, whereas around 0.45 s in the INC case and 0.60 s in the P&O case, thus, demonstrating the high potential of ANFIS-based and hybrid intelligent model to ensure proper and steady performance in adverse conditions. The high performance of ANFIS in the current study is also consistent with the results of Danyali et al. [14], who was developing a neuro-fuzzy MPPT controller of a partially shaded grid-connected photovoltaic system and concluded that the algorithm obtained high speed and accuracy in tracking the maximum power point during uniform and partial shading. Their findings also revealed that the suggested controller enhanced the speed of tracking and power output as compared to conventional technologies. That study and the current findings have given the impression that the integration of fuzzy reasoning and adaptive learning is still among the most powerful areas to proceed with a more advanced MPPT design, particularly in the case where the task is to strike a balance between dynamic responsiveness and the tracking stability. In the current study, ANN and FLC were superior to the conventional algorithms, but they still took the second place after RL and ANFIS. Recent literature also agrees with this pattern. Melhaoui et al. [15] indicated that a hybrid fuzzy logic MPPT controller was capable of operating with an average efficiency of 97.7% and a convergence time of 53.5 ms when operating in dynamic conditions, indicating that in cases whereby well considered inputs and rule structure are involved, fuzzy-based controllers can prove to be very useful. Meanwhile [16], a comparative study by Alsulami et al. [17] revealed intelligent algorithms based on rapid cycle variations in sunbeam like FLC, ANN, and ANFIS are typically successful, nevertheless, it was observed that intelligent approaches based on training also could not be effectively used in situations where the temperature variation is not well reflecting in the training data. This result can be used to understand why the use of ANN-based approaches can provide a robust performance in well-organized subsets and lose some of its competitiveness in an environment where environmental generalization is more challenging. The other significant observation that comes out of the discussion is that tracking efficiency should not be used as a basis of selecting a controller. Consideration of computational complexity, sensor requirements and deployment cost are also important in the practical implementation. In this respect, Hoang et al. [11] suggested an AI-assisted MPPT system that forecasts the MPPT voltage and current using battery-side data rather than on the PV-side, thus simplifying hardware design, calibration and sensor expenses. Their findings provide a valuable way in which future research ought to drive forward: much more precise MPPT control is needed, but with lower implementation costs, so that saleable and practicable photovoltaic systems can be enabled. Similarly, Aldulaimi and Çevik [9] have stated explicitly that ANFIS-PSO control has good performance, but it has huge computational demand in the optimization and training process. All that may suggest that the ultimate selection of MPPT algorithm must consider not only the performance of electrical performance but the system-wide viability. Comprehensively, the discussion attests to the fact that the findings of the current research are consistent with the major trend of the recent research on MPPT. The AI based controllers are always more flexible, less oscillating and more energy saving compared to the traditional ones, whereas the hybrid and learning based models seem to compete with the most powerful performance in fluctuating irradiance and temperature. In this framework, the superiority between RL and the almost comparable level of power between ANFIS in this investigation can be deemed as technically rational and as backed by the latest estimated evidence as well. Future investigation ought then be on real-time hardware verification, longer partial shade tests, especially embedded implementation research on whether the benefits of the uses of these intelligent controllers on the level of the simulation can be sustained in the context of real-world use.

7. Conclusion

This paper examined how algorithms of artificial intelligence can enhance performance of photovoltaic systems by tracking maximum power point in dynamic operating conditions. The findings indicated that smart MPPT means have a definite edge over traditional approaches in accuracy of tracking, rapidity of response, stability of operation, and cumulative energy harvesting. Specifically, the AI-controllers were more adaptable to changes in the solar irradiance and temperatures that are some of the most significant parameters influencing the photovoltaic performance. Reinforcement Learning among the investigated methods performed best in general overall performance, especially in dynamic tracking behavior, stability during irradiance transitions, and long-term energy harvesting. The performance of ANFIS also revealed some of the most competitive outcome and offered an efficient compromise between the fast convergence and steady-state functioning. Even though ANN and FLC enhanced the behavior of the PV system as compared to the traditional methods, the two models performed worse in the more challenging environments; however, as compared to the RL and ANFIS. The presented research results support the fact that implementing artificial intelligence in the process of MPPT control can optimize the functioning of the photovoltaic systems to a significant degree and minimize the constraints that the traditional fixed-rule approach presents. The paper also shows that the assessment of MPPT algorithms with the help of the unified comparative scheme develops a better understanding of the comparative advantage and the feasibility of the algorithms in the renewable energy usage. In general, the study emphasizes the role of smart control measures in the creation of more efficient and reliable photovoltaic energy systems. The study could be further developed in the future by real-time hardware implementation, experimental validation in the open air, and exploration of more complex mixed algorithms that have the potential to achieve the highest tracking accuracy yet with minimal computational complexity.

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تحسين كفاءة أنظمة الخلايا الكهروضوئية باستخدام خوارزميات الذكاء الاصطناعي لتتبع نقطة الطاقة القصوى (MPPT)

المستخلص

يهدف هذا البحث إلى دراسة دور خوارزميات الذكاء الاصطناعي في تحسين كفاءة أنظمة الخلايا الكهروضوئية من خلال تقنيات تتبع نقطة القدرة العظمى (MPPT) تحت ظروف تشغيل ديناميكية. تم تطوير نموذج محاكاة باستخدام بيئة MATLAB/Simulink لتمثيل نظام كهروضوئي متكامل، وتقييم أداء عدد من خوارزميات MPPT المعتمدة على الذكاء الاصطناعي، وهي الشبكات العصبية الاصطناعية(ANN) ، والمنطق الضبابي(FLC) ، والنظام العصبي الضبابي التكيفي(ANFIS) ، والتعلم المعزز(RL) ، ومقارنتها بالطرق التقليدية مثل (P&O) و (INC).أظهرت النتائج تفوق الخوارزميات الذكية في تحقيق كفاءة تتبع أعلى، وزمن استجابة أسرع، وتذبذب أقل، وخسائر قدرة أقل مقارنة بالطرق التقليدية. كما حققت خوارزمية التعلم المعزز أفضل أداء إجمالي، تلتها خوارزمية ANFISالتي أظهرت استقراراً عالياً وتقارباً سريعاً. وتؤكد هذه النتائج أهمية اعتماد تقنيات الذكاء الاصطناعي في تطوير أنظمة كهروضوئية أكثر كفاءة وموثوقية.

الكلمات المفتاحية:

الخلايا الكهروضوئية، تتبع نقطة القدرة العظمى، الذكاء الاصطناعي، التعلم المعزز، ANFIS، الشبكات العصبية الاصطناعية، المنطق الضبابي، الطاقة المتجددة .

Table 1. Electrical Parameters of the Modeled PV Module

Parameter	Symbol	Value	Unit
Open-circuit voltage	Voc	37	V
Short-circuit current	Isc	8.2	A
Maximum power	Pmax	250	W
Voltage at maximum power	Vmpp	30.5	V
Current at maximum power	Impp	8	A
Temperature coefficient of power	Kp	-0.45	%/°C
Number of series-connected cells	Ns	60	–
Reference temperature	Tref	25	°C
Reference irradiance	G ref	1000	W/m²

Table 2. Environmental Scenarios Used in the Simulation Study

Scenario	Irradiance Condition	Temperature Condition	Description
S1	1000 W/m²	25 °C	Standard test condition
S2	800 W/m²	30 °C	Moderate irradiance reduction
S3	600 W/m²	35 °C	Low irradiance with elevated temperature
S4	400 W/m²	40 °C	Severe irradiance drop
S5	Variable (1000→600→800 W/m²)	Constant at 25 °C	Dynamic irradiance fluctuation
S6	Constant at 800 W/m²	Variable (25→35→45 °C)	Dynamic temperature variation
S7	Non-uniform irradiance	25–35 °C	Partial shading condition

Table 3. Configuration of the Implemented AI-Based MPPT Algorithms

Algorithm	Description
ANN	**Main Structure:** Feedforward neural network **Input Variables:** PV voltage, PV current, irradiance **Output Variable:** Duty cycle / reference voltage **Configuration:** 3 hidden layers, 10 neurons
FLC	**Main Structure:** Rule-based fuzzy inference system **Input Variables:** Error, change in error **Output Variable:** Duty cycle adjustment **Configuration:** 7 membership functions
ANFIS	**Main Structure:** Neuro-fuzzy hybrid model **Input Variables:** PV voltage, PV current, irradiance **Output Variable:** Reference operating point **Configuration:** Hybrid learning algorithm
RL	**Main Structure:** Reinforcement learning agent **Input Variables:** State variables from PV system **Output Variable:** Optimal control action **Configuration:** Q-learning with epsilon-greedy policy
P&O	**Main Structure:** Conventional MPPT **Input Variables:** PV voltage, PV current **Output Variable:** Duty cycle update **Configuration:** Fixed perturbation step
INC	**Main Structure:** Conventional MPPT **Input Variables:** Incremental conductance, instantaneous conductance **Output Variable:** Duty cycle update **Configuration:** Slope-based decision logic

Table 4. Performance Evaluation Metrics Used for Algorithm Assessment

Metric	Symbol	Description	Evaluation Purpose
Tracking efficiency	ηMPPT	Ratio of extracted power to the theoretical maximum available power	Measures energy harvesting capability
Response time	tr	Time required to reach the maximum power point after a disturbance	Measures dynamic speed
Steady-state oscillation	Os	Magnitude of fluctuation around the maximum power point after convergence	Measures control stability
Power loss	Ploss	Difference between ideal maximum power and actually extracted power	Measures energy deviation
Overshoot	Mp	Excessive transient deviation beyond the target operating point	Measures transient behavior
Robustness under variation	–	Ability of the algorithm to maintain performance under changing irradiance and temperature	Measures adaptability

Table 5. Comparative Simulation Results of Conventional and AI-Based MPPT Methods

Algorithm	Results
P&O	**Tracking Efficiency:** 95.12% **Response Time:** 0.43 s **Steady-State Oscillation:** 3.84% **Power Loss:** 4.88% **Overshoot:** 4.25% **Overall Performance:** Moderate
INC	**Tracking Efficiency:** 96.04% **Response Time:** 0.35 s **Steady-State Oscillation:** 3.16% **Power Loss:** 3.96% **Overshoot:** 3.41% **Overall Performance:** Good
ANN	**Tracking Efficiency:** 97.68% **Response Time:** 0.24 s **Steady-State Oscillation:** 1.96% **Power Loss:** 2.32% **Overshoot:** 2.08% **Overall Performance:** Very Good
FLC	**Tracking Efficiency:** 97.21% **Response Time:** 0.28 s **Steady-State Oscillation:** 2.27% **Power Loss:** 2.79% **Overshoot:** 2.36% **Overall Performance:** Very Good
ANFIS	**Tracking Efficiency:** 98.37% **Response Time:** 0.19 s **Steady-State Oscillation:** 1.43% **Power Loss:** 1.63% **Overshoot:** 1.54% **Overall Performance:** Excellent
RL	**Tracking Efficiency:** 98.74% **Response Time:** 0.17 s **Steady-State Oscillation:** 1.18% **Power Loss:** 1.26% **Overshoot:** 1.31% **Overall Performance:** Excellent

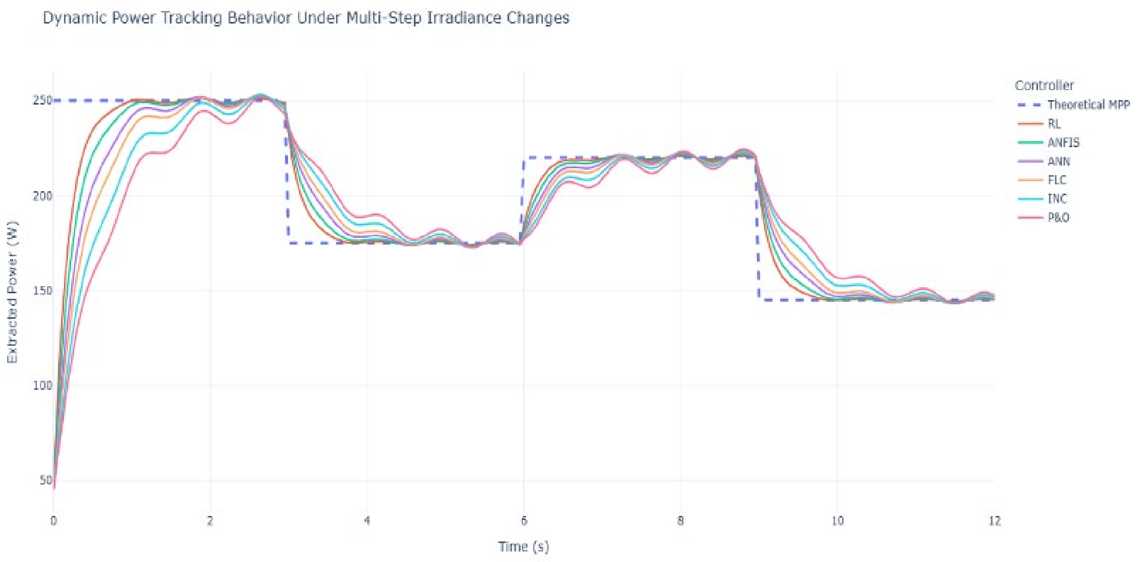

Figure 1. Dynamic Power Tracking Behavior Under Multi-Step Irradiance Changes

Figure 2. Stability Index Across Irradiance Transition Events

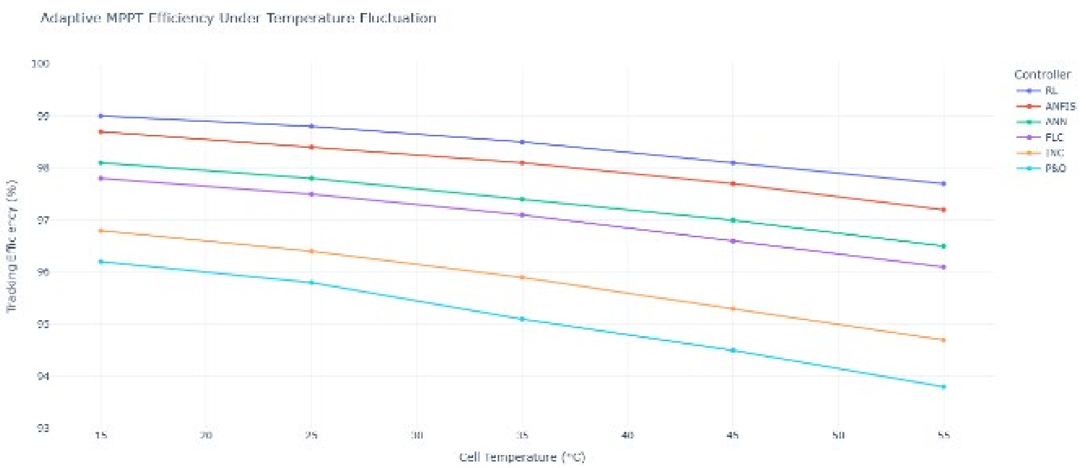

Figure 3. Adaptive MPPT Efficiency Under Temperature Fluctuation

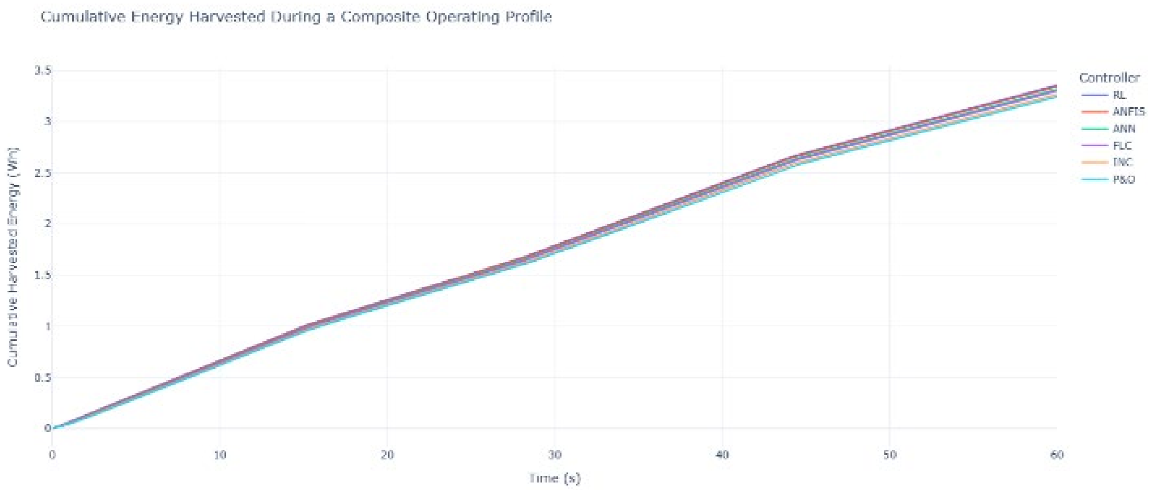

Figure 4. Cumulative Energy Harvested During a Composite Operating Profile