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A Machine Learning Based Approach for Estimating Renewable Energy Production

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ABSTRACT
With the every increasing severity of global warming, climate change and depleting fossil fuel reserves globally, it is imminent that the world would need to migrate towards renewable energy rapidly. As the population of the world increases, the energy consumption would also increase in accordance. Hence, it is necessary to estimate the amount of renewable energy would we can produce in future so as to estimate the magnitude increase in renewable energy to meet total energy demands of the future. This in turn necessitates the pattern recognition of the renewables to total primary energy supply (TPES), through regression analysis. While conventional statistical algorithms have been employed thus far for the purpose, with the emergence of machine learning and deep learning algorithms, better forecasting accuracies have been achieved. This paper evaluates the renewable energy scenario and its salient features and presents a machine learning based approach to forecast future renewable generation so as to aid meeting energy demands of the future through renewable energy sources. Different renewable energy sources have been analyzed such as wind, solar, biomass and hydro. The forecasting MAPE has been computed as the performance metric.

Keywords: Renewable Energy, to total primary energy supply (TPES), Machine Learning, Regression Analysis, MAPE.

I. INTRODUCTION

The urgency to migrate towards renewable energy sources has never been greater. As the world grapples with the consequences of climate change, dwindling fossil fuel reserves, and rising energy demands, the transition to sustainable and clean energy solutions is essential. Renewable energy sources such as solar, wind, hydro, and geothermal power offer viable alternatives that can help mitigate environmental damage, enhance energy security, and drive economic growth. One of the most compelling reasons to shift to renewable energy is its potential to significantly reduce greenhouse gas emissions. Unlike fossil fuels, which release large amounts of carbon dioxide and other pollutants into the atmosphere, renewable energy sources produce little to no emissions. This reduction in emissions can help combat climate change, decrease air pollution, and improve public health. By harnessing the power of the sun, wind, and water, we can create a cleaner and healthier environment for future generations.

Adopting renewable energy sources also provides a multitude of economic advantages. The renewable energy industry is a substantial contributor to job growth, offering employment prospects in the manufacturing, installation, and maintenance of renewable energy systems. Moreover, allocating funds towards renewable energy can result in decreased energy expenses over an extended period. Although the initial capital required for renewable energy infrastructure may be significant, the subsequent operational expenses are comparatively less, resulting in significant long-term cost savings. Moreover, renewable energy sources have the ability to stabilize energy prices, as they are not susceptible to the same market volatility as fossil fuels. Renewable energy improves energy security by broadening the range of available energy sources and decreasing reliance on imported fuels. Numerous nations are significantly dependent on imported petroleum and natural gas, rendering them susceptible to geopolitical conflicts and interruptions in supply. Countries can enhance their energy autonomy and durability by cultivating domestic renewable energy sources. Furthermore, renewable energy systems are frequently characterized by their decentralized and modular nature, which reduces their vulnerability to major failures and allows for faster recovery from interruptions.

The transition to renewable energy is propelling technological innovation and progress. Ongoing research and development in this subject are resulting in increasingly efficient and economically viable renewable energy systems. Technological advancements such as cutting-edge solar panels, high-performance batteries, and intelligent grid systems are revolutionizing the way we generate, store, and utilize energy. These technological improvements enhance the efficiency and dependability of renewable energy sources while also creating new opportunities. The adoption of renewable energy can significantly influence communities, particularly those located in distant and neglected regions. Renewable energy solutions that operate independently from the standard power grid, such as solar and wind power, can supply electricity to areas that do not have access to it. Access to clean energy can enhance the standard of living by providing power to residences, educational institutions, and healthcare facilities, thereby promoting social and economic progress. In addition, renewable energy projects that are owned by the community have the ability to give power to local residents, encourage energy democracy, and guarantee that the advantages of renewable energy are spread fairly. The rate of growth of renewable energy is shown in figure 1.

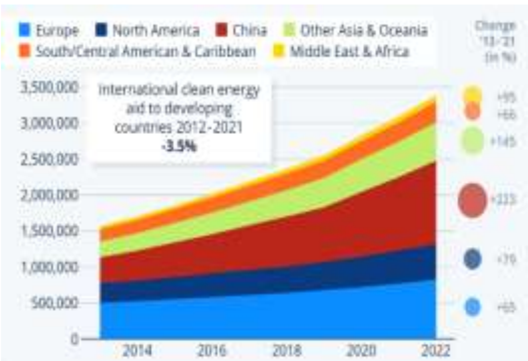

Fig.1 Global Renewable Growth Rate (Source: https://www.statista.com/chart/31091/renewable-energy-capacity-by-region/)

From figure 1, it can be observed that the renewable energy capacity around the world more than doubled in the 10 years between 2013 and 2022, a newly released report from the International Renewable Energy Agency has found.

However, progress has been quite lopsided, with large capacities having been built up in Europe and huge progress especially in the last decade happening in China. Other regions, namely South and Central America as well as the Middle East and Africa, have neither large capacity already built nor have they experienced above-average growth over the specified time period - creating the danger of being left behind in the global energy transition. International financial aid to developing countries in support of clean energy research, development and production having been cut down in 2021 to below 2012 levels is certainly not helping this issue.

Countries in Asia and Oceania other than China showed above-average growth of renewable energy as its capacity is now two-and-a-half times as big as it was in 2013. The region overtook North America in megawatts of renewable energy installed in the process, but given the continents' much larger population, it is safe to say that renewable energy progress in Asia has been relatively slower outside of China. The current progress in renewable energy installation means that in 2021, 27.8% of the world's electricity was created via renewable sources. This was only a slight 0.2% increase over 2020 as non-renewable energy production—conversely also a specialty of China—picked up more speed once again. Considering not just electricity, but all energy sources in the world, renewables' share shrinks once more to just 8% in 2022. This means that renewable energy still has a long way to go, especially in a 2030 net zero emissions scenario, as seen in data by the International Energy Agency (IEA).

II. RENEWABLE ENERGY INVESTMENTS AND ESTIMATION.

To completely migrate towards renewable energy, two major steps need to be taken:

- Estimating the amount of renewable energy which can be produced at the current rate.
- Estimate the amount by which the rate needs to be increased to meet future energy demands and invest in renewable energy infrastructure.

To estimate the amount of energy which can be produced, a typical regression analysis can be performed:

$$\mathbf{Energy\ Generation} = \mathbf{f(time, other\ govering\ variables} \quad \textbf{(1)}$$

While statistical models have been employed thus far, yet machine learning algorithms are proving to be more powerful in this regard in terms of forecasting accuracy.Accurate energy

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forecasting is crucial for maintaining the balance between energy supply and demand. Overestimating demand can lead to unnecessary energy production and wasted resources, while underestimating demand can cause energy shortages and grid instability. By leveraging ML models, utility companies and grid operators can make more precise predictions, minimizing these risks and optimizing energy production and distribution.

The integration of renewable energy sources, such as solar and wind, into the energy grid presents unique challenges due to their intermittent nature. ML models can address these challenges by forecasting not only the energy demand but also the availability of renewable energy. By predicting fluctuations in renewable energy production, grid operators can better manage energy storage systems and backup power sources, ensuring a steady supply of electricity even when renewable generation is low.

Moreover, the need to invest in renewable energy infrastructure is paramount for achieving environmental sustainability, economic growth, energy security, technological innovation, and social development. As we face the dual challenges of climate change and resource depletion, prioritizing renewable energy investments is not only a prudent choice but an urgent necessity. By committing to renewable energy infrastructure, we can build a cleaner, healthier, and more prosperous future for all.The primary environmental imperative for investing in renewable energy infrastructure is the urgent need to reduce greenhouse gas emissions. Fossil fuel-based energy production is a major contributor to global warming and environmental degradation. Renewable energy sources such as solar, wind, hydro, and geothermal power produce little to no emissions, offering a cleaner alternative that helps mitigate climate change. By investing in renewable infrastructure, we can significantly reduce our carbon footprint and protect natural ecosystems. Figure 2 shows the investments in renewable energy infrastructure by both developing and developed countries.

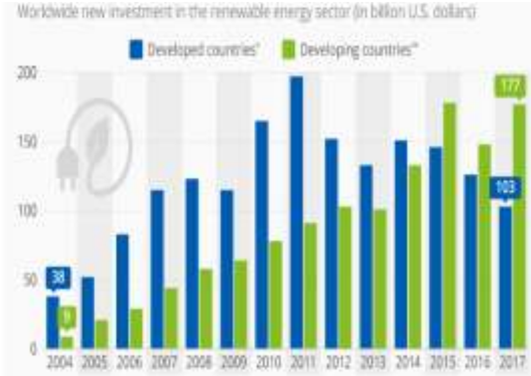

Fig.2 Investments in Energy Infrastructure (Source: https://www.statista.com/chart/13491/worldwide-new-investment-in-the-renewable-energy-sector/)

The share of energy extracted from renewable sources worldwide increased year-over-year from 11 percent to more than 12 percent in 2017. According to a report by the Frankfurt School of Finance & Management and the United Nations Environment Programme (UNEP), this amounts to 1.8 gigatonnes less carbon dioxide released into the atmosphere. Also, total investment in this sector rose by two points to close to $280 billion in 2017. As our infographic shows, developing countries first overtook the developed countries in 2015. Last year the gap grew to $74 billion.

III. PROPOSED METHODOLOGY

As the data to be analyzed exhibits high variability and dependence on several socio-economic and political factors, hence it is imperative to design an appropriate machine learning model to fit the data accurately.

The proposed methodology presents an amalgamation of the following two approaches:

1. Particle Swarm Optimization (PSO)
2. Artificial Neural Networks (ANN)

Each of the approaches are explained next.

The PSO:

The PSO algorithm is an evolutionary computing technique, modeled after the social behavior of a flock of birds. In the context of PSO, a swarm refers to a number of potential solutions to the optimization problem, where each potential solution is referred to as a particle. The aim of the PSO is to find the particle position that results in the best evaluation of a given fitness function. In the initialization process of PSO, each particle is given initial parameters randomly and is 'flown' through the multi-dimensional search space. During each generation, each particle uses the information about its previous best individual position and global best position to maximize the probability of moving towards a better solution space that will result in a better fitness. When a fitness better than the individual best fitness is found, it will be used to replace the individual best fitness and update its candidate solution according to the following equations:

$$\mathbf{v_{id}(t) = w \times v_{id}(t-1) + c_1 Ø_1 (p_{id} - x_{id} (t-1)) + c_2 Ø_2 (p_{gd} - x_{id}(t-1))} \quad \textbf{(2)}$$

$$\mathbf{x_{id}(t) = x_{id}(t-1) + v_{id}(t)} \quad \textbf{(3)}$$

Table. 1 List of variables used in PSO equations.

v	The particle velocity
x	The particle position
t	Time
c_1,c_2	Learning factors
Φ_1 ,Φ_2	Random numbers between 0 and 1
p_{id}	Particle's best position
p_{gd}	Global best position
w	Inertia weight

The PSO is used to adaptively update the weights of the neural network based on the minimization of the performance function.

The ANN Model:
The ANN model is one of the most powerful regression models which has been used multiple times for traffic speed forecasting.
The mathematical model of the ANN is depicted in figure 1.

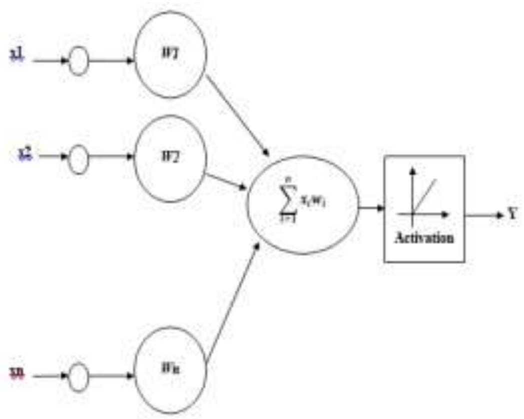

Fig.3 Mathematical Model of Neural Network

The output of the neural network is given by:

$$y = f(\textstyle\sum_{i=1}^{n} \mathbf{XiWi} + \Theta) \quad \textbf{(4)}$$

Where,
Xi represents the signals arriving through various paths,
Wi represents the weight corresponding to the various paths and
Θ is the bias.

In this approach, the back propagation based neural network model has been used.A backpropagation neural network for traffic speed forecasting typically consists of an input layer, one or more hidden layers, and an output layer. The number of nodes in the input layer corresponds to the features used for prediction, The hidden layers contain nodes that learn and capture the intricate patterns within the data, while the output layer provides the predicted traffic speed.The training of a backpropagation neural network involves the iterative application of the backpropagation algorithm. During the training process, historical data is used to feed the network, and the algorithm calculates the error between the predicted and actual energy demands. This error is then propagated backward through the network, adjusting the weights and biases of the connections to minimize the prediction error. This iterative process continues until the network converges to a state where the error is minimized.Successful backpropagation neural network models for traffic speed forecasting can be integrated into energy management systems.

The training is stopped based on the mean square error or mse given by:

$$\mathbf{mse = \frac{\sum_{i=1}^{n} e_i^2}{n}} \textbf{(5)}$$

The final computation of the performance metric is the mean absolute percentage error given by:

$$\mathbf{MAPE = \frac{100}{M} \sum_{i=1}^{N} \frac{E - E_i|}{i}} \textbf{(6)}$$

The accuracy of prediction is computed as:

$$\mathbf{Ac = 100 - \frac{100}{M} \sum_{i=1}^{N} \frac{E - E_i|}{i} \%} \quad \textbf{(7)}$$

Here,
n is the number of errors
i is the iteration number
E is the actual value

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E_i is the predicted value

IV. RESULTS AND DISCUSSIONS

The regression model has been simulated on MATLAB. The wind, solar, biomass and hydro datasets have been analyzed through the designed ANN model which are presented next:

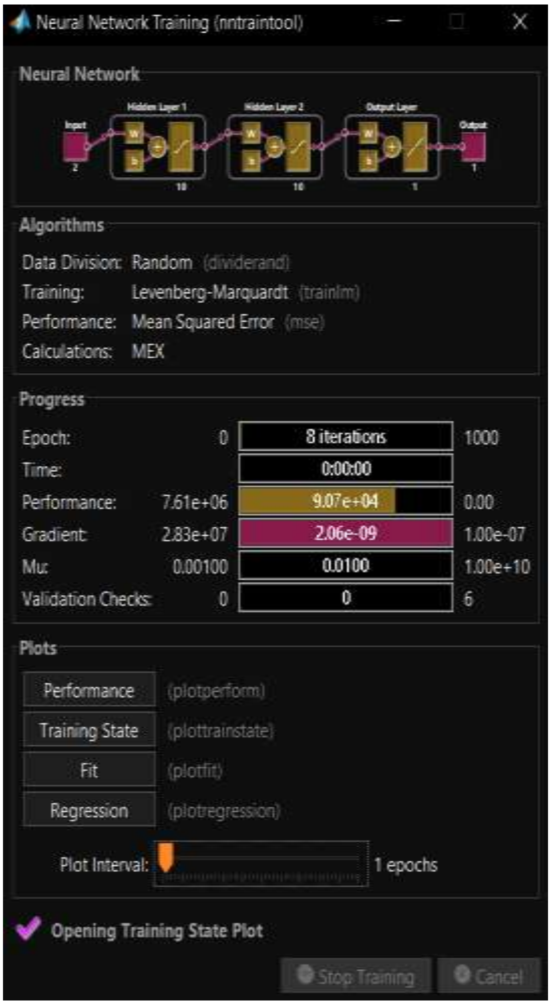

Fig.4Model Design Parameters

The details of the training are depicted in the figure above, which clearly shows the designed neural network, the training function, the data division and the iterations.

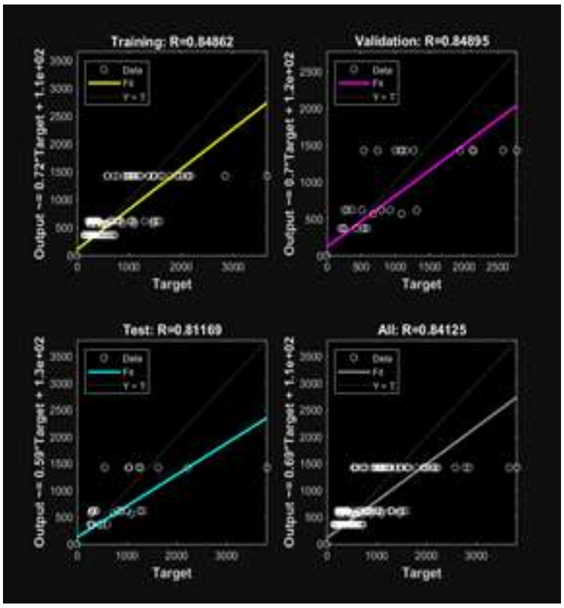

Fig.5 Regression

The figure above depicts the regression obtained in the proposed approach which is a sort of similarity among two random variables. The maximum allowable regression is unity depicting complete similarity.

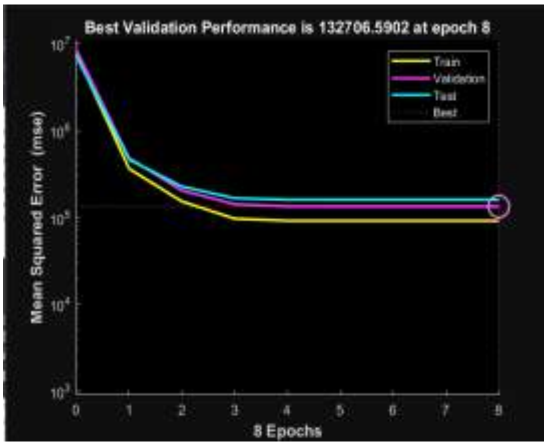

Fig.6 Performance Function

The performance function that decides the culmination of training is the mean squared error or mse.

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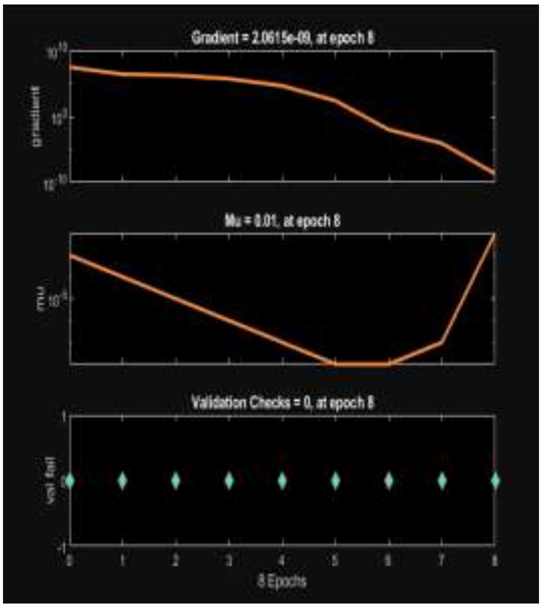

Fig.7Training States

The training state parameters such as gradient, combination co-efficient and validations checks are depicted in the figure above.

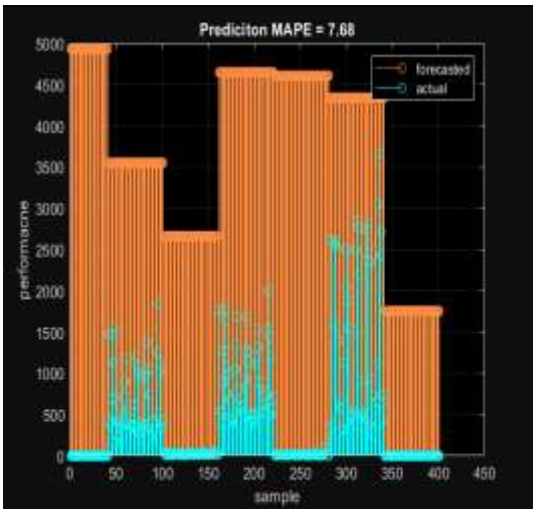

Fig.8 Actual and Modelled values (wind)

The actual and forecasted values for wind energy are depicted in figure above which attains an MAPE of 7.68%.

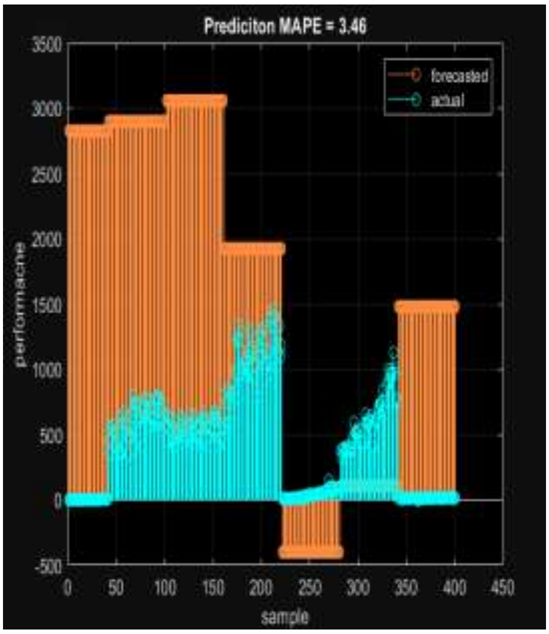

Fig.9 Actual and Modelled values (solar)

The actual and forecasted values for solar energy are depicted in figure above which attains an MAPE of 3.46%.

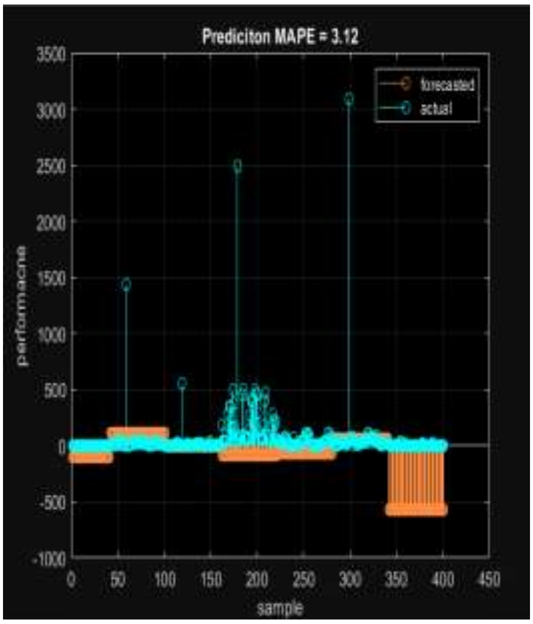

Fig.10 Actual and Modelled values (hydro)

The actual and forecasted values for hydro energy are depicted in figure above which attains an MAPE of 3.12%.

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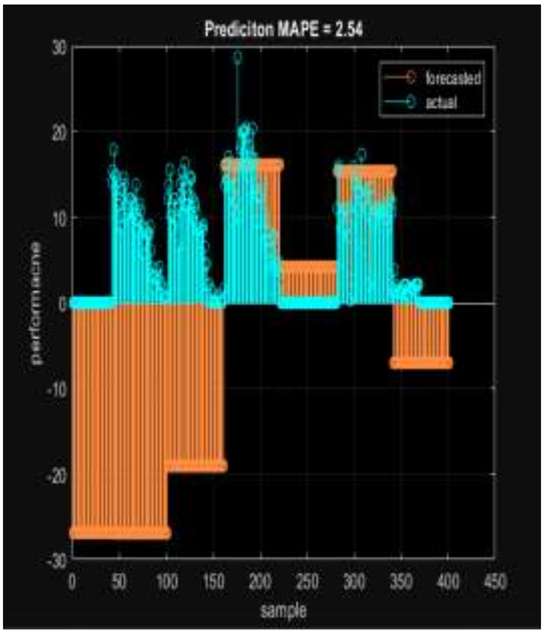

Fig.11 Actual and Modelled values (biomass)

The actual and forecasted values for biomass energy are depicted in figure above which attains an MAPE of 2.54%.

Table. 2Summary of Results

S.No	PARAMETER	VALUE
1.	Energy Types	Wind, solar, biomass, hydro
2.	Proposed Model	PSO-ANN
3.	Iterations	8
4.	R^2 value	0.84125
5.	MAPE (wind)	7.68%
6.	MAPE (solar)	3.46%
7.	MAPE (hydro)	3.12%
8.	MAPE (biomass)	2.54%

The summary of results is presented in table 2. Theperformance of the proposed approach attains MAPE values of 7.68%, 3.46%, 3.12% and 2.54% for wind, solar, hydro and biomass respectively.

V. CONCLUSION

From the previous discussions, it can be concluded that with increasing population, higher energy demand and drastic climate changes, it is mandatory to migrate towards renewable energy sources rapidly. This in turn needs an accurate estimate of the energy demands in future and also the renewable energy generation capacity so as to match the demand and supply. While several statistical techniques have been employed thus far for forecasting problems, machine learning models happen to exhibit higher forecasting accuracy compared to conventional techniques. This paper presents a PSO-ANN hybrid model for forecasting renewable energy generation. It has been shown through the results that the proposed work attains an MAPE values of 7.68%, 3.46%, 3.12% and 2.54% for wind, solar, hydro and biomass respectively.Thus, the proposed model with high accuracy can be employed for renewable energy forecasting to estimate increase or adjustments in present generation rates to meet all energy demands through renewable energy sources in future.

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