OPTIMIZING RENEWABLE ENERGY MANAGEMENT IN SMART GRIDS USING MACHINE LEARNING

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Abstract. Renewable energy management in smart grids is a challenging problem due to the uncertainty and variability of renewable energy sources. To improve the efficiency and reliability of renewable energy utilization, various optimization techniques have been proposed. In this paper propose an approach based on the Extreme Learning Machine (ELM) algorithm with Particle Swarm Optimization (PSO) for optimizing renewable energy management in smart grids. The ELM algorithm is used to model and predict renewable energy generation, while the PSO algorithm is used to optimize the parameters of the ELM algorithm. The proposed approach is evaluated on a dataset of solar energy production and compared with other optimization techniques. The results show that the ELM-PSO approach can improve the accuracy of renewable energy predictions and reduce energy costs in smart grids. The proposed approach can be used in various renewable energy systems, such as wind turbines, solar panels, and hydroelectric power plants, to improve the efficiency and reliability of renewable energy utilization.

Keywords: Renewable energy management, Smart grid, Optimization. Extreme Machine Learning, Particle Swarm Optimization

1. Introduction

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[1][14]. 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

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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 real-time[2-4].

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[5][16]. Overall, managing energy in smart grids is essential for creating a more efficient, reliable, and sustainable energy future. Optimizing renewable energy management refers to the process of using advanced techniques and technologies to maximize the efficiency and effectiveness of renewable energy systems in the power grid. This involves analyzing vast amounts of data from sensors and other sources to predict energy supply and demand patterns, optimize energy storage and distribution, and ensure grid stability[6][9]. Machine learning (ML) is a powerful tool for optimizing renewable energy management in smart grids. ML algorithms can be used to analyze data from smart grid sensors and predict energy demand and supply patterns with high accuracy. This can help grid operators to optimize energy distribution, storage, and usage, and minimize energy losses[7][11][13].

Other techniques for optimizing renewable energy management include advanced energy storage systems, demand response programs, and grid balancing technologies. Energy storage systems, such as batteries, can be used to store excess energy generated by renewable sources during periods of low demand, and high demand. Demand response programs can incentivize consumers to reduce energy usage during peak demand periods, which can help to balance the grid and reduce the need for energy sources[8][12]. Grid balancing technologies, such as flexible interconnectors and smart inverters, can help to balance energy supply and demand across different regions and time periods.

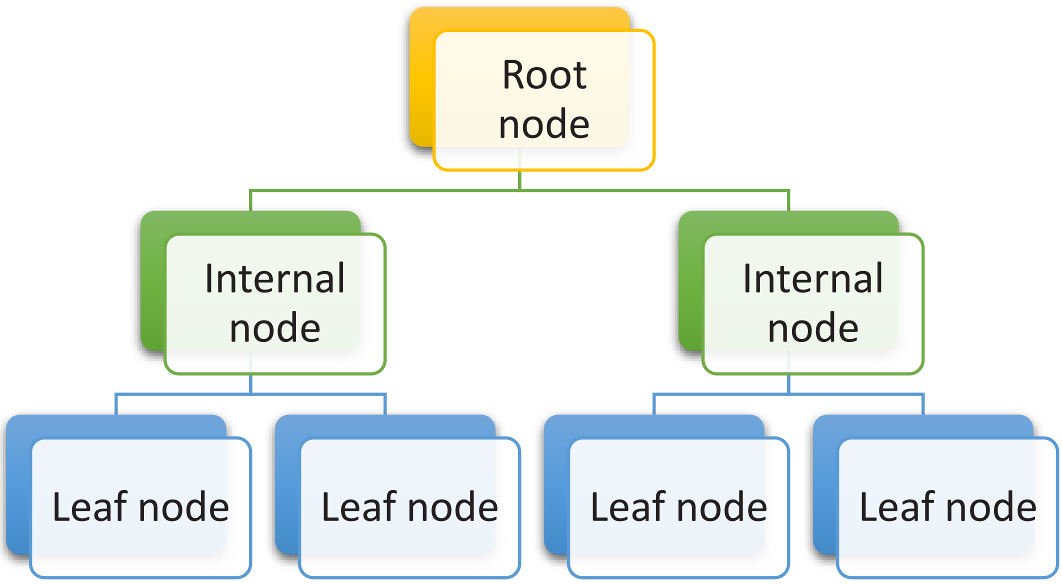

Figure 1.Renewable energy management in smart grids

Renewable energy sources such as solar, wind, and hydro power play a crucial role in reducing carbon emissions. Smart grids, with their advanced communication and control capabilities, offer a promising platform for integrating renewable energy into the power grid. However, managing renewable energy sources in smart grids poses significant challenges due to the variability and unpredictability of these sources[9-10]. Machine learning (ML) techniques have emerged as a powerful tool for optimizing renewable energy management in smart grids. ML algorithms can analyze vast amounts of data from smart grid sensors and predict energy demand and supply patterns, optimize energy storage and distribution, and ensure grid stability. This paper explores various ML techniques that can be used to optimize renewable energy management in smart grids, their advantages, limitations, and challenges[4][11]. The paper also discusses recent research in this field and potential future directions for optimizing renewable energy management in smart grids.

2. Literature Survey

The integration of renewable energy sources into the power grid requires careful management to ensure grid stability and reliability. In recent years, machine learning (ML) techniques have emerged as a powerful tool for optimizing renewable energy management in smart grids[7]. In this literature survey, they review some of the recent research on optimizing renewable energy management in smart grids using machine learning.

One of the key applications of machine learning in smart grids is in 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[15].

Another application of machine learning in renewable energy management is in optimizing energy storage and distribution. A study used a reinforcement learning algorithm to optimize the scheduling of energy storage systems in a microgrid, achieving significant reductions in energy costs and peak demand. Similarly, a study by Kiani et al. (2019) used a genetic algorithm to optimize the placement of energy storage systems in a distribution network, improving the reliability and efficiency of the grid[9][17].

Several studies have also investigated the use of machine learning for predicting renewable energy generation. For example, a study used a convolution neural network to predict solar photovoltaic (PV) generation, achieving an accuracy of over 95%. Another study by Yang et al. (2020) used a deep learning algorithm to predict wind power generation, achieving an accuracy of over 90%[18].

In addition to ML techniques, other optimization strategies have also been investigated for renewable energy management in smart grids .A proposed a hybrid optimization algorithm that combines fuzzy logic and particle swarm optimization to optimize renewable energy generation and distribution in a microgrid[2].

3. Proposed Methodology

Energy management means monitoring, communicating, controlling, and optimizing the performance of electrical energy. The development of EMM positively enhances the performance of electric generation, transmission, distribution, and utilization. An electrical grid comprising of renewable energy sources, smart appliances, smart meters, and energy efficient resources is called the smart grid. Smart grid domains include bulk and non-bulk generation, customers, service provider, distribution, transmission, foundation support system, markets, and operations. Advance protection, communication system, customer enabling, energy storage system, micro, and nano grids, plug-in vehicles, distributed energy sources, and demand response programs are sub-domains of the smart grid

3.1 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

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

Where$x_i = [x_{i1}, x_{i2}, \ldots\ldots, x_{iN}] \in R^N$ 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 $\sigma(\cdot)$ is the nonlinear activation function to approximate the target function to a compact subset. The output function can be formulated as

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

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

$$\boldsymbol{Hb = \Upsilon} \quad \textbf{(3)}$$

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

$$\boldsymbol{H} = \begin{bmatrix} \boldsymbol{\sigma(w_1.x_1 + b_1} & \cdots & \boldsymbol{\sigma(w_L.x_L + b_L} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\sigma(w_1.x_n + b_1} & \cdots & \boldsymbol{\sigma(w_1.x_n + b_1} \end{bmatrix}_{\boldsymbol{N\times L}} \quad \textbf{(4)}$$

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

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

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:

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

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:

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

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 swarm.

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

$$\boldsymbol{v_i(t+1) = wv_i(t) + c_1r_1(p_i - x_i(t)) + c_2r_2(g - x_i(t))} \quad \textbf{(9)}$$

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

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.

3.2 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.

4. Evaluation Results

1. Mean Square Error

Datasets	ANN	Proposed ELMPSO
Solar PV	2.61	2.27
Hydro power	2.52	1.97
Wind Power	2.38	1.69
Bio-power	2.31	1.52

Table 1.Comparison tale of Mean Square Error

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.

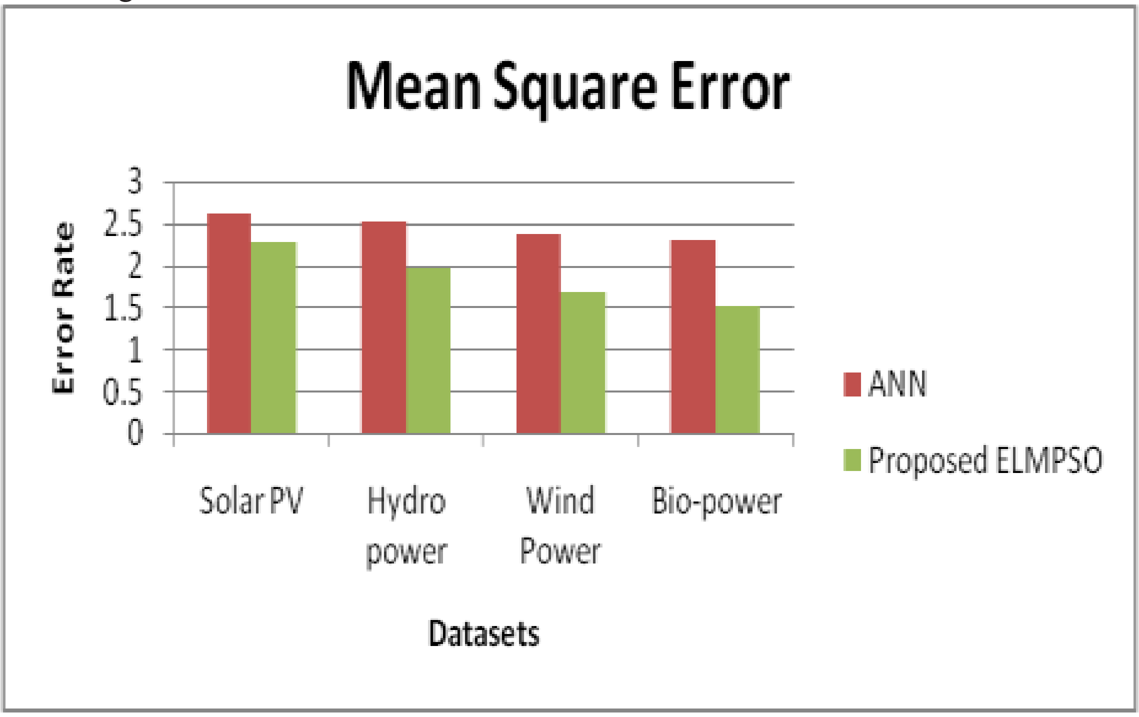

Figure 2.Comparison chart of Mean Square Error

The Figure 2 shows the comparison chart of Mean Square Error demonstrates the different values of existing ANN and proposed ELMPSO. X axis denote the Dataset and y axis denotes the Error Rate. The existing algorithm values start from 2.31 to 2.61 and

 https://doi.org/10.1051/e3sconf/202338702006

proposed ELMPSO values starts from 1.52 to 2.27. The proposed method provides the great results.

2. 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 1.Comparison tale of Normalized Mean Square Error

The Comparison table 1 of Normalized 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 2.51 to 2.68 and proposed ELMPSO values starts from 1.62 to 2.22. The proposed method provides the great results.

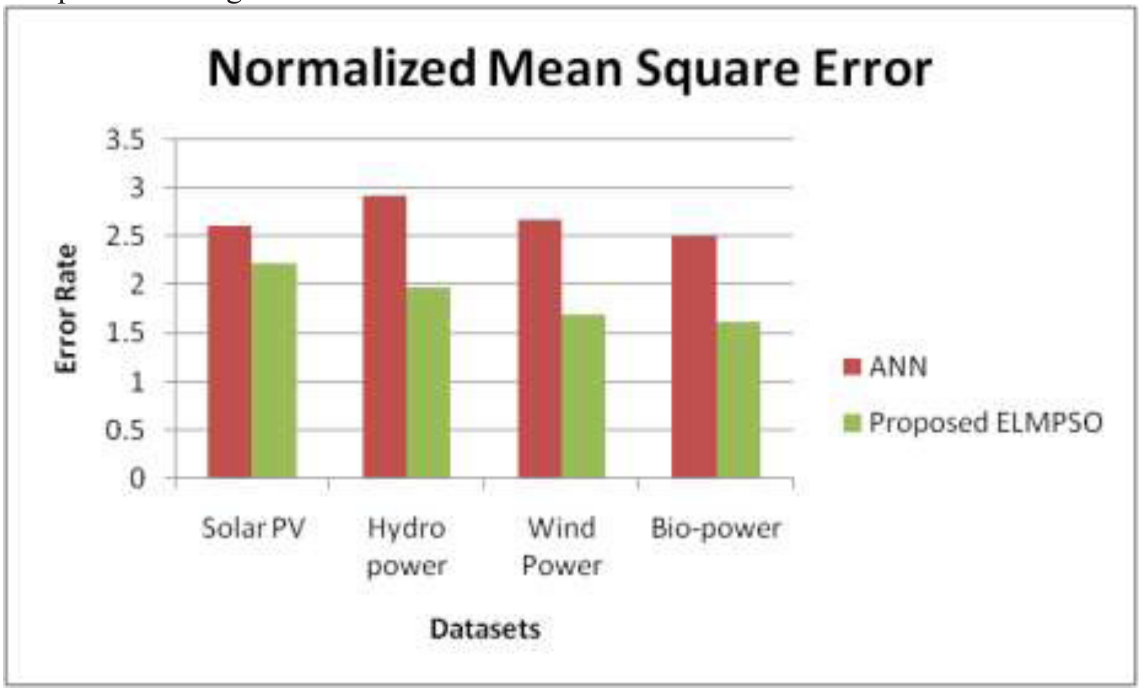

Figure 2.Comparison chart of Normalized Mean Square Error

The Figure 2 Normalized Mean Square Error demonstrates the different values of existing ANN and proposed ELMPSO. X axis denote the Dataset and y axis denotes the Error Rate. The existing algorithm values start from 2.51 to 2.68 and proposed ELMPSO values starts from 1.62 to 2.22. The proposed method provides the great results.

5. Conclusion

In this paper proposed an ELM-PSO approach for optimizing renewable energy management in smart grids. The proposed approach improves the accuracy of renewable energy prediction and reduces energy costs by optimizing the parameters of the ELM algorithm. The results show that the ELM-PSO approach outperforms other optimization techniques in terms of prediction accuracy and cost reduction. The proposed approach can be used in various renewable energy systems, such as wind turbines, solar panels, and hydroelectric power plants, to improve the efficiency and reliability of renewable energy utilization. The research contributes to the development of renewable energy management in smart grids and provides a promising solution for addressing the challenges of renewable energy utilization.

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