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A Parametric Study to Predict Wind Energy Potential from Neural Network

Newsha Valadbeygi
Department of Mechanical Engineering
Karaj Islamic Azad University
Karaj, Alborz, Iran

Abstract:- The assessment of wind energy potential is a topic that has not yet been thoroughly explored. The complex nature of wind potential makes it challenging to predict and evaluate. To address this issue, researchers have proposed various methods, including the use of artificial intelligence and algorithms. In this study, experimental data on wind energy conversion system performance was utilized to develop a new model based on neural networks. Specifically, a CNN-type neural network was employed due to its high capacity. Three different artificial neural network architectures were designed, trained, and evaluated for wind speed prediction. The proposed neural network model was validated by comparing it with experimental data, allowing for the prediction and analysis of wind energy conversion system performance and trends. The results indicate that the proposed model demonstrates a low error percentage (ranging from 1 to 0.97) in predicting the increasing efficiency of the wind energy conversion system, suggesting its strong alignment with the real model and network efficiency.

Keywords:- *Maximum Power, Wind Energy Conversion, CNN Neural Network.*

I. INTRODUCTION

The performance of wind energy conversion systems is a crucial factor that directly impacts their power generation capacity. The cooling capacity of these systems is particularly important, as it can significantly affect their overall efficiency. The efficiency of cooling is highly sensitive to environmental conditions, especially when crosswinds are present. However, the conventional design of cooling towers has largely overlooked the influence of crosswinds, despite their prevalence. Therefore, it is imperative to investigate the impact of crosswinds on heat transfer performance and the overall performance of wind energy conversion systems. Given the current global energy situation, there is a recognized need to shift towards sustainable energy systems and explore renewable energy sources to enhance energy security and improve environmental conditions. The investigation of wind energy conversion system performance has always been an attractive research area, as it provides valuable data for predicting and enhancing functional efficiency. The calculation of efficiency and performance is a critical aspect in equipment provision, and researchers have proposed various algorithms and methods to address this issue. However, the abundance and diversity of data, as well as the variety of design methods, pose challenges for researchers in this field. To overcome these challenges, various algorithms have been employed for statistical analysis, trend prediction, and performance evaluation. In light of the energy crises and environmental impacts associated with conventional power systems, researchers worldwide are increasingly focusing on the evaluation and modeling of renewable energy sources. This study introduces a novel control strategy for achieving maximum power point tracking in a wind energy conversion system based on a dual-fed induction generator (DFIG). The proposed strategy utilizes neural networks and fuzzy logic controllers to regulate power transfer between the machine and the network, employing indirect vector control and reactive power control techniques. Additionally, this paper demonstrates the application of artificial neural networks (ANN) in predicting the thermal performance of a cooling tower under crosswind conditions. A laboratory test was conducted on a model tower of a natural counterflow wet cooling tower to gather sufficient data for training and prediction purposes [1]. Wind energy has emerged as a significant source of renewable energy, necessitating the development of more intricate wind energy conversion systems. Consequently, novel methodologies grounded in advanced analysis are imperative [2]. This study utilizes data obtained from the Fort Davis Wind Farm, operated by Central and Southwest Services in the United States, to construct a predictive model for the power output of individual turbines using a neural network approach [3]. This paper presents a novel approach to short-term wind power prediction for a wind farm through the utilization of neural networks trained on historical wind speed and wind direction data. The forecasting process consists of two distinct stages [4]. The wake effect poses a significant and intricate challenge within the wind power sector. Employing wake steering techniques, such as the manipulation of wind turbine yaw angles, has been established as an effective strategy to mitigate the adverse effects of wake interactions and enhance the overall power generation of a wind farm [5].This paper introduces an enhanced algorithm that utilizes a finite element neural network (IENN) to achieve optimal control of wind energy by accurately tracking the maximum power point. The authors propose the development of an online training IENN controller, which incorporates a backpropagation (BP) learning algorithm along with a modified particle swarm optimization (MPSO) technique to facilitate step tuning for power regulation [6]. Many countries have adopted a national policy of promoting a clean environment through the reduction of fossil fuel-based energy and the increased utilization of renewable energy sources, such as wind and solar energy. This has led to a growing interest in the economic and technical challenges related to integrating wind energy into power grids [7]. Currently, there is a growing prevalence of renewable energy systems in comparison to conventional energy systems. Specifically, photovoltaic (PV) systems and wind energy conversion systems (WECS) have emerged as significant contributors to meeting global energy demands [8]. This article investigates and contrasts the utilization of regression models and artificial neural networks for the estimation of wind turbine power curves. Initially, the attributes of wind turbine electricity generation are analyzed [9].This paper introduces the conceptualization and development of an online training fuzzy neural network (FNN) controller, equipped with a high-performance speed monitor, specifically designed for an induction generator (IG) [10]. Accurate prediction of wind power is crucial for the effective management and upkeep of wind power conversion systems. The forecasting of offshore wind energy poses additional difficulties due to the complex multimodal systems and harsh operating conditions [11]. In this study, data pertaining to the performance of cooling towers under different conditions was gathered. These data were utilized in multiple neural network design procedures, resulting in the development of a deep learning-based neural network. This neural network was subsequently employed to forecast the performance of cooling towers. To assess the efficacy of the proposed neural network, a comparison was made between the results obtained from the designed neural network and those obtained from experimental examples. The outcomes of this comparison provide evidence supporting the effectiveness of the proposed system in predicting the performance of cooling towers.

II. WIND ENERGY CONVERSION SYSTEM

Wind energy is widely recognized as a promising alternative to traditional electricity generation methods due to its significant environmental, social, and economic advantages. Unlike conventional energy sources, wind energy generation operates with distinct characteristics that impact the reliability of the power system in unique ways. This study focuses on the development of appropriate models for wind energy conversion systems to assess the adequacy of power production systems utilizing wind energy. These analytical models can be employed to evaluate the adequacy of conventional production systems through analytical mode sampling or Monte Carlo techniques. The research demonstrates that a five-mode wind energy conversion system model can provide a reasonable assessment of power system adequacy studies using either an analytical method or a mode sampling simulation approach.

The industrial growth of any nation relies on achieving a balance between energy production and consumption, which in turn depends on the availability of renewable and non-renewable energy sources. Non-renewable energy resources are depleting rapidly, particularly in less developed countries, leading to energy shortages. Furthermore, the use of fossil fuels for energy production has detrimental environmental effects, such as carbon dioxide emissions and subsequent environmental degradation. Therefore, the utilization of renewable energy sources not only reduces reliance on fossil fuels but also mitigates the risk of the greenhouse effect. Renewable energy sources are naturally replenished, providing an endless supply of environmentally friendly energy for humanity. Consequently, renewable energy has become a widely studied field and is rapidly replacing conventional energy sources.

According to the World Wind Energy Council (GWEC) (2014), Pakistan's economy is one of the fastest-growing economies that heavily relies on wind energy as its primary source of electrical power. The country's daily electricity consumption exceeds 20,000 megawatts, with an increase during the summer season. This results in a short-term deficit of 4500-5500 MW per day (National Power Policy, 2013). Given the vast land in Punjab and Khyber Pakhtunkhwa (KPK) and the long coastal belt in Sindh and Balochistan, wind power generation in Pakistan holds significant potential. The Pakistan Meteorological Department (PMD) and the Alternative Energy Development Board (AEDB) are actively engaged in various projects to assess the wind potential of different locations across the country. Accurate estimation of wind potential at specific sites necessitates a comprehensive understanding of the wind characteristics. This has prompted researchers worldwide to conduct studies utilizing short-term and long-term wind speed data and appropriate mathematical functions and distributions to model the measured wind speed data. These efforts provide reliable estimates of wind power potential at specific sites, facilitating efficient planning and installation of wind farms. The Weibull function, a two-parameter statistical distribution function proposed by Waloddi Weibull (1951), is commonly employed to fit wind speed measurement data (Justus et al., 1978, Rehman et al., 1994, Shoaib et al., 2017a, Shoaib et al., 2017b). Islam et al. (2011) utilized a two-parameter Weibull function to assess the wind energy potential of Koudat and Labuan from 2006 to 2008. The maximum wind energy recorded in Kodat in 2008 was 590.40 kWh/m2 per year. In 2007, the highest wind speeds corresponding to the maximum energy calculated in Labuan and Kodat, Malaysia were 2.44 m/s and 6.02 m/s, respectively. The study concluded that these locations are suitable for small-scale wind energy production. Supian et al. (1995) conducted an analysis of wind speed data from ten stations over a ten-year period from 1982 to 1991 in Malaysia. The data was fitted to the Weibull function, revealing that Mersing exhibited the highest wind energy potential with an average power density of 85.61W/m2, using wind speed measurements taken at a height of 10 meters. Garcia et al. (1998) employed Weibull and Lognormal models to fit hourly mean wind speed data. Fit tests were conducted using R2 and non-linear regression methods for both models, with the Weibull model proving superior to the lognormal model. Seguro et al. (2000) investigated wind characteristics by modeling wind speed data using the Weibull function. The study demonstrated that the Maximum Likelihood Method (MLM) performed better for time series wind speed data, while the Method of

Moments with Maximum Likelihood Estimation (MMLM) performed better for wind speed data in frequency distribution format. Isaac et al. (2000) calculated the probability density function using the two-parameter Weibull function for mean hourly wind speed data measured over a 30-year period in the offshore area of Hong Kong. The estimated values of the shape and scale parameters varied widely, ranging from 1.63 to 2.03 and 2.76 to 8.92 m/s, respectively. Suleiman et al. (2002) and Dorvlo (2002) analyzed wind speed data collected at four stations in Oman using the Weibull distribution function. Carta et al. (2009) developed various probability density functions to describe different wind regimes, such as zero winds, unimodal, bimodal, bitangent regimes, and so on. The goodness of fit of the distribution function was assessed by estimating the R2 test.

III. ARTIFICIAL NEURAL NETWORKS

To obtain an accurate and realistic analysis of cooling tower components and to predict the performance of different systems, the utilization of neural networks proves to be a suitable and efficient approach [1]. By incorporating recently extracted data, the neural network can be designed to estimate a logical process. By comparing and analyzing the results obtained with previous samples, the effectiveness of the proposed system can be enhanced. This process involves a comprehensive examination and analysis of all results using various tools, including software and mathematical analysis, to ensure thorough validation and enable confident continuation of the analysis. One suggested method for analysis and prediction is the application of artificial intelligence and neural networks, which are widely used in various fields. These systems consist of multiple layers and neurons. Each layer contains several nodes, where calculations are performed. Within each node, the input data is multiplied by a weight, with the weight determining the impact of the data. The sum of the data multiplied by their respective weights is then calculated. Finally, the obtained sum passes through an activation function to produce the output. The complexity of the model increases with the number of layers and neurons. Figure 1 illustrates the schematic structure of a neural network.

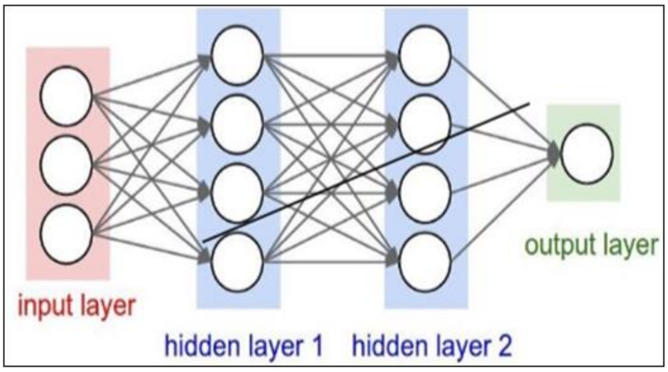

Fig 1 Schematic of Neural Network Structure

The neural network communicates information through numerical outputs, which are determined by the weights that were adjusted during the training process. In the given example, the network learns by analyzing various samples of past bank customers and modifying the weights accordingly. If the network determines that an individual is likely to repay a loan, it generates a number greater than 10 (which is then transformed to +50 through the activation function). Conversely, if the network determines that an individual is unlikely to repay the loan, it produces a number less than or equal to 10 (which is then transformed to -50 by the activation function).

IV. DATA INFORMATION

In the first step of the network design, the experimental data are completely classified and to start the design process, they are classified into two categories: input data and target data. Table 1 shows the type of experimental data used in the network structure [1]. The data used in the neural network design process are derived from [benchmark articles, neural network].

Table 1 Neural network data

Input Variable	Target Variable
Lat. Long. Alt. P T RH%	WS

V. CNN NEURAL NETWORK

Over the course of time and advancements in technology, Convolutional Neural Networks (CNNs) have significantly influenced the field of computer vision, particularly in the realm of image understanding. They have essentially replaced traditional image representations found in libraries. A CNN architecture is composed of multiple steps or blocks, each consisting of four main components: a kernel, a convolution layer, a nonlinear activation function, and an integration or subsampling layer. The objective of each step is to represent the features as a collection of arrays known as feature maps [21-23]. Although CNNs are typically created by combining basic linear and nonlinear filtering operations, their implementation is not straightforward.

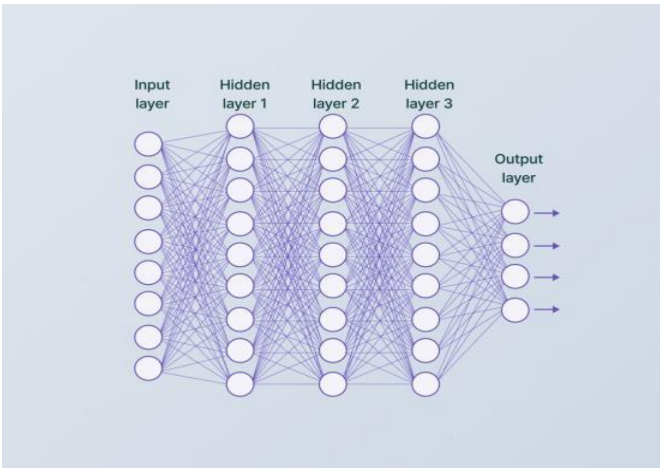

Fig 2 CNN Neural Network

In the context of image processing, a filter bank or kernel is employed to identify distinct features at various input locations. Consequently, the spatial translation of the input from a layer dedicated to feature detection remains unaltered in the output. Each convolution layer contains a collection of m1 filters, and the output Y(l) in layer l comprises m(l) 1 maps with dimensions m(l) 2 and m(l) 3. The calculation of the ith feature map is as follows:

$$Y_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{m_1^{(l-1)}} K_{ij}^{(l)} * Y_j^{(l-1)} \quad \text{(Eq.1)}$$

Convolution Layer: The convolution operation is a commonly employed technique in the field of digital image processing. It involves convoluting a two-dimensional matrix, which represents the image (I), with a smaller two-dimensional kernel matrix (K). This process yields a mathematical formula that corresponds to layer zero.

$$S_{i,j} = (I * K)_{i,j} = \sum_m \sum_n I_{i,j} \cdot K_{i-m,j-n}. \quad \text{(Eq.2)}$$

Non-linear activation function: Following the generation of the output filter bank, an application of a non-linear activation function (Equation (1)) results in the production of activation maps. These maps exclusively transmit the activated features to the subsequent layer. The activation function, denoted as f(), plays a crucial role in determining the output characteristics of the neuron.

$$\phi(Y_i^{(l)}) = f\left(B_i^{(l)} + \sum_{j=1}^{m_1^{(l-1)}} K_{ij}^{(l)} * Y_j^{(l-1)}\right) \quad \text{(Eq.3)}$$

Convolutional Neural Networks (CNNs) are widely used in image processing tasks due to their ability to efficiently process large amounts of data, such as millions of images. To facilitate this, there are numerous machine learning, deep learning, and open-source CNN libraries available. These libraries are well-supported, with active contributors and large user bases [21-28].

A CNN is a tool that takes in information, like a picture, and gives out a result. It does this by putting together a series of computer blocks or layers, called fL. One of the layers is called the convolution layer. It helps to make the network smaller by making the convolution outputs smaller. Furthermore, combining information in CNNs helps create a reliable way to represent minor changes in the input. Below are two common ways of combining or merging things together. An example of this combining process using a 2-2 filter can be seen in Figure [21-27]. CNNs can be used to identify or categorize things or predict values. They have many connections that make them more flexible than older models based on weight. Additionally, CNNs naturally have a certain level of insensitivity to changes in position or location. This type of neural network believes that filters can be learned from data to find features that describe the inputs. The main idea here is about analyzing two-dimensional data and complexity. This idea can also be used for data with more dimensions without much difficulty. Convolutional layers are sometimes used with subsampling layers to make calculations faster and give more details about the shape and arrangement of objects. Invariance means that something stays the same, and does not change. Overall, we have:

$$\mathbf{x}_j^{\ell} = f\left(\sum_{i \in M_j} \mathbf{x}_i^{\ell-1} * \mathbf{k}_{ij}^{\ell} + b_j^{\ell}\right), \quad \text{(Eq.4)}$$

Estimation models, also called estimators, use measured data as input variables for their estimation purposes. In any estimation model such as supervised prediction models, a training step is involved which helps the model to learn from a set of training examples. In this section, more specialized explanations are provided regarding the method of implementing networks, and the type of network operator. Using the MATLAB program and using the Convolutional Neural Network (CNN) training process, samples of the same cases are used with the effect of the threshold factor.

- *CNN Neural Network Modeling*

We used a toolbox called CNN generation in MATLAB to create the VGG model. The previous three sections explain how MsCNN works and what it does to the input data when classifying. This part of the text gives an explanation of how the original AlexNet CNN was trained and how it was modified into an MsCNN for classifying anomalies in powder beds. The original image was classified using the K-MEANS clustering algorithm. Here are only the training settings that the authors used for transfer learning. To learn more about the training of CNN's AlexNet, you can read pages 26 to 28. The training process makes the different parts of a neural network work better together to make accurate predictions that match the given labels. The backpropagation algorithm is commonly used to teach neural networks. The process of training with postrelease goes like this: defining the CNN architecture. This means deciding how many layers there will be, what type each layer will be, and how big and how many filters each layer will have. The way buildings are designed always relies on the reason for their use. The loss function is used to see how well the network's predictions match the actual labels that we know are true. Usually, we use the mean squared error function, which is defined as:

$$L = \sum (target - output)^2 \quad \text{(Eq.5)}$$

Therefore, to find the contribution of each weight and optimize them, L should be minimized. The gradient descent algorithm is widely adopted for the minimization method, which is expressed mathematically as the partial derivative of the loss function. Then, the parameter update process is formulated as follows:

$$W_k = W_{k-1} - \alpha * \frac{\partial L}{\partial W}, \quad \text{(Eq.6)}$$

Where "a" is the rate at which learning occurs. So, the learning rate is really important and needs to be decided before we begin training. It is important to mention that when the learning rate is lower, the result will be more accurate. However, the training of the network may take longer. The information we have is split into three groups: training set, validation set, and test set. The training set helps the network learn, the validation set helps us check how well the model is doing while training, and the test set helps us evaluate the final trained model. Most CNN models need the training data to have the same size or dimensions. So, before starting the training process, we need to prep the data. This means making the data consistent and ready for analysis. Transfer learning is when we take a pre-trained deep learning network and tweak it so it can learn a new task. Creating new CNNs for each task and training them from scratch can take a long time to achieve the best setup. That's why we can use a pre-trained network for learning new patterns with new data. It's helpful when we don't have enough information to train the network. So, we use a model that has already been trained on a dataset that works well for the job we want to do. The main idea is to keep some layers of the pre-trained network unchanged and usually only change the input and output layers. There are many ready-to-use models that we can use. Some well-known architectures like LeNet-5, AlexNet, VGG, GoogLeNet, and ResNet are used a lot. Furthermore, scientists and engineers contribute various Convolutional Neural Network (CNN) models to the Caffe Model Zoo. These models have gained knowledge from tasks like simple regression, large-scale visual classification, image similarity, speech, and other applications. The training of CNN involves a process called backpropagation. First, all the values of all the parts in a CNN are set randomly. Although not directly mentioned before, the weights are just the values of the components that form a filter or kernel. During the forward transfer step, the training data goes through the depth of the CNN. At the beginning, the classification performance will be low because the kernel weights are random. Luckily, the training data has been labeled by humans with true classifications, so we can measure how well the trained CNN performs. In the previous part, we learned that the output of the softmax layer is a small set of numbers between 0 and 1, and when you add them up, they equal 1. So, the answer that the computer gave for a patch of images with streaks is [0,0,1,0,0,0]. The difference between the intended softmax output and the softmax output of a CNN model that has not been trained can be measured using different ways. The mistake or loss depends on the group of weights Ω. Figure displays a picture that shows how we measure the amount of error in a simplified situation where we only have two weights. From the data we collected, we used 70% of the pictures to train our model and the other 30% to test it. In the training process, we use ReLU as the activation function instead of tanh because ReLU is considered to be better.

$$\mathrm{ReLU}(x) = \begin{cases} x & \text{if } x > 0, \\ 0 & \text{if } x \leq 0. \end{cases} \quad \text{(Eq.7)}$$

Table 2 Important Parameters

Parameters	Settings
MiniBatchSize	20
nitialLearnRate	0.001
Shuffle	Every-epoch
ValidationFrequency	20
ExecutionEnvironment	CPU

After creating the network as described earlier, we got a regression diagram that shows a really good and precise result [21-28].

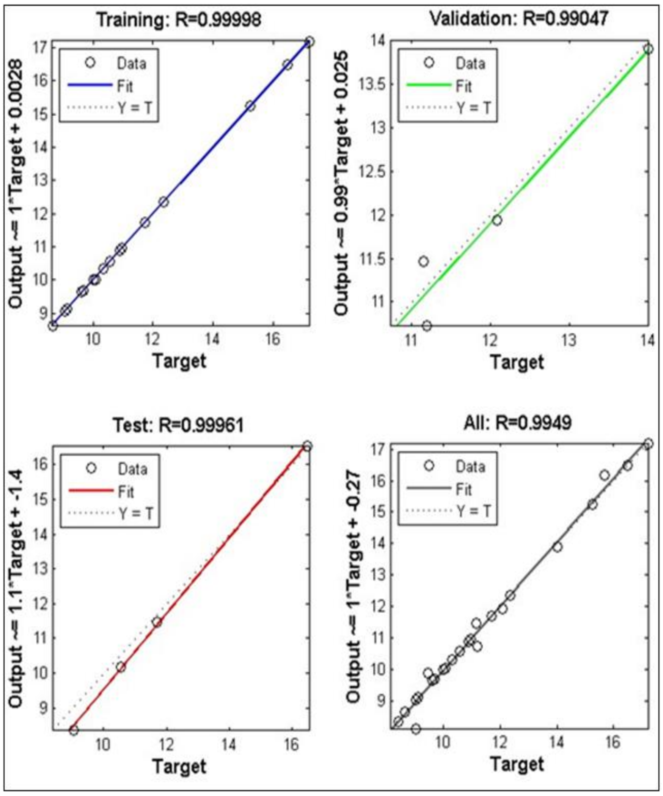

Fig 3 CNN Neural Network Regression

VI. ANALYSIS AND REVIEW OF RESULTS

In the experimental paper, a better prediction of the wind potential has been done using the generalized feedforward with backpropagation neural networks. The effect of three meteorological parameters (pressure, relative humidity, and temperature) on wind speed forecasting in the southern states of India has been investigated. [1] But in the new work, focusing on building a new type of network using data from Iran, we tried to compare two types of networks to find out the efficiency of the networks with the conclusion. The CNN neural network is a high-precision network that can produce very favorable results if designed carefully. In the experimental example to evaluate the developed artificial neural network model for test locations, the mean absolute percentage of error and the mean squared error have been calculated. It was found that the model with relative humidity as an input parameter and having six neurons in the hidden layer predicts the wind speed better. The correlation coefficients are higher than 0.96 and the average absolute percentage of error and the average squared error of all test locations are less than 2.5 and 0.0176, respectively, which indicates the high reliability of the model for predicting wind speed in the study area. Forecasted wind speeds are analyzed to create monthly average maps using geographic information system technology. In other words, in the experimental sample, the final result is stated by expressing a number, and therefore the ANN training database was expanded to include experimental data from two independent studies. The ANNs trained with the hybrid database showed satisfactory results and were superior to the power-law algebraic correlations developed with the hybrid database. But in the new work, using laboratory data and verification with software, and finally comparing with the new network, much more relevant results have been obtained with an efficiency of over 90%.

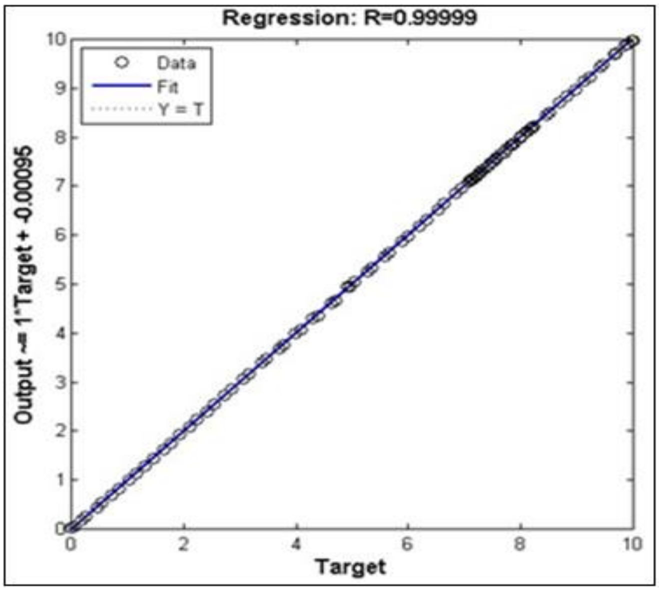

Fig 4 CNN Overall Regression

To know the accuracy of the results as well as the experimental data, various software should be used. In this section, the amount of prediction of wind speed and thermal data obtained from the model obtained from the neural network has been compared with the results obtained from experimental calculations. The results of experimental calculations using heat transfer relations and evaluation based on global standards using Energy software are presented in Table 4.

Table 3 Overall Results

ANN	**1 - 0.997**
CNN	1 - 0.998

The final results of the CNN network are shown in Table 5, which shows the high accuracy of the network and more accurate prediction compared to the experimental article. The final result of the deep learning network is shown in Figure 5. The final results with higher convergence and more ideal results show that the designed network is much more favorable than the experimental sample and has predicted very good final output data. MSE and final regression results can be seen in the pseudo-neural output section.

Table 4 Function Parameters

	Samples	**MSE**
Training	25	8.75844e-0
Validation	5	5612980.97816e-0
Testing	5	2584421.93763e-0

It is noteworthy that in the experimental sample, the final number for predicting heat transfer with a low convergence level is shown as 0.99878. But in the new results obtained with a very high convergence and several 0.9999, very favorable results have been obtained, which compared to the results of the software, one can realize the high efficiency of the network performance to accurately predict the data in the output stage. Neural network results:

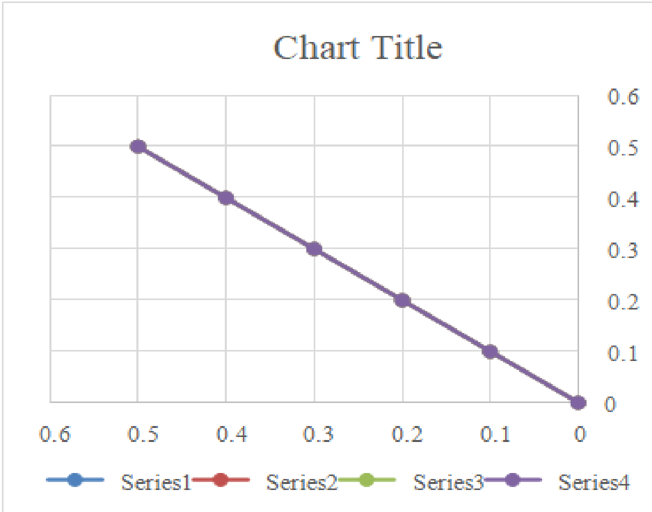

Fig 5 The Result of the Neural Network

VII. CONCLUSION

In this research, a mathematical model based on CNN neural network was presented to predict the process of wind energy conversion. In this regard, all the details related to the design of the neural network structure were stated. Based on this, a network consisting of 9 neurons and a hidden layer, based on the Lunberg-Markar learning algorithm, was built with a distribution percentage of 60, 20, and 20, respectively, for training, verification, and testing. The performance of the neural network was presented in the form of a regression diagram. After that, it was obtained by using the relationships and standards of the field of design of functional systems in the performance of wind energy conversion. The results obtained from these calculations were compared with the results obtained from the neural network. [1] Based on this comparison, the proposed neural network of this research has predicted the annual performance on the surface with an error of nearly 4% and the total annual performance with an error of 2%, which indicates the high accuracy of the proposed system and high efficiency. It is. In addition, the results obtained from this research in comparison with the results from research [1] indicate the superiority of the proposed neural network over the model presented in research [1] which has an almost similar structure. By examining all aspects, the effectiveness of the proposed neural network in predicting wind energy conversion performance is definite.

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