Wet Cooling Tower Heat Transfer and Function Prediction using MLP Neural Network

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Abstract:- Calculating and predicting the performance of cooling towers has posed a significant challenge for researchers in this field. Over time, various methods, including the utilization of artificial intelligence and algorithms, have been proposed to address this issue. In this study, experimental data pertaining to cooling tower performance has been employed to develop a novel model based on neural networks. The objective is to predict the performance of cooling towers and analyze performance trends in this particular type of structure. To achieve this, a multi-layer perceptron neural network is utilized due to its high capacity, with real data serving as input. Subsequently, the efficiency of the neural network model is assessed by comparing the results with real-world samples. The validation process involves predicting cooling tower performance, examining performance trends, and analyzing tower behavior under windy conditions.

Keywords:- *Cooling Tower Performance, Functional Prediction, Multilayer Perceptron Neural Network.*

I. INTRODUCTION

Coolers or humid cooling towers are commonly utilized to increase humidity in the air and convert dry air into saturated air. This process aims to achieve an output temperature that closely matches the wet bulb temperature. Cooling towers are essential components in power plant cooling systems, as their efficiency directly impacts the overall power generation capacity. Environmental conditions, particularly crosswind conditions, significantly affect cooling efficiency. However, the impact of crosswind on conventional cooling tower designs has received limited attention. Researchers have been actively investigating cooling tower performance to develop efficient processes for predicting and enhancing tower functionality. The calculation of efficiency and performance is crucial in equipment provision, and researchers have proposed various algorithms and methods to address the challenges posed by the large volume and diversity of data and design methods in this field [1]. This study focuses on the application of artificial neural networks to predict the thermal performance of a cooling tower under crosswind conditions. A laboratory experiment was conducted on a model tower to collect sufficient data for training and prediction [2]. The use of artificial neural networks for predicting the thermal performance of a cooling tower in crosswind conditions was investigated in another study, which also involved a laboratory test on a wet cooling tower against natural flow to gather data for training and prediction [4]. The study analyzed an unfilled cooling tower, known as a shower cooling tower, due to the impracticality of using tower packing in applications where salt deposition and subsequent blockage occur [5]. A model based on a wavelet neural network was developed to predict the performance of the shower cooling tower, and data from an experimental shower cooling tower under steady-state conditions were used to train and test the proposed model [6]. Another study focused on predicting the performance characteristics of a cooling tower with reversible use under cross flow conditions for a heat pump heating system in winter using artificial neural network techniques [7]. The thermal performance evaluation of a cooling tower used in the heating, ventilation, and air conditioning industry to dissipate heat to the atmosphere was investigated using an artificial neural network model [8]. The reduction of cooling effectiveness during cooling tower operation was modeled using local linear wavelet neural networks, and the particle swarm optimization algorithm was employed to optimize the model parameters [9]. An artificial neural network model based on the Froude number level was developed to predict the performance parameters of a wet cooling tower under crosswind conditions, and data from testing the thermal state model were collected to complete the neural network [9]. The optimization of cold water temperature in forced draft cooling towers with different operating parameters was considered in a study that utilized the response level method and an artificial neural network to predict the cold water temperature [10]. Another study proposed a numerical and experimental scheme to enhance cooling tower performance by combining the particle swarm optimization algorithm with a neural network and considering packing density as a significant factor for improved accuracy [11]. The researchers collected data related to cooling tower performance in diverse conditions, which were used in various neural network design processes. Ultimately, a neural network based on a deep learning algorithm was developed and used to predict cooling tower performance. The effectiveness of the proposed system was verified by comparing the results of the designed neural network with experimental examples, which demonstrated the accuracy of the proposed system in predicting cooling tower performance.

ISSN No:-2456-2165

II. WET COOLING TOWER

Based on their performance and structural mechanism, cooling towers can be categorized into three main types: wet (evaporative), dry (air-cooled), and combined (a combination of the first two types). These three types differ significantly from each other, and the choice of which type to use depends on the prevailing weather conditions, with the wet and dry types being the most commonly selected. The wet cooling tower operates similarly to a conventional cooling tower, where evaporation occurs, allowing the water temperature to approach the wet temperature. In wet cooling towers, water circulates within the device through nozzles and is distributed to the heat transfer surfaces, known as packing. The driving force of the electromotor comes into contact with the water, causing it to evaporate. The water that evaporates absorbs latent heat from the remaining water flow, resulting in the cooling of the water. On the other hand, other cooling towers function as heat exchangers, aiming to lower the temperature of hot water. In these towers, direct contact between water and air occurs on the cooling surfaces, leading to the evaporation of a small amount of water flow (approximately 0%). The heat required for this evaporation is obtained from the main water flow, causing the temperature of the remaining 99% of the water to decrease. Consequently, heat and mass transfer occur simultaneously in this type of cooling tower. The wet cooling tower, with its simultaneous heat and mass transfer, effectively cools the water during the return process. The cooling process in a wet cooling tower involves the high-temperature water entering and passing through the packing or cooling surfaces, coming into contact with the fresh airflow from the external environment, and subsequently accumulating in the pan or cool water storage tank after being cooled. In the fluid circulation cycle within the wet cooling tower, the water containing heat is directly exposed to the airflow, resulting in a decrease in water temperature for two reasons.

In the context of heat transfer in a water-air system, there are two primary mechanisms at play. The first is direct heat transfer, which occurs as a result of the temperature disparity between the incoming hot water and the dry ambient air outside. This type of heat transfer is known as sensible heat transfer. The second mechanism is indirect heat transfer, which takes place through the evaporation of a portion of the water flow. This process utilizes the heat energy present in the water to facilitate the necessary energy for evaporation, known as the latent heat of evaporation.

➢ *Types of Wet Cooling Towers*

- *Counter-Flow Wet Cooling Tower*

In the realm of heat transfer within a water-air system, two fundamental mechanisms are at play. The first mechanism involves direct heat transfer, which arises from the temperature difference between the incoming hot water and the surrounding dry ambient air. This particular form of heat transfer is commonly referred to as sensible heat transfer. The second mechanism, on the other hand, entails indirect heat transfer, which occurs through the evaporation of a fraction of the water flow. This process harnesses the heat energy inherent in the water to facilitate the requisite energy for evaporation, known as the latent heat of evaporation.

- *Cross-Flow Wet Cooling Tower*

In the context of cooling towers, the cross-flow type 9 refers to a specific configuration where air is drawn from both sides of the tower, and the flow of incoming dry and cool air is perpendicular to the flow of falling water. This type of cooling tower typically has air inlets, known as louvers, on both sides. It is commonly used for open-circuit cooling, where the tower comes into direct contact with incoming dry air across all packing layers or heat exchange surfaces.

- *Cubic Wet Cooling Tower*

The cubic cooling tower 01 is an example of an open-circuit cooler with a fixed water-spraying system. It is characterized by its cubic shape. The water distribution and spraying system in this type of cooling tower consists of a series of water spraying nozzles. These nozzles emit a spray of water that is directed onto the packing or cooling surfaces. The aeration system of the cubic cooling tower can be customized based on the specific type of fan or suction impeller, as well as the choice between an axial blower or centrifugal fan.

➢ *Conical Wet Cooling Towers*

The Rotary cooling tower, also known as the Round Cooling Tower, is characterized by its rotating and conical shape. It utilizes a water distribution system for spraying water. The circular cooling tower employs a sprinkler head or central water spreader to distribute water on the media packing surfaces in a rotating manner, ensuring flow distribution. The air circulation system of this industrial cooling model typically utilizes axial fans for induction suction. In the design of cooling towers, calculations are performed to determine cooling capacity, efficiency, and condensation water. These calculations serve as the foundation for selecting the appropriate cooling tower and estimating water consumption. Accurate calculations contribute to the optimal performance of the cooling tower and the efficient operation of other equipment that relies on the cooling system. The calculations are categorized into different aspects, such as determining the water outlet temperature, considering cooling capacity and operating conditions, and estimating water consumption for peripheral equipment in the water circulation system.

➢ *Cooling Tower Approach Temperature*

The distinction lies in the ambient wet cold water temperature, specifically in relation to the cooling tower outlet temperature, commonly referred to as the approach temperature. This approach temperature is determined by the difference between the cold tower bulb temperature and the bubble temperature in the surrounding environment.

➢ *Cooling Tower Disagreement*

Another essential factor in the calculation of the cooling tower is the inlet and outlet temperature difference in the cooling tower. In calculation) Range (the difference between hot water temperature) inlet (and cold water temperature) output (called temperature or delta differences of efficiency and calculation of cooling capacity, inlet, and output temperature difference is of great importance.

➢ *Cooling Tower Efficiency*

One of the crucial aspects in the design and computation of the cooling tower is the determination of its efficiency. The efficiency of a well-performing cooling tower relies on various factors, including the calculation of the Range and Approach parameters. The efficiency of a cooling tower, similar to other design parameters, is influenced by the ambient temperature and humidity. It is worth noting that the power output of the cooling tower instrument was slightly below the optimal level. To calculate the efficiency of the cooling tower, the following equation was employed:

$$\eta = R/(R + A) \times 100 \qquad (1)$$

The difference between the temperature and above is the input relationship.

➢ *Concentration Cycle Calculations in the Cooling Tower*

Another significant parameter in the calculations of cooling towers is the Concentration Cycle (COC). COC, also known as the Cycle of Concentration, plays a crucial role in the design of water coolers. It refers to the ratio of conductivity in the main cycle to conductivity in the compensatory water cycle. The COC in a cooling tower can be determined using the following formula.

$$\text{COC} = \text{Conductivity of Cooling Water} / \text{Conductivity of Makeup water} \qquad (2)$$

One of the crucial aspects in the design and calculation of a cooling tower involves estimating the quantity of water consumed by the cooling tower under varying climatic and seasonal conditions. The term "UP" refers to the amount of cooling water consumed within a specific time frame. This fluid is lost through three distinct methods during a fluid circulation cycle. The calculation of compensatory water encompasses several parameters. In a wet cooling tower or circuit, a continuous input of water is necessary to establish a permanent cycle and maintain mass balance. The calculation of compensatory water in the cooling tower is influenced by three primary parameters, namely water evaporation and water droplet discharge. Essentially, the compensatory water is expended in the appropriate direction, depending on various functions within the cooling tower. Accurate calculation of compensatory water is crucial as it needs to be practically feasible during the warm seasons in the initial design phase. The calculation of compensatory water in the tower cooling process can be performed using three general methods. The first method involves estimating the compensatory water as 0.11 to 3% of the circulating water. Additionally, compensatory water can be calculated using online tools and engineering software such as SPX Calculator and Water.

➢ *Evaporation of Water in the Cooling Tower*

The primary factor contributing to water loss in the cooling tower is evaporation, which occurs when water comes into contact with the airflow generated by the cooling tower fan. This evaporation process results in a decrease in water temperature as heat is absorbed. The evaporative cooling process leads to the formation of compensatory or make-up water. The calculation of compensatory water in the cooling tower is greatly influenced by the rate of water evaporation. The amount of water evaporation is dependent on factors such as the temperature difference between the inlet and outlet, climatic conditions, and the specific installation environment of the cooling tower. Accurately determining the quantity of water evaporation in the cooling tank is crucial for obtaining reliable results in compensatory water calculations. The precise determination of water consumption is a critical aspect of cooling tower calculations and is achieved by utilizing the synthetic heat coefficient of evaporation. This parameter can be easily determined and plays a significant role in the calculation of compensatory water in the cooling tower.

➢ *Bludan Cooling Tower*

The second factor contributing to water loss in the cooling tower system is bleed off, which is necessary for maintaining the desired discharge current and preventing the accumulation of minerals. The calculation of cooling tower performance is crucial in ensuring effective cooling. The continuous or intermittent removal of a certain percentage of water, known as blowdown, is necessary to prevent the concentration of minerals from increasing in the cooling water. The total dissolved solids (TDS) and other unintended substances also play a role in determining the appropriate amount of blowdown. The calculation of cooling tower capacity depends on factors such as the quality of the inlet and outlet water, as well as the temperature and concentration cycle. If the concentration of soluble materials in the cooling tower exceeds the standard level, it can lead to sedimentation and reduced efficiency. Additionally, an increase in bleed off can result in excessive water consumption for compensation in the cooling process. Therefore, accurately adjusting the flow rate of water in the cooling tower is a critical factor in the calculation of compensatory water requirements.

➢ *Adjustment of the Cooling Tower Flow*

Manual Blow Down In such cases, a small discharge flank and valve are used to adjust the amount of cooling tower. Range (depends on. Automatic Blow Down Generally, to reduce the amount of discharge and coolers in the cooling tower, a smart TDS meter and sprinkler are used. TDS meter by increasing the concentration of water from the standard water, on the on-command) on It expresses to the valve for water drainage. By draining and concentrating water from the container of the cooling tower, the concentration of soluble materials is reduced, and the TDS meter is turned off after a specified time (of the command).

➢ *Drift or Throwing Water Droplets*

Drift (in the cooling tower) draws water droplets out of the sprinkler or waterfront by passing air. A very small percentage makes up for 3 % (compensatory water consumption). Drift Elminator (Drift Drift in the cooling tower) Drift Elminator (used to reduce drift consumption. Outside the coiling reaches approximately 1 ... droplet.

ISSN No:-2456-2165

Numerical calculations of the cooling tower. The two main factors in the compensatory calculations of the cooling tower are the evaporation and imagination of water. The basic calculation of the water consumption is as follows:

$$M=E+B+D \tag{3}$$

Where M is compensatory water or mix, E is the evaporation of water, B is Bolt, D is the Drift of fine water droplets

➢ *Calculation of Water Evaporation in the Cooling Tower*

Two general methods can be used to calculate the water evaporation in the cooling tower.

The first method (use of the specialized formula for calculating the evaporation of the cooling tower: According to this method, the following formula is used to calculate the amount of compensatory water resulting from evaporation in the cooling tower.

$$E = 0.00085 * R * 1.8 * C \tag{4}$$

Where E is 0.00085 x R x 1.8 x C, E is Evaporation Loss, R is Range and C is Circulating Cooling Water (m3/hr)

The second method (uses the second specialized formula to calculate the evaporation rate of the cooling tower numerically: In this method, heat absorbed in evaporation is generally used. According to this method, the following formula was used to calculate the compensation water resulting from evaporation in the cooling tower:

$$E = C * R * Cp / HV \tag{5}$$

Where E is Evaporation Loss, C is Cycle of Concentration, R is Range, Cp is Specific Heat = 4.184 and HV is Latent heat of vaporization = 2260

- *Calculation of Cooling Tower Blued*

Similar to evaporation, Bludan can be calculated using two methods. The first method (numerical calculation of the amount of cooling-tower noise according to the following formula:

$$B = E/ (COC-1)) \tag{6}$$

Where B is Blow Down, E is Evaporation Loss, and COC is Cycle of Concentration (a dimensionless parameter between 2 and 7 that is determined by the cooling tower manufacturer)

The second method (approximate calculations of cooling tower noise according to the following table: the amount of discharge and bludgeon in the cooling tower to maintain the concentration of dissolved minerals within an acceptable range) depends on the cooling range of the cooling tower (range) and the initial conditions of the water (TDS).

For example, a cooling tower device. One ton of refrigeration with a circulating water flow. 1 cubic meter per hour and a temperature difference of 1.1 degrees Celsius, the amount of compensated water according to the above method is calculated as follows [23-31]:

Where E is 350*2 =700 , M is B+E = 865 and B is 50000*(0.0033)=165

III. ARTIFICIAL NEURAL NETWORKS

The use of an artificial neural network allows for high speed and low cost to obtain a model for the cooling tower to predict the temperature of the cooling tower in a wide range of input data. Finally, the results of the artificial neural network are compared with those of the heat transfer and mass model, indicating that the model error designed by the artificial neural network is a mathematical model to obtain a desirable analysis close to the reality of cooling tower components. And predicting the performance of different systems is the neural network of good and efficient choices. Neural networks have been used in various areas. These systems consist of multiple layers and neurons. Figure 1 shows the structure of the neural network.

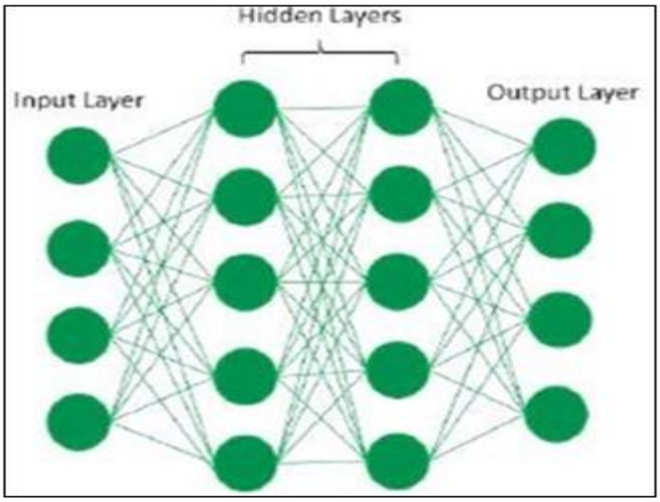

Fig 1 MLP Neural Network Structure

IV. METHODS

The multilayer perceptron neural network is a type of artificial neural network that consists of multiple layers of interconnected neurons. It typically includes an input layer, a hidden layer, and an output layer, with each layer containing nodes that utilize nonlinear activation functions. Unlike a linear perceptron, the multilayer perceptron is capable of handling non-linear data. The training of the multilayer perceptron involves a monitoring learning technique known as refund, which involves calculating error gradients for each network parameter (i.e., weight or bias) and adjusting them accordingly. This process allows the algorithm to determine the necessary changes to the weights in order to minimize errors. Overall, the multilayer perceptron is trained through a process of adjusting the weights in its layers.

➢ *Data information*

In the initial phase of network design, the experimental data is thoroughly classified, and the design process is divided into two distinct categories: input data and target data. The various types of experimental data utilized in the network structure are outlined in Table 1, as referenced in [1]. The neural network design process incorporates data derived from benchmark articles on neural networks.

Table 1 Neural Network Data

Input Variable	Target Variable
Dry bubble temperature of inlet air θin Wet bubble temperature τin Inlet water temperature in tin circulation Inlet mass flow rate of circulating water ˙min Inlet wind speed Vin	Tout circulating water outlet temperature temperature difference T Cooling efficiency coefficient η

➢ *Multi-Layer Network Network Modeling*

In this study, a multilayer Perceptron network was employed to construct a prediction model, as depicted in Figure 2. The hidden layer consisted of nine neurons, while the output layer contained two neurons. To ensure robustness, the dataset used for model development was divided into three distinct sets: training, testing, and validation. The training set accounted for 70% of the dataset, while the remaining portion was allocated for validation of Model 1 and Model 2. The optimal configuration for the input layer, hidden layer, and output layer was determined to be 1 [12-15].

The dataset comprised a total of 355 instances. The network was trained using the back-propagation algorithm and the Levenberg-Marquard strategy. Training continued until the training error reached a sufficiently small value or when negligible changes in the training error were observed. In essence, training was terminated when the regression coefficient R approached unity. A schematic representation of the neural network can be seen in Figure 3 [13-15].

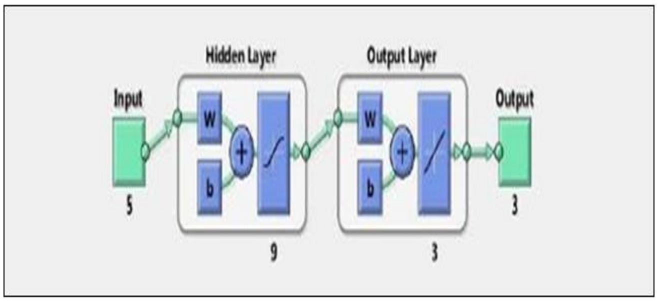

Fig 2 Schematic of MLP Neural Network

Normally, network design is performed in such a way that according to trial and error and referring to reliable sources, the values of the network variables are selected. The simulation results are shown in Fig. 3.

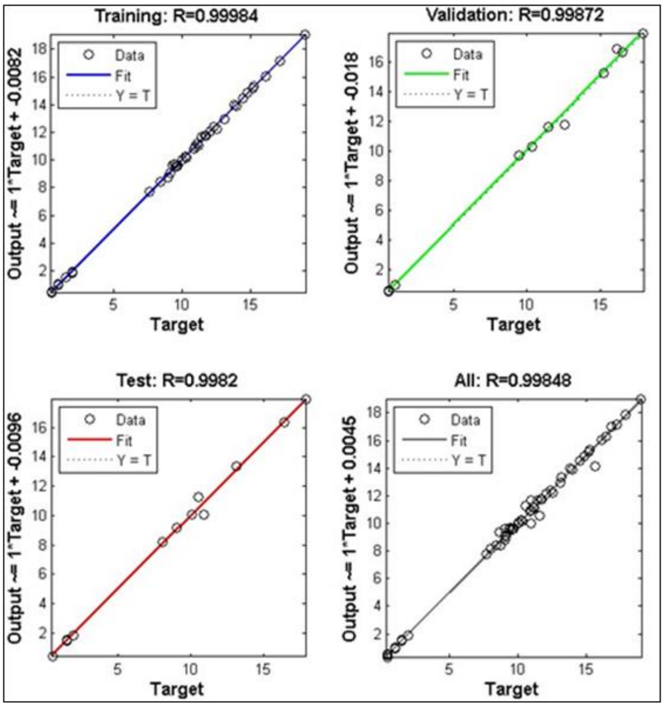

Fig 3 MLP Neural Network Regression

V. ANALYSIS AND REVIEW OF RESULTS

In this research study, a laboratory experiment was conducted to collect sufficient data for the purposes of training and prediction on a natural counterflow wet cooling tower [1]. This section aims to compare the performance of different components of the Hankah tower, as obtained from the neural network model, with the results obtained from experimental calculations [1]. To evaluate the accuracy of the results, it is necessary to utilize both the experimental data and various software packages. The experimental calculations were carried out using heat transfer relations and assessed based on internationally recognized standards. These calculations were then validated using CoolSpec software, and the outcomes are presented in Table 4. To further examine the prediction of heat transfer in the crown and compare it with the results from the designed neural network, the final data from the regression graphs should be analyzed using Data Graph Digitizing software.

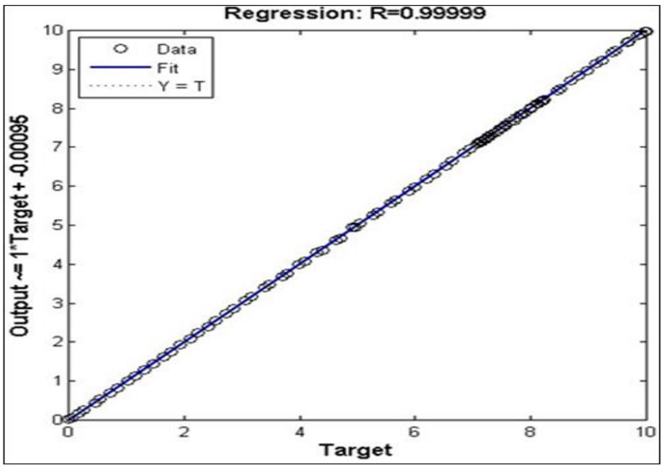

Fig 4 The Final Regression of the MLP Network

ISSN No:-2456-2165

The outcomes of the deep learning network are presented in Figure. The final results exhibit enhanced convergence and more desirable outcomes, indicating that the designed network outperforms the experimental sample and accurately predicts the final output data. The Mean Squared Error (MSE) and final regression results can be observed in the pseudo-neural output section.

Table 2 Training Function

	Samples	MSE	R
Training	25	3559.29075e-0	9.99964e-1
Validation	5	4294860.30898e-0	9.12059e-1
Testing	5	1853728.98074e-0	9.50070e-1

The final results of the multilayer Perceptron network are shown in Figure 5. The final coefficient for predicting heat transfer with a very high level of convergence is 0.9999, which indicates favorable results. Compared with the results of the software, it is possible to realize the high efficiency of network performance to accurately predict the data in the output phase.

Table 3 The Results of the Neural Network for Paper1

Performance parameter	Output parameter	4	5	6	7	8	9	10
R	Tout	0.992	0.998	0.999	0.998	0.997	0.995	0.991
	_t	0.995	0.998	0.998	0.997	0.995	0.992	0.990
	η	0.991	0.992	0.995	0.994	0.992	0.990	0.985
MSE	Tout (◦C)	0.064	0.049	0.044	0.048	0.052	0.058	0.065
	_t (◦C)	0.072	0.065	0.066	0.073	0.070	0.079	0.087
	η (%)	0.71	0.62	0.53	0.59	0.68	0.75	0.92

Table 4 The results of the MLP neural network

Performance parameter	Output parameter	3	4	5	6	7	8	9
R	*Tout*	0.993	0.999	0.9999	0.999	0.999	0.997	0.994
	_t	0.997	0.999	0.999	0.999	0.997	0.995	0.993
	η	0.993	0.995	0.997	0.997	0.995	0.993	0.989
MSE	*Tout* (◦C)	0.067	0.051	0.047	0.051	0.055	0.061	0.068
	_t (◦C)	0.075	0.067	0.069	0.077	0.073	0.081	0.091
	η (%)	0.73	0.65	0.55	0.61	0.71	0.78	0.95

VI. CONCLUSION

In this study, a mathematical model based on a multilayer perceptron neural network is introduced as a means to predict the performance of cooling towers. The design of the neural network structure is thoroughly described, encompassing all relevant details. The performance of the cooling towers was evaluated through functional systems. The results obtained from these evaluations were then compared with those derived from the neural network. The findings indicate that the proposed neural network accurately predicts the annual performance on the surface with an error rate of approximately 4%, and the total annual performance with an error rate of 2%. This demonstrates the high accuracy and efficiency of the proposed system. Furthermore, a comparison between the results of this research and those of a previous study [1] reveals the superiority of the proposed neural network over a similar model presented in the aforementioned research. Considering all aspects, the effectiveness of the proposed neural network in predicting the performance of cooling towers is evident.

REFERENCES

[1]. Gao M, Sun FZ, Zhou SJ, Shi YT, Zhao YB, Wang NH. Performance prediction of the wet cooling tower using an artificial neural network under cross-wind conditions. Interna-tional Journal of Thermal Sciences. 2009 Mar 1;48(3):583-9.

[2]. Hosoz M, Ertunç HM, Bulgurcu H. Performance prediction of a cooling tower using artificial neural network. Energy Conversion and Management. 2007 Apr 1;48(4):1349-59.

[3]. Gao M, Sun FZ, Zhou SJ, Shi YT, Zhao YB, Wang NH. Performance prediction of the wet cooling tower using an artificial neural network under cross-wind conditions. Interna-tional Journal of Thermal Sciences. 2009 Mar 1;48(3):583-9.

[4]. Qi X, Liu Z, Li D. Numerical simulation of shower cooling tower based on artificial neural network. Energy Conversion and Management. 2008 Apr 1;49(4):724-32.

[5]. Qi X, Liu Y, Guo Q, Yu S, Yu J. Performance prediction of a shower cooling tower using wavelet neural network. Applied Thermal Engineering. 2016 Sep 5;108:475-85.

[6]. Wu J, Zhang G, Zhang Q, Zhou J, Wang Y. Artificial neural network analysis of the performance characteristics of a reversibly used cooling tower under cross flow conditions for heat pump heating system in winter. Energy and buildings. 2011 Jul 1;43(7):1685-93.

[7]. Islamoglu Y. Modeling of thermal performance of a cooling tower using an artificial neural network. Heat transfer engineering. 2005 May 1;26(4):073-6.

[8]. Guo Q, Qi X, Wei Z, Yin Q, Sun P, Guo P, Liu J. Modeling and characteristic analy-sis of fouling in a wet cooling tower based on wavelet neural networks. Applied Thermal En-gineering. 2019 Apr 1;152:907-16.

[9]. Gao M, Shi YT, Wang NN, Zhao YB, Sun FZ. Artificial neural network model re-search on effects of cross-wind to performance parameters of wet cooling tower based on level Froude number. Applied thermal engineering. 2013 Mar 1;51(1-2):1226-34.

[10]. Ramakrishnan R, Arumugam R. Optimization of operating parameters and perfor-mance evaluation of forced draft cooling tower using response surface methodology (RSM) and artificial neural network (ANN). Journal of Mechanical Science and Technology. 2012 May;26(5):1643-50.

[11]. Alimoradi H, Soltani M, Shahali P, Moradi Kashkooli F, Larizadeh R, Raahemifar K, Adibi M, Ghasemi B. Experimental investigation on improvement of wet cooling tower effi-ciency with diverse packing compaction using ANN-PSO algorithm. Energies. 2020 Dec 30;14(1):167.
[12]. Roshani GH, Nazemi E, Roshani MM. Flow regime independent volume fraction es-timation in three-phase flows using dual-energy broad beam technique and artificial neural network. Neural Computing and Applications. 2017 Dec;28(1):1265-74.
[13]. Mohamad-Saleh J, Hoyle BS. Improved neural network performance using principal component analysis on Matlab. International journal of the computer, the internet and Man-agement. 2008 May;16(2):1-8.
[14]. Chiddarwar SS, Babu NR. Comparison of RBF and MLP neural networks to solve the inverse kinematic problem for 6R serial robot by a fusion approach. Engineering applica-tions of artificial intelligence. 2010 Oct 1;23(7):1083-92.
[15]. Toshani H, Farrokhi M. Real-time inverse kinematics of redundant manipulators us-ing neural networks and quadratic programming: A Lyapunov-based approach. Robotics and Autonomous Systems. 2014 Jun 1;62(6):766-81.
[16]. Jha P, Biswal BB, Sahu OP. Inverse kinematic solution of robot manipulator using hybrid neural network. Int J Mater Sci Eng. 2015 Mar;3(1):31-8.
[17]. Petra I, De Silva LC. Inverse Kinematic Solutions Using Artificial Neural Networks. InApplied Mechanics and Materials 2014 (Vol. 534, pp. 137-143). Trans Tech Publications Ltd.
[18]. Setiawan E, Adiono T. Implementation of systolic co-processor for deep neural net-work inference based on SoC. In2018 International SoC Design Conference (ISOCC) 2018 Nov 12 (pp. 36-37). IEEE.
[19]. Ghosh MM, Maghari AY. A comparative study on handwriting digit recognition us-ing neural networks. In2017 international Conference on promising electronic technologies (ICPET) 2017 Oct 16 (pp. 77-81). IEEE.
[20]. Banzato T, Cherubini GB, Atzori M, Zotti A. Development of a deep convolutional neural network to predict grading of canine meningiomas from magnetic resonance images. The Veterinary Journal. 2018 May 1;235:90-2.
[21]. Sento A. Image compression with auto-encoder algorithm using deep neural network (DNN). In2016 Management and Innovation Technology International Conference (MITi-con) 2016 Oct 12 (pp. MIT-99). IEEE.
[22]. Sento A. Image compression with auto-encoder algorithm using deep neural network (DNN). In2016 Management and Innovation Technology International Conference (MITi-con) 2016 Oct 12 (pp. MIT-99). IEEE.
[23]. Lemouari M, Boumaza M, Mujtaba IM. Thermal performance investigation of a wet cooling tower. Applied thermal engineering. 2007 Apr 1;27(5-6):902-9.
[24]. Al-Waked R, Behnia M. CFD simulation of wet cooling towers. Applied thermal en-gineering. 2006 Mar 1;26(4):382-95.
[25]. Papaefthimiou VD, Zannis TC, Rogdakis ED. Thermodynamic study of wet cooling tower performance. International journal of energy research. 2006 May;30(6):411-26.
[26]. Kloppers JC, Kröger DG. Loss coefficient correlation for wet-cooling tower fills. Applied thermal engineering. 2003 Dec 1;23(17):2201-11.
[27]. Kloppers JC, Kröger DG. The Lewis factor and its influence on the performance pre-diction of wet-cooling towers. International journal of thermal sciences. 2005 Sep 1;44(9):879-84.
[28]. Al-Waked R, Behnia M. Enhancing performance of wet cooling towers. Energy Conversion and Management. 2007 Oct 1;48(10):2638-48.
[29]. Asvapoositkul W, Kuansathan M. Comparative evaluation of hybrid (dry/wet) cool-ing tower performance. Applied Thermal Engineering. 2014 Oct 5;71(1):83-93.
[30]. Hasan A, Siren K. Theoretical and computational analysis of closed wet cooling tow-ers and its applications in cooling of buildings. Energy and buildings. 2002 Jun 1;34(5):477-86.
[31]. Wang K, Sun FZ, Zhao YB, Gao M, Ruan L. Experimental research of the guiding channels effect on the thermal performance of wet cooling towers subjected to crosswinds–air guiding effect on cooling tower. Applied Thermal Engineering. 2010 Apr 1;30(5):533-8.