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Performance Improvement of Photovoltaic Panels in Solar Systems using Artificial Intelligence Techniques

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ABSTRACT

In the contemporary landscape, the significance of renewable energy is progressively escalating, and artificial intelligence (AI) is poised to play a crucial role in its swift advancement. There exists a challenge associated with the diverse routine components employed to ensure the accuracy of speech recognition. Hidden Markov Models (HMMs) have been utilized to enhance and evaluate inputs, serving as a mechanism for validating the precision of speech inputs while also facilitating further development. This study examines the performance of speech signal inputs across various platforms utilizing the HMM process. However, many speech signals exhibit ambiguity, which can disrupt the continuity of uninterrupted segments. To address this irregularity, numerous researchers have previously proposed various techniques; this paper specifically evaluates the performance across different platforms using HMM technology to enhance the consistency of speech signals.

Keywords: - Performance, Photovoltaic, CSP, Hybrid system and Deep Learning**.**

I. Introduction

As a result of the global energy extremity, numerous scientists and experts are fastening their attention on renewable energy sources [1]. As a result of these findings, experimenters were impelled to probe new inventions and resources [2] and tactics for converting sun into electrical energy or some form of energy. The conversion of solar radiation into electrical energy is fulfilled through the use of photovoltaic (PV) systems. The high cost of installing solar systems has been a significant challenge in their widespread adoption and enforcement. While solar energy offers numerous benefits such as environmental sustainability and long-term cost savings, the initial installation costs can be a barrier for many individuals and businesses. The cost of solar system installation includes several factors such as the solar panels, inverters, mounting equipment, electrical components, and labor costs. Additionally, the size of the system required depends on the energy needs of the property, which further influences the overall cost. However, it's worth noting that the cost of solar installations has been decreasing over the years, thanks to advancements in technology, increased production efficiency, and economies of scale. Government incentives, tax credits, and rebate programs in many countries also aim to offset the installation costs and promote solar energy adoption. There is a significant body of literature and research focused on making solar systems more successful and cost-effective. These efforts aim to address the challenges associated with the installation, operation, and maintenance of solar systems while also increasing their overall efficiency and durability.

. The combination of these research efforts, technological advancements, and supportive policies contributes to the success and cost-effectiveness of solar systems, making them a more viable and attractive option for renewable energy generation. It has been demonstrated that artificial intelligence (AI) algorithms have a substantial impact on the performance of PV systems [3]. In photovoltaic systems, AI algorithms can be employed for modelling, sizing, control, fault diagnostics, and affair estimation. It compares artificial intelligence algorithms with classical algorithms for each type of operation [4]. The keys of AI applications in solar panel technology shown in figure 1.

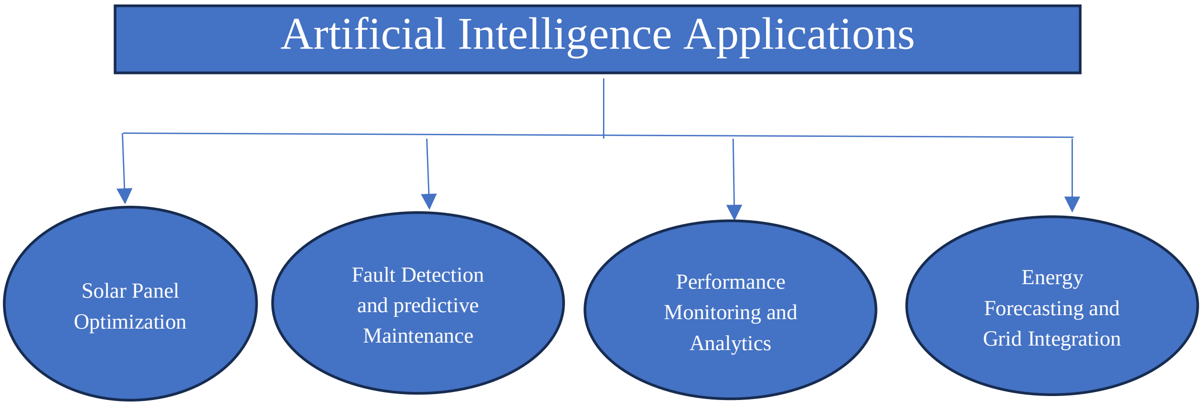

Figure 1: Keys of Artificial Intelligence in Solar Panel Technologies

The control unit in a solar system plays a crucial role in managing various aspects of the system, including solar tracking and energy management. It serves as the central module that coordinates and controls the operation of different components within the system. Accurate modeling of solar cells is indeed crucial for research and development in the field of photovoltaic (PV) systems. Solar cell modeling allows researchers to understand the behavior of solar cells under different conditions, optimize their performance, and predict their electrical output accurately. These models are essential for designing efficient PV systems and assessing their potential applications. Various applications of PV system are shown in Figure 2.

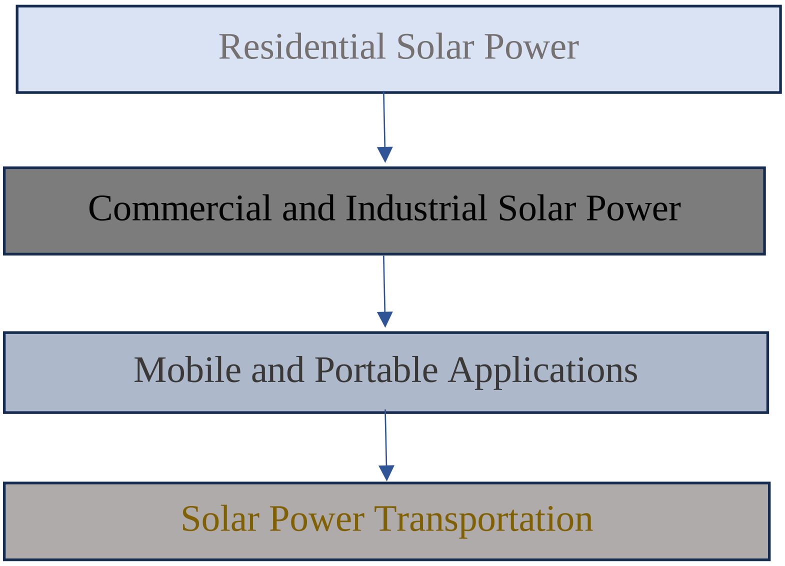

Figure 2: Applications of PV system

The parameters of solar cells, such as diode achromatism current, series resistance, shunt resistance, and photocurrent, play a crucial role in modeling and sizing photovoltaic (PV) systems. Accurate estimation of these parameters is essential for the performance analysis and optimization of solar cell circuits. [5]. There are two commonly used circuit models for solar cells: the single-diode model and the double-diode model. The single-diode model consists of five parameters, while the double-diode model has seven parameters. These models provide a mathematical representation of the behavior of solar cells under varying conditions. [6]. To determine the values of these parameters, various standard procedures have been published and are available online. These procedures outline methodologies for parameter extraction based on experimental measurements and data analysis. However, traditional methodologies may not always accurately predict the characteristics of solar cell modules. [7]. As a result, researchers have started exploring the use of artificial intelligence (AI) technologies for parameter discovery in solar cells. AI techniques, such as machine learning and optimization algorithms, can analyze large datasets and identify patterns and correlations that may not be apparent through traditional methods. By leveraging AI, scientists aim to improve the accuracy of parameter estimation and enhance the performance prediction of solar-electricity generating modules. [8]. The synergy between artificial intelligence and other technologies holds great potential for developing advanced computer systems in the field of solar energy. Through the integration of AI with solar cell technologies, researchers can tackle complex challenges, optimize system designs, and improve the overall efficiency of PV systems [9–15]. The community between artificial intelligence and other technologies can be used to make extremely important computer systems.

II. Related Works

An Artificial Neural Network (ANN) is composed of interconnected computational nodes called artificial neurons or nodes. These artificial neurons are arranged in layers, and each neuron receives inputs, performs a computation, and produces an output. The neurons are connected to each other through weighted connections, forming a network structure. The basic unit of computation in an artificial neuron is typically a mathematical function that takes the weighted sum of the inputs, applies an activation function to it, and produces an output. The weights of the connections between neurons determine the strength of the influence each neuron has on its connected neurons. An ANN consists of multiple layers, including an input layer, one or more hidden layers, and an output layer. The input layer receives the initial input data, and the output layer produces the final output or prediction. The hidden layers, located between the input and output layers, perform intermediate computations and help the network learn complex patterns and relationships in the data. Basically, these factors act as channels for the transmission of information. It's possible to attach both an input and a weight to the data of an incoming connection. It's possible to calculate the affair of a unit by adding up all of the values. Indeed, though ANNs are enforced using computers, there are no preprogrammed jobs associated with them. rather, through training, they're trained to fete patterns in the datasets that are used as inputs to the machine learning algorithms. It's possible to submit new patterns to them for vaticination or categorization after they've been tutored. Artificial neural networks [16– 20] can be trained using a variety of styles, including computer programmes, physical models, and real- world systems.

In an artificial neural network, the neurons in each subcaste are connected to those in the subcaste above them by a network of connections known as a neural network. Data is fed into the neural network through the input subcaste, while the network response to the data is stored in the affair subcaste. There may be redundant layers between input and affair in addition to the input and affair layers. It's necessary to reuse the sum of the weights of each input and affair to acquire a result in all hidden and affair neurons [21–26], which is fulfilled through the use of a nonlinear transfer function. Indeed, One of the strengths of neural networks, particularly deep learning models, is their ability to learn and extract patterns from massive volumes of data without relying on predefined rules or explicit programming. Neural networks excel at processing large amounts of data in parallel and automatically discovering complex relationships and representations within the data.

The process of training a neural network involves presenting it with a vast amount of labeled or unlabeled data and adjusting its internal parameters (weights and biases) to optimize its performance on the given task. Through this iterative learning process, the network learns to recognize patterns, make predictions, classify inputs, or generate outputs based on the data it has been trained on. The advantage of this data-driven approach is that the neural network can extract and utilize intricate features and relationships from the data that may be challenging to define manually using explicit rules. This ability to learn directly from data makes neural networks highly adaptable and powerful in various domains, including image and speech recognition, natural language processing, recommendation systems, and many more, and it can do so indeed when the input is disposed or else inaccurate. Up to this point, traditional emblematic or sense- grounded strategies have been ineffective at dealing with these capabilities [27–30].

III. PROPOSED METHODS

new evolutionary computing approaches have been used to facilitate the tuning and design of neural networks. These approaches leverage evolutionary algorithms, which are inspired by natural selection, to optimize the performance of neural network models. Additionally, evolutionary algorithms can be employed to improve the performance of neural network models in various tasks, including literacy tasks.

In the context of solar cell modeling, the single-diode model consists of four parameters: single-diode achromatism current, single-diode series resistance, single-diode shunt resistance, and single-diode photogenerated current. These parameters are essential for accurately representing the behavior of the single-diode model.

Sizing renewable energy power systems is a complex process that involves coordinating various components, including renewable energy sources, energy storage systems, and loads. The system's operation is regulated by these components. In the case of a photovoltaic (PV) array, optimization algorithms can be employed to maximize the energy harvested from the solar panels. By utilizing sophisticated algorithms and computational resources, the PV array's output can be transformed into a usable form for end-users.

In the proposed model, the inputs to the system are latitude and longitude coordinates, and the outputs are hybrid-sizing parameters based on these inputs (f, u). The number of significant sizing parameters is determined through the results of the hybrid-sizing approach. Based on the available information, it is concluded that the relative error does not exceed 6%.

When it comes to prediction tasks, Multilayer Perceptron (MLP) models employing the sigmoid function are commonly used. The sigmoid function maps input values to a range of (0, 1) and is particularly useful in deep learning architectures for its ability to compress input values within a specific range. To prevent overfitting, the Early Stopping technique with a five-day tolerance period can be employed, which stops the learning process after a consecutive period of failure.

For network training, the Adam optimizer function is utilized with 100 batches and a learning rate of 0.001. These parameters help control the optimization process and adjust the weights and biases of the neural network during training to minimize errors and improve performance.

IV. RESULT AND PERFORMANCE ANALYSIS OF DIFFERENT DIODES

We executed the above investigation on the following platforms: 12 Gen Intel® Core™ i5-1235U 16 GB, 2 x 16 GB, DDR4, 3200 MHz

The entire number of results in this study is equal to the hunt agents that are assigned as 30 Figure 3 shows the confluence speed.

Grounded on these findings, we may conclude that the MLP- deduced PV model parameter values are within a suitable range and are original to those attained using other optimization styles similar as ANN.

Upon farther examination of the angles under colorful temperatures and situations of irradiation, it was discovered that the PV model with a five- diodes is accurate in all circumstances.

V. CONCLUSION

The utilization of artificial intelligence (AI) in PV system sizing has proven to be significant and effective. AI methods have demonstrated the ability to accurately and successfully size photovoltaic systems based on available data. This has become increasingly popular, especially in rural areas where traditional approaches may not be feasible.

AI can serve as a design tool to assist in determining the appropriate size of solar PV systems. By analyzing and processing relevant data, AI algorithms can provide valuable insights and optimize the sizing process. It's important to note that the examples provided are not exhaustive, as the potential applications of AI in this field are extensive.

In the context of reducing environmental impact, this research explores various AI-driven solutions for different types of PV power systems, including standalone, grid-connected, and hybrid systems. By leveraging AI techniques, such as machine learning and optimization algorithms, it becomes possible to improve the environmental performance of these systems.

While conventional sizing methods can still be viable when all the necessary information is available, they become challenging or even impossible to apply when data is limited or inaccessible. In such cases, AI-based approaches offer an alternative that can deliver accurate and efficient results.

The proposed AI model showcased in this research demonstrates its effectiveness compared to traditional models. By leveraging the power of AI, researchers can achieve more sophisticated and refined results in PV system sizing.

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