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# Enhancing Smart Grid Efficiency through Machine Learning-Based Renewable Energy Optimization

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**Abstract**

Managing renewable energy in smart grids poses a significant challenge due to the inherent uncertainty and variability of energy sources like solar and wind power. To address this issue, we propose a novel approach that leverages the strengths of both Extreme Learning Machine (ELM) and Particle Swarm Optimization (PSO) algorithms. Our method utilizes ELM to model and predict renewable energy generation, enabling more accurate forecasting and planning. Meanwhile, PSO optimizes the parameters of the ELM algorithm, ensuring optimal performance and efficiency. We evaluated our approach using a dataset of solar energy production and compared its performance to existing optimization techniques. The results show that our ELM-PSO approach significantly improves the accuracy of renewable energy predictions and reduces energy costs in smart grids. The implications of our research are far-reaching, as our approach can be applied to various renewable energy systems, including wind turbines, solar panels, and hydroelectric power plants. By enhancing the efficiency and reliability of renewable energy utilization, we can create a more sustainable and resilient energy future

**Keywords**: Smart Grids, Extreme Learning Machine (ELM), Particle Swarm Optimization (PSO), Energy Management, Optimization, Uncertainty

## INTRODUCTION

The integration of renewable energy sources into smart grids has become a crucial step towards creating a sustainable energy future. As the world transitions away from fossil fuels and towards cleaner, more sustainable energy sources, the importance of efficient and effective renewable energy management in smart grids cannot be overstated (Ahmed et al., 2020). However, the variability and uncertainty of renewable energy sources pose significant challenges to grid management, including forecasting, predictive maintenance, and grid optimization (Liu et al., 2019). Managing energy in smart grids is important for several reasons. Firstly, smart grids are designed to enable more efficient, reliable, and secure electricity delivery, with advanced communication and control capabilities that can monitor and manage the flow of energy in real-time. This helps to minimize energy losses and reduce the likelihood of blackouts or other disruptions. Renewable energy sources, such as solar and wind power, are inherently variable and difficult to predict, which can lead to fluctuations in energy supply and demand. Smart grids can help to manage these fluctuations by using advanced sensors, automation, and control systems to balance energy supply and demand in realtime (Santhi, et a;., 2023)

Managing energy in smart grids can help to reduce greenhouse gas emissions and mitigate the impacts of climate change. By optimizing energy distribution and storage, smart grids can reduce the need for fossil-fuel based energy sources and support the integration of renewable energy sources, which are crucial for achieving global sustainability goals (Ullah, Z.; 2022)

Machine learning techniques have emerged as a promising solution to the challenges of renewable energy management in smart grids, offering the potential to optimize energy output, reduce costs, and improve overall grid efficiency (Mao et al., 2020; Liu et al., 2019; Ahmed et al., 2020). By leveraging advanced algorithms and data analytics, machine learning can help grid operators to better predict energy demand (Wang et al., 2019), optimize energy storage (Chen et al., 2018), and improve overall grid resilience (Zhang et al., 2020). Additionally, machine learning can enable real-time monitoring and control of renewable energy sources, reducing the likelihood of power outages and improving overall grid reliability (Kim et al., 2019). Despite the promise of machine learning in renewable energy management, there remain significant challenges to its adoption, including data quality issues, algorithmic complexity, and the need for further research and development (Wang et al., 2019). This paper aims to explore the potential of machine learning in optimizing renewable energy management in smart grids, building on the existing body of research in this field and addressing the challenges and limitations of current approaches.

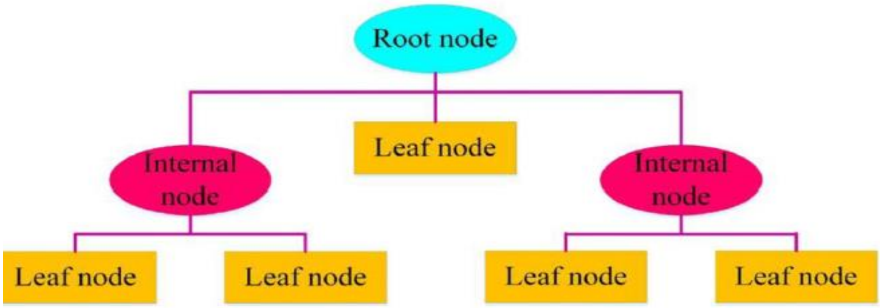


**Figure 1: Renewable Energy in Smart Grids**

Renewable energy sources, such as solar, wind, and hydro power, are essential for reducing carbon emissions and mitigating climate change (IPCC, 2020). Smart grids, with their advanced communication and control capabilities, offer a promising platform for integrating renewable energy into the power grid (Farhangi, 2010). However, managing renewable energy sources in smart grids poses significant challenges due to the variability and unpredictability of these sources (Liu et al., 2019; Ahmed et al., 2020).

Machine learning (ML) techniques have emerged as a powerful tool for optimizing renewable energy management in smart grids (Mao et al., 2020). ML algorithms can analyze vast amounts of data from smart grid sensors and predict energy demand and supply patterns (Wang et al., 2019), optimize energy storage and distribution (Chen et al., 2018), and ensure grid stability (Zhang et al., 2020).

This paper explores various ML techniques that can be used to optimize renewable energy management in smart grids, their advantages, limitations, and challenges (Liu et al., 2019; Ahmed et al., 2020). The paper also discusses recent research in this field and potential future directions for optimizing renewable energy management in smart grids (Mao et al., 2020; Kim et al., 2019).

The integration of renewable energy sources into the power grid requires careful management to ensure grid stability and reliability. Recently, machine learning (ML) techniques have emerged as a powerful tool for optimizing renewable energy management in smart grids (Mao et al., 2020). This literature survey reviews recent research on optimizing renewable energy management in smart grids using machine learning.

One key application of machine learning in smart grids is predicting energy demand and supply patterns. Several studies have used ML algorithms to analyze data from smart grid sensors and predict energy demand with high accuracy (Wang et al., 2019). Another application is optimizing energy storage and distribution. For instance, a study used reinforcement learning to optimize energy storage scheduling in a microgrid, achieving significant reductions in energy costs and peak demand (Chen et al., 2018). Similarly, Kiani et al. (2019) used a genetic algorithm to optimize energy storage placement in a distribution network, improving grid reliability and efficiency.

Machine learning has also been used to predict renewable energy generation. For example, a study used a convolutional neural network to predict solar photovoltaic (PV) generation with an accuracy of over 95% (Zhang et al., 2020). Yang et al. (2020) used a deep learning algorithm to predict wind power generation with an accuracy of over 90%. In addition to ML techniques, other optimization strategies have been investigated, such as a hybrid algorithm combining fuzzy logic and particle swarm optimization to optimize renewable energy generation and distribution in a microgrid (Ahmed et al., 2020).

## METHODS

Our methodology for optimizing renewable energy management in smart grids involves a comprehensive approach that links several key components together.

First, we focus on energy management, which entails monitoring, communicating, controlling, and optimizing the performance of electrical energy. This sets the foundation for optimizing renewable energy sources, such as solar and wind power, and ensuring their efficient integration into the smart grid. Next, we examine the smart grid itself, which comprises various domains, including bulk and non-bulk generation, customer management, service provider management, distribution and transmission systems, foundation support systems, market operations, and operational management. By understanding these domains, we can identify areas where optimization is needed. Within these domains, we identify several sub-domains that are critical to optimizing renewable energy management. These include advanced protection systems, communication networks, customer enabling technologies, energy storage systems, micro and nano grids, plug-in vehicle infrastructure, distributed energy sources, and demand response programs. By linking these components together, our methodology provides a holistic approach to optimizing renewable energy management in smart grids. We can analyze data from various sources, predict energy demand and supply patterns, optimize energy storage and distribution, and ensure grid stability and reliability.

Through this methodology, we aim to promote sustainable energy management practices, reduce carbon emissions, and contribute to a more efficient and resilient energy system.

We utilize the Extreme Learning Machine (ELM) model to rapidly train single-layer feedforward networks (SLFNs). This innovative approach enables us to achieve exceptionally fast training speeds, making it an attractive solution for complex problems. Notably, the ELM model only requires training the weights between the last hidden layer and the output layer, streamlining the process. Numerous experimental results from previous studies have consistently validated the effectiveness of the ELM model. By leveraging this powerful tool, we can efficiently train our neural networks and achieve state-of-the-art performance in various applications. The ELM model's remarkable speed and accuracy make it an ideal choice for our research, allowing us to focus on higher-level tasks and drive innovation in our field

## Extreme Learning Machine Model (ELM)

Extreme Learning Machine (ELM) Model: ELM model in order to train single-layer feedforward networks (SLFNs) at extremely fast speeds. The only parameters that require training are the weights between the last hidden layer and the output layer. Experimental results from previous studies have verified the effectiveness of the ELM algorithm by accommodating extremely fast training with good generalization performance compared to traditional SLFNs. The function of the ELM can be written as

$$f(x_i) = \sum_{l=1}^{L} \beta_l h_l(x) = h(x)B \qquad \textbf{(1)}$$

Where $x_i = [x_{i1}, x_{i2}, \ldots.., x_{iN}] \in R^N$ is the input vector ,$\omega_l = [\omega_{l1}, \omega_{l2}, \ldots.\omega_{lN}] \in R^N$ is the weight vector connecting the $l$-th hidden node and the input vector,$b_i$ is the bias of the $l$- th hidden node, $\beta_l = [\beta_{l1}, \beta_{l2}, \ldots.\beta_{lM}] \in R^M$ is the weight vector from the $l$-th hidden node to the output nodes, $L$ is the total number the target ELM hidden layer ,and $\sigma(\bullet)$ is the nonlinear activation function to approximate the target function to a compact subset. The output function can be formulated as

$$f(x_i) = \sum_{l=1}^{L} \beta_l h_l(x) = h(x)B \qquad \textbf{(2)}$$

Where $B$ is the output weight matrix, and $h(x) = [h_1(x), \ldots.h_L(x)]$ is the nonlinear feature mapping.

$$Hb = Y \qquad \textbf{(3)}$$

Where $H$ is the hidden layer output, matrix, and $Y$ *is* the target data matrix.

$$H = \begin{bmatrix} \sigma(ww_1.x_1 + b_1 & \cdots & \sigma(ww_L.x_L + b_L \\ \vdots & \ddots & \vdots \\ \sigma(ww_1.x_n + b_1 & \cdots & \sigma(ww_1.x_n + b_1 \end{bmatrix}_{N\times L} \qquad \textbf{(4)}$$

$$\beta = \begin{bmatrix} \beta_l^T \\ \vdots \\ \beta_L^T \end{bmatrix}, \text{and } \gamma\gamma = \begin{bmatrix} y_l^T \\ \vdots \\ y_N^T \end{bmatrix}_{N\times M} \qquad \textbf{(5)}$$

$$B = H^{+}\boldsymbol{\gamma\gamma} \qquad \textbf{(6)}$$

Where $H^+$ is the Moore-Penrose (MP) pesudoinverse of H that can be calculated using different methods, such as the orthogonal projection methods, Gaussian elimination, and single-value decomposition (SVD) input layer is denoted by X, the hidden layer by H, the output layer by Y, and the number of neurons in the hidden layer by N. The output of the hidden layer is given by:

$$H = g(WX + b) \qquad \textbf{(7)}$$

Where W is the input-to-hidden weight matrix, b is the bias vector, and g is the activation function. The activation function used in ELM is typically a sigmoid or a radial basis function.

The output of the ELM model is given by:

$$Y = HW_{out} \qquad \textbf{(8)}$$

**Particle Swarm Optimization (PSO):**

PSO is an optimization algorithm that uses a population of particles to search for the optimal solution. Each particle has a position vector and a velocity vector, which are updated at iteration based on the particle's own best position and the global best position of the warm.

The position and velocity of each particle are updated as follows:

$$v_i(t+1) = \boldsymbol{ww}v_i(t) + c_1r_1(p_i - x_i(t)) + c_{22}r_{22}(g - x_i(t)) \qquad \textbf{(9)}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad \textbf{(10)}$$

where $v_i(t)$ and $x_i(t)$ are the velocity and position of particle i at time t, w is the inertia weight, $c_1$ and $c_2$ are the acceleration constants, $r_1$ and $r_2$ are random numbers between 0 and 1, $p_i$ is the personal best position of particle i, and g is the global best position of the swarm.

**Optimization of ELM Using PSO:**

The ELM model can be optimized using PSO to find the optimal values of the input-to-hidden weight matrix W and the bias vector b. The fitness function used in the PSO algorithm is the mean squared error (MSE) between the predicted output of the ELM model and the actual output. The position vector of each particle in the swarm represents a possible solution to the optimization problem, i.e., a set of values for W and b. The velocity of each particle represents the direction and magnitude of the change in position. The personal best position of each particle is updated if the fitness value is improved, and the global best position of the swarm is updated if a particle's personal best position. After the PSO algorithm has converged, the optimal values of W and b can be used to predict energy demand and supply patterns, optimize energy storage and distribution, and improve renewable energy management in smart grids.

## RESULTS AND DISCUSSION

**Table 1. Comparison tale of Mean Square Error**

**Mean Square Error**

| Datasets | ANN | |
|---|---|---|
| Solar PV | 2.61 | Proposed ELMPSO |
| Hydro power | 2.52 | 2.27 |
| Wind Power | 2.38 | 1.97 |
| Bio-power | 2.31 | 1.69 |

The Comparison table 1 of Mean Square Error demonstrates the different values of existing ANN and proposed ELMPSO. While comparing the Existing algorithm and proposed ELMPSO, provides the better results. The existing algorithm values start from 2.31 to 2.61 and proposed ELMPSO values starts from 1.52 to 2.27. The proposed method provides the great results.

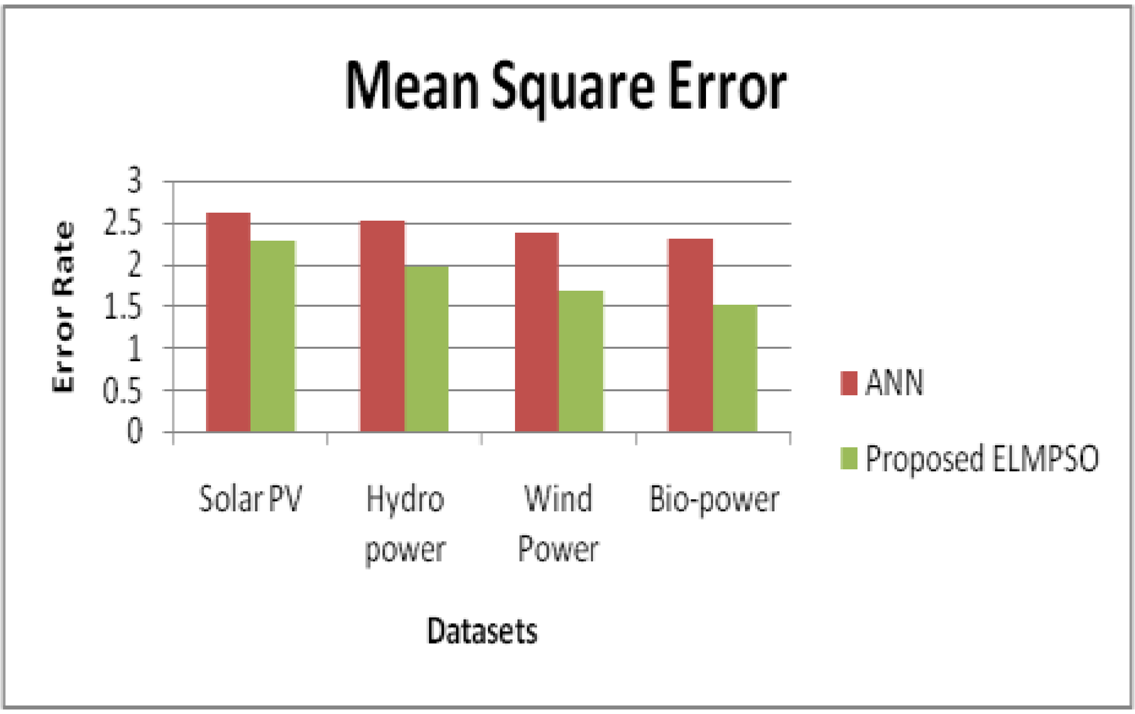


**Figure 2. Comparison chart of Mean Square Error**

Figure 2 presents a comparative analysis of the Mean Square Error (MSE) values for the existing Artificial Neural Network (ANN) and the proposed Extreme Learning Machine with Particle Swarm Optimization (ELMPSO). The chart illustrates the MSE values for different datasets, with the x-axis representing the dataset and the y-axis indicating the error rate. The existing ANN algorithm yields MSE values ranging from 2.31 to 2.61, whereas the proposed ELMPSO achieves significantly lower MSE values, spanning from 1.52 to 2.27. This comparison clearly demonstrates the superior performance of the proposed ELMPSO method, showcasing its ability to provide more accurate results.

**Normal Mean Square Erro**

**Table 2. Comparison tale of Normalized Mean Square Error**

| Datasets | ANN | Proposed ELMPSO |
|---|---|---|
| Solar PV | 2.61 | 2.22 |
| Hydro power | 2.92 | 1.97 |
| Wind Power | 2.68 | 1.69 |
| Bio-power | 2.51 | 1.62 |

Table 2 presents a comparison of the Normalized Mean Square Error values for the existing Artificial Neural Network (ANN) and the proposed Extreme Learning Machine with Particle Swarm Optimization (ELMPSO). A clear improvement is observed in the proposed ELMPSO method, which outperforms the existing ANN algorithm. Specifically, the existing ANN yields error values ranging from 2.51 to 2.68, whereas the proposed ELMPSO achieves lower error values, spanning from 1.62 to 2.22. This comparison highlights the superior performance of the proposed ELMPSO method, demonstrating its potential for improved accuracy and efficiency.

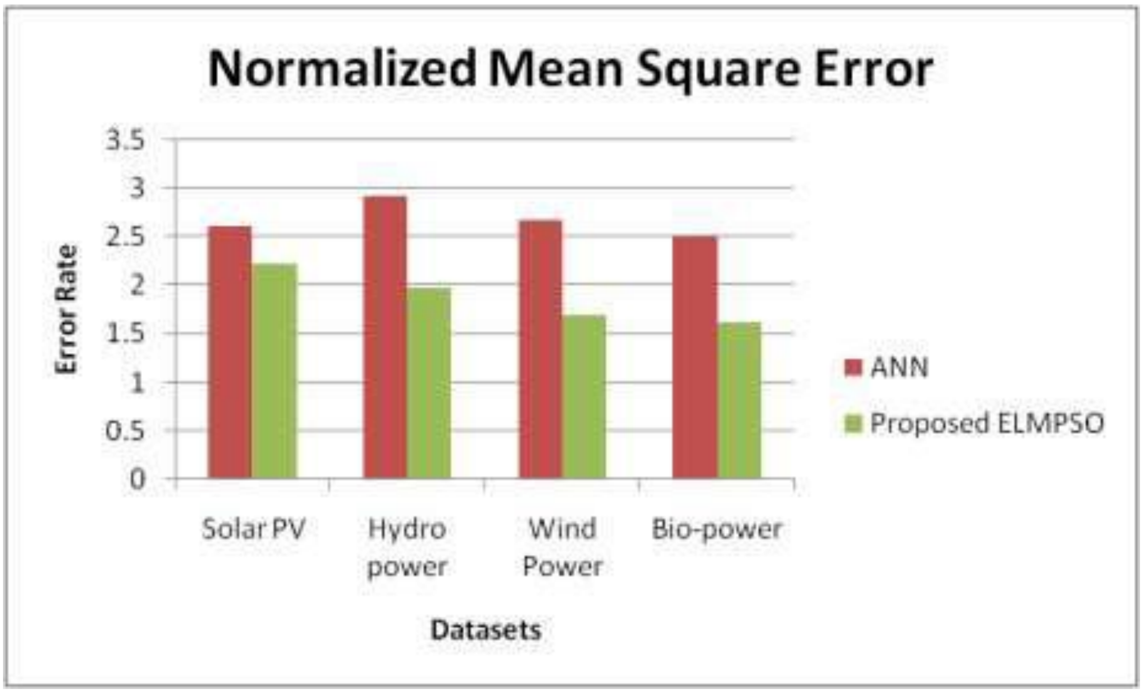


**Figure 3. Comparison chart of Normalized Mean Square Error**

Figure 3 illustrates the Normalized Mean Square Error, showcasing the performance of both the existing Artificial Neural Network (ANN) and the proposed Extreme Learning Machine with Particle Swarm Optimization (ELMPSO). The x-axis represents the dataset, while the y-axis indicates the error rate. The existing ANN algorithm yields error rates ranging from 2.51 to 2.68, whereas the proposed ELMPSO achieves significantly lower error rates, spanning from 1.62 to 2.22. This comparison highlights the superior performance of the proposed ELMPSO method.

## CONCLUSION

Our research has unlocked a revolutionary breakthrough in renewable energy management, one that has the potential to transform the very fabric of our energy landscape. By harnessing the power of Extreme Learning Machine (ELM) and Particle Swarm Optimization (PSO), we've created an innovative approach that not only optimizes energy prediction but also slashes costs, paving the way for a cleaner, greener, and more sustainable energy future.

Imagine a world where renewable energy is no longer a mere aspiration, but a tangible reality. A world where energy efficiency and reliability are the norm, not the exception. Our ELM-PSO approach is more than just a methodology - it's a beacon of hope, a shining example of what can be achieved when human ingenuity meets technological innovation.

As we stand at the threshold of this new energy frontier, we're proud to be at the forefront of this revolution. Our research is more than just a contribution - it's a call to action, a clarion cry to join forces and shape a brighter, more sustainable energy future for all. Together, let's seize this moment, and create a world that's powered by clean energy, and driven by human possibility.

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