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Overview of the Application of Neuroevolution and Genetic Algorithms in the Control of Power Grids with Renewable Energy

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Abstract. The integration of renewable energy sources into electrical grids introduces significant challenges, particularly in ensuring stability and reliability in dynamic, nonlinear environments. These sources create fluctuations, uncertainties, and voltage regulation issues that traditional control systems struggle to manage, compromising the grid's ability to deliver a stable power supply. Addressing these challenges requires advanced, adaptive control solutions capable of responding to the variable nature of renewable energy.

This article explores advanced techniques, focusing on reinforcement learning and Neuroevolution, to develop innovative control strategies for electrical systems. Neuroevolution, which combines neural networks with evolutionary algorithms, optimizes control without relying on gradient-based methods, making it suitable for complex, unpredictable scenarios. These approaches enhance grid stability, improve response times, and enable real-time anomaly detection and corrective actions, offering a resilient and efficient solution to the limitations of traditional control methods.

Key words. Renewable energy integration, Reinforcement learning, Neuroevolution, Electrical grid stability, Control systems.

1. Introduction

Conventional control systems face significant challenges due to the increasing integration of renewable energy sources, such as solar and wind, due to their intermittent and nonlinear nature. These traditional control systems, designed for more predictable power grids, struggle to manage voltage fluctuations and operate efficiently in high-uncertainty scenarios. Therefore, it is necessary to explore new approaches that can enhance performance and ensure the stability of modern power grids[1].

Reinforcement learning offers a promising solution to these problems, as it allows the creation of agents that learn to make control decisions autonomously and adaptively. This approach can replace conventional control systems by training an agent that optimizes its performance by maximizing rewards through continuous interaction with the environment [2]. In the context of power systems, the agent can manage voltage fluctuations and disturbances more efficiently, quickly adapting to changing conditions and operating optimally without the need for an accurate model of the system. Additionally, these agents can control several system elements simultaneously, optimizing multiple critical variables such as frequency, voltage, and transmission capacity within a single learning process [3].

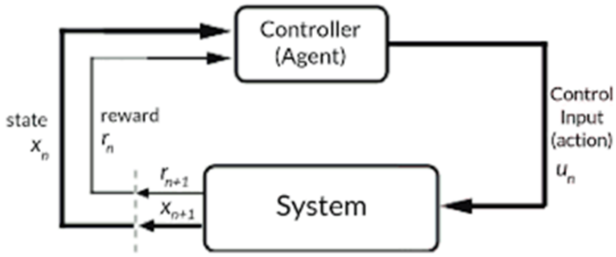

Fig. 1. Flow diagram of reinforcement learning

Among the reinforcement learning algorithms analysed in this study is Deep Q-Learning (DQL), which uses deep neural networks to train a control policy that optimizes the power system's performance. This algorithm iteratively adjusts the agent's policy through exploration and learning, enabling the control of key system variables [4]. However, this method may require extended training times due to the need for gradient calculations.

As an alternative, a reinforcement learning algorithm based on Neuroevolution is proposed, which uses Genetic Algorithms (GA) [5] to train a neural network, directly adjusting the network's weights without calculating gradients. This approach emulates biological evolution principles, such as mutations and crossovers, to optimize the power system's performance. By avoiding gradient calculations, GAs significantly reduces training time compared to traditional methods like DQL.

Similarly, an approach based on Particle Swarm Optimization (PSO) is analysed to train the neural network's weights. This algorithm is inspired by the collective behaviour of swarms, such as birds or fish, to search for optimal solutions [6]. Like GAs, PSO adjusts only the weights of the neural network without modifying its structure. This method stands out for its rapid adaptation and shorter training times, making it an effective tool to enhance power system control in dynamic and high-uncertainty environments [7].

This study explores reinforcement learning and Neuroevolution techniques to enhance electrical system control under high uncertainty and dynamic conditions from renewable energy integration. It assesses Deep Q-Learning (DQL), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) for optimizing stability, real-time response, and adaptability. These methods aim to outperform traditional controls by improving anomaly detection and robustness against voltage fluctuations. The research also compares these approaches with conventional methods to develop adaptive, efficient solutions for modern grids, providing a foundation for future real-world implementation.

The document is structured into sections covering key aspects of advanced control techniques in electrical systems. The introduction outlines challenges in integrating renewable energy and the need for innovative solutions. The Theoretical Framework details reinforcement learning and Neuroevolution techniques. The Methodology section examines control strategies analytically. The Literature Review assesses Neuroevolution applications, advancements, and challenges. Future Perspectives explore potential real-world applications, and the Conclusion summarizes findings and their impact on future research and renewable energy integration.

2. Theoretical Framework

Currently, the integration of renewable energy sources into electrical grids is presenting new challenges in the stability and control of these systems. Traditional methods of electrical grid control, which rely on linear approaches and static predictive models, struggle to adapt to the variable and unpredictable nature of renewable energy sources such as solar and wind power. These sources are inherently intermittent and subject to changing weather and environmental conditions, making their behavior difficult to predict and control using conventional methods.

As the proportion of renewable energy in the energy mix increases, the need for more flexible and adaptive solutions becomes more urgent. In this context, new control techniques based on deep learning, such as reinforcement learning and Neuroevolution, emerge as promising alternatives. These methodologies allow for the adaptive optimization of electrical system behavior, adjusting dynamically to real-time changes without relying on conventional methods, which often fail to effectively manage the uncertainty and variability inherent in renewable energy sources.

Through the ability to learn from experience and adapt to changing scenarios, these techniques offer a significant advantage over traditional approaches. Throughout this theoretical framework, the main innovative techniques will be explored, including their fundamental principles, advantages over traditional methods, and the challenges that must be overcome for their effective implementation in dynamic electrical grids with high uncertainty. Additionally, the discussion will focus on how these methodologies could transform the control and management of electrical grids in the future, providing the necessary flexibility to more efficiently integrate renewable energy sources [1] [2] [3].

A. Reinforcement Learning

Reinforcement learning is an unsupervised machine learning technique in which an agent learns to make decisions through interaction with its environment. Rather than relying on labelled data, the agent receives rewards or penalties based on its actions, enabling it to autonomously learn to maximize its performance over time. This methodology has proven effective in complex systems, such as electrical control systems, where conditions change dynamically and are not always predictable [8].

B. Deep Q-Learning

Deep Q-Learning (DQL) is one of the most widely used techniques within reinforcement learning. Although it is an unsupervised approach, DQL utilizes deep neural networks to estimate the value function of an agent. Through this algorithm, the agent learns to select the best action in each state of the environment to maximize long-term rewards. However, as it is a gradient-based algorithm, its training time may be slower compared to other approaches, especially when facing environments with high variability [4].

C. Neuroevolution

Neuroevolution is a technique that combines neural networks with evolutionary algorithms to optimize both the structure and parameters of the network, without the need for gradient-based methods. In this approach, solutions are evolved iteratively, adapting to environmental changes, to improve system efficiency and performance. The primary advantage of Neuroevolution is that it can optimize neural networks more quickly and efficiently than gradient-based methods, and it is also parallelizable, which enhances training speed in complex scenarios.

D. Neuroevolution with Genetic Algorithms

In the context of Neuroevolution, genetic algorithms (GA) are used to adjust the parameters of neural networks, such as weights and biases. Genetic algorithms operate by simulating the process of natural selection, where the fittest solutions are preserved and combined through mutations and crossover. This allows for the discovery of optimal solutions without the need for gradient calculations. This approach is particularly useful for optimization tasks in electrical systems, where conditions change continuously, and a differentiable loss function may not always be available [6].

E. Neuroevolution with PSO

Another variant of Neuroevolution employs the Particle Swarm Optimization (PSO) algorithm. Unlike genetic algorithms, PSO is based on the movement of particles in a search space, with particles cooperating to find the optimal solution.

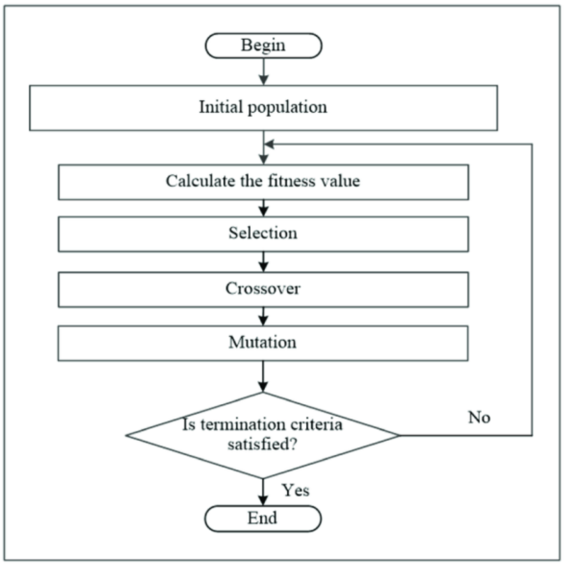

Fig. 2. Flow diagram of genetic algorithm

This approach also enables the optimization of the neural network's weights and biases without requiring gradient-based methods. PSO excels in efficiently exploring complex search spaces and is faster compared to methods that rely on gradient calculations, making it an attractive option for optimization in dynamic electrical systems [7].

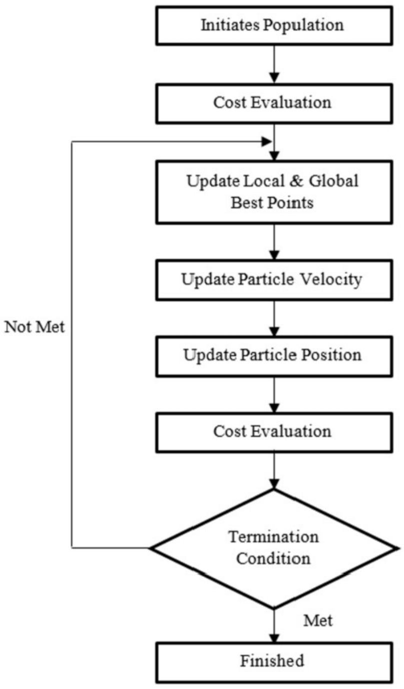

Fig. 3. Flow diagram of PSO

F. Challenges and Advantages of Neuroevolution

Although Neuroevolution has shown promising results in controlling dynamic systems such as electrical systems, it presents certain challenges. One of the main drawbacks is that the convergence of evolutionary algorithms may be slower compared to other methods, especially in scenarios with large search spaces. However, evolutionary algorithms do not require gradient calculations, making them more effective in non-differentiable problems, such as those found in electrical systems where simulations may not always be continuous or smooth. Furthermore, the ability to parallelize the training process enhances response times in complex control systems.

3. Methodology of the Analysis

Based on the reviewed literature, we have selected the methodologies described below, which focus on the use of genetic algorithms (GA) and neural networks for controlling dynamic electrical systems. This selection was made considering not only the relevance and impact of these technologies in controlling key variables in electrical systems, but also their potential to address emerging challenges, particularly the integration of renewable energy sources and energy optimization. In a context where the variability and uncertainty of renewable energy sources (such as solar and wind energy) are key factors in the operation of electrical systems, these methodologies are presented as essential tools to maintain system stability and operational efficiency. Advances in processing power and computational capabilities, along with improvements in evolutionary optimization algorithms, open new prospects for implementing adaptive techniques that can more efficiently manage the changing and dynamic conditions of electrical systems [6] [7].

Analysis and Organization of the Methodology

Once the relevant literature was collected and thoroughly reviewed, the studies were organized into thematic categories to provide a clear and understandable structure. The studies were grouped according to the main approaches and methodologies adopted, allowing for a more detailed analysis of their application in the field of electrical system control. These approaches were defined by the following research lines:

- Application of Genetic Algorithms (GA) in Power Grids: Numerous studies were reviewed in which GAs were applied to optimize key aspects of energy distribution, improve operational efficiency, and manage generation in electrical systems. Special attention was given to studies that considered the presence of renewable energy sources, which introduce fluctuations and variability in energy production, making it essential to have flexible and adaptive methodologies. GAs were shown to be effective in finding optimal solutions for resource allocation and improving the operation of electrical grids, especially in contexts with high demand and production variability [9] [7].

- Use of Neural Networks in Electrical System Control: This category analyzed research that employs neural networks, particularly those aimed at predicting and modeling key variables such as voltage, frequency, and power flow in grids. Studies were highlighted in which neural networks were used to optimize system stability and performance in real-time, addressing both the prediction of future behaviors and adaptation to sudden changes in demand or energy supply. Furthermore, the benefits of the neural networks' ability to handle large volumes of data were discussed, making them ideal tools for controlling complex and dynamic electrical systems [6].

- Integration of Evolutionary Algorithms and Neural Networks: This hybrid approach, combining genetic algorithms with neural networks, has demonstrated significant potential in recent literature. It is an emerging trend that seeks to integrate the best of both worlds: the adaptability and optimization of GAs alongside the predictive and modeling capabilities of neural networks. In the studies reviewed, it was highlighted how Neuroevolution, by enabling the dynamic adaptation of controller parameters, facilitates continuous improvement in stability and efficiency in electrical systems. This approach allows for the management of the inherent complexity of next-generation electrical systems, optimizing their performance even under changing conditions and uncertainty. The combination of neural networks with evolutionary algorithms has also shown great potential in reducing the dependency on historical data and improving real-time adaptability [10].

4. Analysis of the Literature on Neuroevolution

In the literature analysis related to Neuroevolution, it was determined that the multilayer perceptron (MLP) neural network architecture, densely connected with one or two hidden layers, seems to be the best option for controlling dynamic electrical systems [1] [2]. This architecture strikes a good balance between complexity and generalization capability, enabling effective optimization of key variables in electrical systems.

A. Method for Assessing Study Quality

A critical approach was adopted to assess the quality of the selected studies, identifying the strengths and limitations of each reviewed article. The following aspects were considered:

- Clarity and Detail of the Methodology: The clarity with which the studies explained the methods used, especially the details of genetic algorithms and neural network structures, was evaluated.
- Relevance of Results: The reported results were reviewed in terms of their practical applicability and the observed improvement in controlled variables (voltage, frequency, energy efficiency).
- Comparison with Traditional Methods: Studies that included comparisons between the proposed methods and traditional approaches (such as PID controllers) were particularly relevant, as they provide evidence of the advantages and disadvantages of evolutionary approaches [4].

B. Analysis of Genetic Algorithms in Electrical Systems

Regarding the use of genetic algorithms, it was found that the approach employing Boltzmann selection, in which the genetic algorithm hyperparameters vary as generations progress, is the most suitable for an environment like an electrical system. This approach allows for more precise adaptation to the variations in the electrical system and enhances the convergence in the optimization of solutions [9].

C. Limitations of the Study and Areas for Future Research

While this review covers a broad range of relevant studies, several limitations are acknowledged. First, many of the reviewed studies primarily focused on simulations and controlled environments, so the implementation in real electrical systems remains an emerging research area. Additionally, some studies did not provide sufficient details on the practical implementation of algorithms in dynamic environments with uncertainty.

Based on the findings of this review, key areas for future research are identified:

- Real-Time Optimization: More research is needed on the implementation of genetic algorithms and neural networks in real-time control environments, especially in systems with high variability and intermittent renewable sources [6].
- Improvements in Computational Efficiency: The development of hybrid techniques combining genetic algorithms and neural networks with more efficient optimization methods could overcome the convergence speed limitations observed in some studies.
- Experimental Validation: More experimental validation studies are necessary to demonstrate the effectiveness of evolutionary approaches in real electrical systems, with changing operational conditions [3].

Table 1 is a comparative table summarizing the main characteristics and outcomes of the analyzed methodologies, highlighting their applicability in the control of electrical systems with renewable energy sources. Specifically, it provides a comprehensive comparison of three methodologies—Deep Q-Learning (DQL), Neuroevolution with Genetic Algorithm (NE-GA), and Neuroevolution with Particle Swarm Optimization (NE-PSO)—based on several critical characteristics relevant to their application in dynamic electrical system control. From the comparison, we can draw several key conclusions. Firstly, while all three methods exhibit high adaptability to network changes, both NE-GA and NE-PSO offer superior dynamic adjustment capabilities compared to DQL, which requires a more complex setup [7].

In terms of robustness, NE-GA and NE-PSO demonstrate very high performance in unexpected scenarios, benefiting from their evolutionary nature and ability to explore large solution spaces. However, this comes with increased computational costs, especially for NE-GA, which evaluates entire populations during its evolutionary process [2].

On the other hand, DQL, while offering high robustness and the ability to learn dynamically, has the drawback of being computationally expensive due to the need for many iterations in Q-model updates [1].

Table I. - Comprehensive Comparison of Advanced Control Methodologies for Electrical Systems

Characteristics	**Deep Q-Learning (DQL)**	**Neuroevolution with Genetic Algorithm (NE-GA)**	**Neuroevolution with PSO (NE-PSO)**
Ease of Initial Implementation	Requires a complex neural network and environment setup [4]	Moderate, depends on initial population design [11]	Moderate, requires particle parameter tuning [12]
Adaptability to Network Changes	High, learns dynamically	Very high, evolves with the system	Very high, fast dynamic adjustment
Interpretability of Decisions	Low, neural network is a "black box"	Low, requires evolutionary analysis to interpret results	Low, requires traceability in particles
Robustness in Unexpected Scenarios	High, if trained with adequate data [8]	Very high, adapts evolutionary solutions	Very high, particles explore large spaces
Convergence Time	High, may require many iterations	Moderate, depends on population size [13]	Moderate, depends on particle configuration
Computational Cost	High, due to Q-model iterations [4]	Very high, due to evaluation of the entire population	High, depends on the number of particles and cycles[14]
Complexity for Dynamic Environments	High, requires continuous simulation	Highly adaptable but costly	Highly adaptable, particles converge faster
Simulation Requirements	Mandatory for training	Extensive simulations required	Extensive simulations required
Dependence on Historical Data	High, depends on the quality of initial data	Low, can evolve with real-time data	Low, adapts particles based on dynamic data
Implementation Time	High, training and initial setup are complex	Moderate, requires defining functions and population	Moderate, initial particle and function design needed

Furthermore, the interpretability of decisions is a common challenge across all methods, as they rely on complex models that are difficult to interpret without advanced analysis. Overall, while each methodology has its own strengths and weaknesses, NE-GA and NE-PSO stand out in terms of their adaptability and ability to evolve in real-time, making them promising alternatives for managing the complexity of renewable energy integration into electrical grids.

5. The future of reinforcement learning and Neuroevolution in the control of electrical systems

The future of reinforcement learning and Neuroevolution in the control of electrical systems appears promising, especially considering the increasing complexity of modern electrical grids and the widespread integration of renewable energy sources. As networks become more dynamic and adaptive, traditional control methods, which rely on predefined models and linear approaches, are increasingly insufficient to manage the variability and uncertainty inherent in renewable energy sources such as solar and wind.

Reinforcement learning, through its ability to learn optimal control policies based on continuous interaction with the environment, promises to provide highly adaptive solutions that can adjust in real-time to unforeseen operational changes [1]. In parallel, Neuroevolution, by combining neural networks with evolutionary algorithms, offers a robust approach to optimizing both the parameters of control systems and their structure, enabling efficient exploration of complex, non-differentiable solution spaces, which is particularly valuable in scenarios where systems are subject to uncertainties and changing conditions [2].

In the future, these techniques could transform electrical system control by providing autonomous solutions that not only enhance efficiency and stability but also enable more effective integration of renewable energy sources. However, for these methodologies to become a viable option for large-scale electrical system control, challenges related to computational capacity, convergence time, and the need for large amounts of historical data for training must be overcome [3]. Nevertheless, with continuous advancements in computing power, more efficient algorithms, and improved optimization techniques, both reinforcement learning and Neuroevolution are likely to play a central role in the design of future electrical grids that are more resilient, intelligent, and sustainable.

6. Conclusion

In conclusion, the efficient control of electrical systems, particularly in dynamic and nonlinear contexts, represents a crucial challenge for the stability and optimal operation of modern power grids. The integration of renewable energies, such as solar and wind power, has added complexity to this process, underscoring the need for more adaptive and precise approaches.

In this context, Neuroevolution emerges as a promising alternative, combining neural networks and evolutionary algorithms to optimize the control of critical variables such as voltage and frequency. Through genetic algorithms (GA) and particle swarm optimization (PSO) techniques, it is possible to overcome the limitations of traditional methods and improve responsiveness to disturbances and changing system conditions.

The study highlights how Neuroevolution can transform electrical system control, adapting to complex and dynamic scenarios without the need for differentiable gradients, which is a significant advantage in systems with high levels of uncertainty. Additionally, the ability of these algorithms to explore large search spaces and avoid local optima enhances their applicability in managing power grids with high penetration of renewable energy.

Although the results obtained are promising, key areas for future research, such as real-time implementation of these controllers and improving their computational efficiency, are identified. The integration of these approaches into real electrical environments, which operate under conditions of high variability, will be crucial to establish Neuroevolution as a strategic tool for the autonomous and efficient control of future electrical systems.

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