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IMPROVING THE EFFICIENCY OF HYBRID COOLING TOWERS: THE INTEGRATION OF ARTIFICIAL INTELLIGENCE FOR WATER OUTLET TEMPERATURE PREDICTION CONSIDERING FOULING EFFECTS

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ABSTRACT
This work investigates the use of Artificial Neural Networks ANN to predict fouling in hybrid cooling towers, aiming to enhance their efficiency sustainability. Fouling, which impairs heat transfer and maintenance cost, is a significant challenge in cooling systems. The aim of this study is to improve the efficiency and long-term viability of hybrid cooling tower systems through the utilization of predictive models powered by artificial intelligence. The present study employs data obtained from a dynamic fouling monitor system at the Green Energy Park in Benguerir, Morocco, analyzing the fouling behavior of different surface materials under both dry and wet conditions. The study compared multiple modeling methods, including Multiple Linear Regression (MLR), MLR with interaction (MLRWI), Response Surface Methodology (RSM), and ANNs. The results reveal that the ANNs model demonstrated a higher accuracy achieving an R^2 value of 0.724 and a remarkable RMSE indicator of 0.06 outperforming the other models. The study underscores the potential of (AI) models to improve the prediction of fouling, hereby optimizing the performance and the efficiency of hybrid cooling tower systems.

INTRODUCTION
Nowadays, solar energy gets the scientific and governmental communities interest as a promising alternative to fossil fuel resources. In the near future 2050, this source of energy will provide 8-15 % of the worldwide electricity demand[1].This is thanks to its clean and disposable production of electricity using concentrated solar power (CSP) technology coupled with thermal energy storage. In that way, it provides the needed heat supply to the steam turbine with zero greenhouse gas emissions as it was the case for conventional thermoelectric baseload power plants. However, the high cooling water consumption of CSP plants presents a big challenge against its viability in the energy market, especially in arid regions: in fact, the steam turbine exhaust should be condensed in order to be recirculated in a closed circuit of the Rankine steam cycle. To overcome this technical challenge, a dry cooling system was recommended when CSP plants were installed in regions with high DNI and poor cooling water resources[2]. It reduces the annual water consumption by 95%[3]. Howbeit, these air-cooling systems have low efficiency compared to wet cooling system, and their fans consume a considerable amount of electricity, which may impact negatively the CSP plant LCOE as it may be illustrated by the following findings: (1) the increased ambient temperature causes a great decrease in heat rejection efficiency[4], (2) a 20% net power reduction had been reached during hot days in summer using dry cooling[5], (3) a windy conditions may affect the air cooled steam condenser performance[6] and besides (4) some CSP plants with low-temperature resources (e.g. low-concentration CSP plants and geothermal plants) may experience a 50% net power reduction at high ambient temperatures[7]. Thus, wet-cooling towers are used to remain the economical choice. However, when water availability decreases its cost and environmental problems related to its exploitation increase dramatically[8]. Thus, the vital challenge to maintain an adequate supply of appropriate makeup water at a rational cost[9], [10].

Recently, as a compromise between the cooling system efficiency and water resources preservation, hybrid dry-wet cooling systems are investigated[11]. Their approach consists at improving the heat transfer by using both sensible and latent heat transfer, the deluge cooling is achieved by exposing the heat transfer bundles to a large amount of water to cool the high ambient temperature at hot days. Therefore, their main purposes are the enhancement of the low efficiency of dry cooling systems from one side, and to reduce water consumption of wet cooling systems from the other side. From 30 to 98% reduction in water had been realized using hybrid cooling system compared to wet cooling systems[12]. The switching between the wet and dry cooling in a hybrid cooling tower experience the bare bundles to a severe fouling over time.

Fouling can be defined as the accumulation of unwanted deposits at the heat surface exchanger, which reduces by time the efficiency of the tower.

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Researchers categorized the waterside fouling into six mechanisms: scaling (if not crystallization or precipitation), corrosion, particulates, biofouling, freezing and chemical reactions fouling [13], [14] and described the basic behavior of the fouling process using a deposition and removal rate[15], [16].

Most parameter that will reproduce the variety of fouling problems is the wide spectrum of the water quality. The emphasis in cooling water management in most industrial cooling systems is on quantity rather than quality. Therefore, to combat fouling deposits it is requested for cooling system to access for treatment. Seawater and rivers involve a potential fouling at their mineral composition and usually these natural resources fitted the cooling systems. The most common scaling deposition on heat transfer is Calcium carbonate (CaCo3), Magnesium sulfate (MgSO4), also affected to minor extents by other substances such as Iron (Fe), silica (Si), sodium chloride (NaCl). In this light Tubaman and Zdiunk and Zaza *et al* [13], [17], [18] conducted a survey on the water quality to an actual cooling tower to understand the factor that affects the cooling water quality.

Many experimental studies had been conducted for a long-term fouling test to quantify the fouling. Rebas [19] manner a survey of condensers over one year operating for three types of enhanced tubes. He concluded that the enhanced tubes had significant fouling rates more than the plain one. A smooth tube and plate heat exchanger in a cooling tower system was tested by Wu[20] to conclude that the fouling deposit is not uniform and that the fouling is present highly at outlet section than the inlet one and the calcium carbonate was the most fouling deposit.

In hybrid cooling systems, fouling phenomena is challenging because of the alternating wet-dry modes, which generate new chemical and physical deposition mechanisms different from those related to fouling in wet only cooling systems. Thus, the fouling problem should be investigated and understood in this novel environment in order to collect a strong knowledge to deal with it[21], [22], [23]. Despite the critical importance of addressing fouling in these systems, the literature remains sparse, particularly concerning hybrid cooling towers designed for concentrated solar power (CSP) plants. Previous studies, including those conducted by the authors, have made advancements in experimentally examining the fouling effects on these systems, focusing on various materials such as galvanized steel and polymers[24], [25]. However, these efforts primarily concentrated on understanding the fouling behavior and material properties rather than predicting and mitigating fouling through advanced techniques. This paper aims to bridge this gap by integrating Artificial Intelligence (AI) into the analysis, providing a novel approach to predicting fouling rates and optimizing the performance of hybrid cooling towers in CSP plants. Through the development of AI models, this research seeks to enhance the predictive accuracy and operational efficiency, thereby offering new insights and potential solutions for maintaining the sustainability and effectiveness of these systems.

The integration of artificial intelligence (AI) for the prediction of fouling in heat exchangers represents a paradigm shift in the realm of maintenance and operational optimization[26]. This research endeavors to deploy machine learning algorithms to analyze historical operational data, discerning intricate patterns and trends associated with fouling incidents[27]. The research methodology involves the comprehensive collection of datasets, encompassing vital parameters such as temperatures, flow rates, pressure differentials, and fluid characteristics. Rigorous preprocessing techniques are subsequently applied to ensure data quality, involving the removal of outliers and addressing missing values. The process of feature engineering is then employed to identify and incorporate crucial variables influencing fouling behavior. By leveraging these advanced techniques, AI models can learn from past fouling incidents and make informed predictions about future occurrences. This predictive capability not only facilitates proactive maintenance strategies but also enhances the overall efficiency and performance of heat exchangers, thereby mitigating the adverse impacts of fouling. The research contributes to the evolving landscape of sustainable and optimized heat exchange systems through the judicious integration of AI for fouling prediction.

The paper is organized as follows: Initially, a comprehensive overview of the experimental test rig and its operational parameters is provided. Subsequently, the focus shifts to the analysis of modeling results, utilizing statistical techniques such as ANOVA and multiple linear regression (MLR) to unveil correlations between environmental variables and thermal fouling resistance. Following this, the paper introduces the application of Artificial Neural Networks (ANN) for predictive modeling. Two distinct implementations are examined: one utilizing MATLAB, and the other employing Python with the Keras framework.

TEST APPARAUTS AND METHOD

Experimental setup

The fouling test rig is a novel experiment to investigate the fouling under hybrid cooling (dry/wet) mode. The system contained two tanks to feed the test with cold and hot water, an electrical resistance is used to heat the water in order to floated inside the tubes. The deluge water is floated over the heated tubes and a tower featured sprayers to inject the cold water through heated tubes and the air is drowned thanks to an axial flow placed at the top of the tower. Fig. 1. The test rig is used to identify

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fouling under accelerated conditions, which are accomplished by recycling hot water under temperature conditions (of 60 °C) (see Table *1*). Thermocouple's props inside the tube are connected to measure the temperature each min (hot water inside the tube, air temperature and deluge temperature). To amplify potential differences in fouling characteristics, tube materials are made of polymer and galvanized steel. The hot water is circulated from a hot water tank using a centrifugal pump. A hot water bath (500L) is used to maintain hot temperature thanks to a resistance heater (208 V, 2000 W). Inside the tower simultaneous modes are functioning; the wet mode; during 5 min the deluge water contained specific mineral salts is agitated and drained into sprayers to distribute the deluge water through tested tubes. During 10 min the dry mode operating by aspiring the air from the bottom to the top by virtue of an axial fan[24].

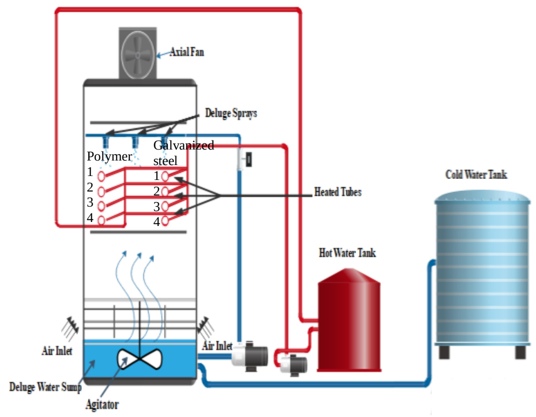

Fig. 1. Schematic diagram of the fouling test rig

Table 1. Test rig parameter and operating conditions

Parameter	**Value**
Deluge water flow rate	2.5 ± 0.1gal/min
Sump volume	150 l
Deluge water sub-cycle time	Wet 5-Rince 0-Dry 10
Heated inlet temperatures	60± 0.1 °C

Preparation of test solutions and experimental methods

The key part of this novel is a specific deluge water hardens that established to simulated the industrials case. The water composition salts are presented at Table *2* The most fouled mineral is calcium carbonite.

Fouling resistance

Each fouling test is operated at constant heat flux, velocity and bulk temperature. Using temperatures measured by the thermocouples, the heat transfer (Q_{hw}) was determined by:

$$Q_{hw} = m_{tw} \times C_{ptw} \times (T_{inh} - T_{outh}) \quad (1)$$

Where m_{tw} is mass flow of the hot water inside the tubes (kg/s); C_{ptw} is the specific heat T_{inh} and T_{outh} are the hot water temperatures at the inlet and the outlet of the tube

Fouling resistance at time t (R_f) can be resolute by heat transfer coefficients using Eq (2)

$R_f = \frac{1}{UA_f} - \frac{1}{UA_i}$ (2) Where Ut (kW/m^2. K) is the overall heat transfer coefficient at time t, U0 is the initial (t = 0) overall heat transfer coefficient for a clean probe. By monitoring temperatures (Ta, T_{hwo}, T_{hwi}), fouling resistance R_f at each time point can be calculated. During each test, fouling data (Tb, Tw and power input) are recorded every 1 min using a data logger.

Anticipating the outlet hot water temperature T_{hwo} is crucial, as it offers valuable insights into fouling resistance. Consequently, within the modeling section, various methods will be employed to predict T_{hwo}. This approach aims to provide a comprehensive understanding of the impact of fouling and assess the efficiency of the hybrid cooling tower.

A validation process was conducted to ensure the reliability of the results. Potential limitations of the setup included possible measurement inaccuracies arising from sensor precision and the impact of external factors that were not entirely controlled within the experimental environment. To address these concerns, a comprehensive uncertainty analysis was performed in an earlier work[24], which enhanced the robustness and credibility of the findings

Table 2. Mineral salt compositions

Mineral salts	**Value(mg/l)**
calcium carbonite ($CaCo_3$)	390
Magnesium sulphate ($MgSO_4$)	220
Iron oxides(FeO)	500
Sodium chloride (Nacl)	1
Kaolinite ($AL_2Si_2O_5(OH)_4$)	1000

MODELING RESULTS

ANOVA was used to estimate statistical parameters and unveil relationships between environmental variables and the thermal fouling resistance. This analysis involved developing multiple models: linear regression (MLR and MLRWI), a mathematical model using response surface methodology (RSM), and assessing their accuracy with R^2, adj-R^2, and RMSE. Additionally, an artificial neural network (ANN) was utilized to address the intricate prediction of heat transfer efficiency of the hybrid cooling tower based on environmental factors.

Multiple linear regression models (MLR)

The relationship between the hot water outlet temperature (Thwo) and the operating and

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environmental conditions where cooling towers are situated was explored by modeling against factors such as ambient air temperature (Ta), humidity(Rh), hot water flow (Fc), hot water inlet temperature(Thwi)), deluge water flow (Fdw), deluge water temperature (Tdw). Employing a Multi-variable linear regression (stepwise method) with a month's worth of data set a benchmark for this analysis. This regression method predicts outcomes based on diverse parameters, enabling an in-depth examination of how each operating and environmental factors influences the overall variance. Notably, this approach encompasses two types: simple regression and regression with interaction.

The equation of a ***simple regression*** is given by:

$$Y_i = \beta 0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_n x_{in} \quad (3)$$

where: $\beta_0, \beta_1, \beta_2, \ldots \beta_n$ are the model parameters.

Multiple linear regression alone doesn't sufficiently capture the intricate interactions among the data parameters needed for accurate prediction. To better comprehend the interplay between environmental data, multiple ***linear regression with interaction (MLRWI)*** was employed. This approach provides a more comprehensive insight into the combinations of environmental factors. The MLRWI equation is formulated as follows:

$$SR = \beta_0 + \beta_1 x_1 \beta_2 x_2 + \ldots \beta_{n-1} x_{n-1} \beta_n x_n \quad (4)$$

As results, the simple regression model has a lower R^2=0.48 while the MLR has R^2=0.507, which will be explained that the interaction between the parameters has a great impact on the output. As it can be seen from the Table 3, the deluge water temperature (Tdw) has a great effect on Rh (P-value<0.01) as well as on the hot water flow. Also the ambient and the relative humidity affect strongly on the output.

Table 3. The ANOVA results for multiple linear regression model with interaction.

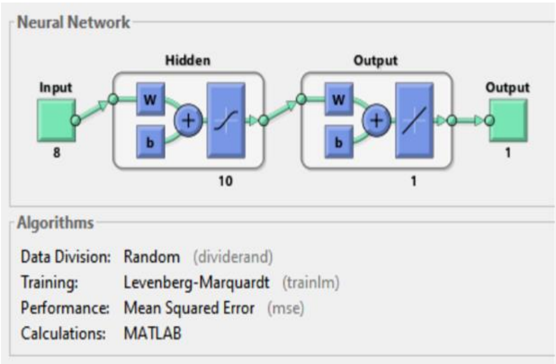
Parametrs	P value	Remarks
Fc*Td	0,650	
Fc*Ta		
Fc*Thwi	0,236	
Fc*Pa		
Fc*RH	0,872	
Fc*Flow	0,353	
Td*Ta	0,518	
Td*Thwi	0,337	
Td*Pa		
Td*RH	**0,0100**	Signifiant
Td*Flow	**0,0036**	Signifiant
Ta*Thwi		
Ta*Pa		
Ta*RH	**0,0023**	Signifiant
Ta*Flow	0,220	
Thwi*Pa		
Thwi*RH		
Thwi*Flow	0,447	
Pa*RH		
Pa*Flow		
RH*Flow	0,148	

ANN with Matlab

The modeling process was carried out with the datasets fed to the neural network using MATLAB software. The model framework was designed as eight input variables (Tdw, Tdi, Ta, Thwi, Pa, Rh, Flow, Thwo _5) while the Thwo5is the output hot water taking into consideration the 5min results before) with one output parameter as the Thwout. The processing parameter settings for the neural network model are presented in Fig. 2 which show a 8-10-1 two-layer feed-forward network with a tansig activation function (AF) for the hidden neurons and linear AF output neurons. This can perform multidimensional mapping to solve complex system solutions. In order to determine the best-performing n-neurons, mean squared error (MSE) and R-values, evaluation criteria were used, which revealed that 10 neurons produced optimal results.

The Neural Net Fitting tool in MATLAB was used to address a data adjustment issue by the implementation of a two-layer feed-forward network, constructed using the Levenberg-Marquardt algorithm. The process involves data selection, partitioning into training, validation, and testing sets, network architecture design, and network shaping.

The Levenberg-Marquardt algorithm (LM) is an enhanced version of the classical Gauss-Newton method. It is commonly employed for solving regression problems involving smaller nonlinear squares. LM is preferred over other general optimization algorithms, such as the quasi-Newton method or the simplex method, due to its superior



effectiveness.

Fig. 2. Setting parameters of the used Model.

The average square error refers to the squared discrepancy between the predicted values of a model and the desired or target values. The module presents the most favorable Mean Squared Error (MSE) values, namely and MSE = 1.82, based on the The data set under consideration has a strong regression relationship (R = 0.92982) with respect to

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the variable Thwo_5. This indicates that the eight independent variables (Tdw, Tdi, Ta, Thwi, Pa, Rh, Flow, Thwo _5) effectively predict the dependent variable (Thwo).

The mean square error (MSE) was the criteria tool used to evaluate the model's performance while randomly selecting different hidden neuron numbers, activation function parameters and training algorithms for validation of the ANN network, as shown in Fig. 3.The graphical results indicated the best validation performance of 2.3555 at epoch 7 for the optimized network (8-10-1). The results indicated a satisfactory performance of the ANN model. It was capable of predicting the target response parameters accurately by generalizing the sets of complex input variables with minimum error

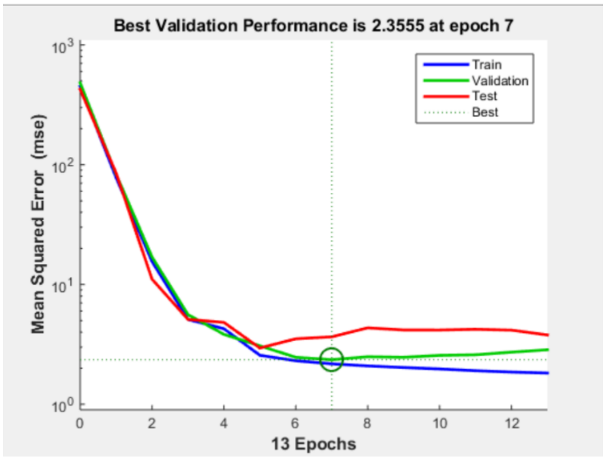

Fig. 3. Validation performance of the ANN.

ANN with Python

Artificial Neural Networks (ANN) draw inspiration from the intricate neural networks found in the human brain. Typically, an ANN model comprises three primary layers—input, hidden, and output—interconnected through weight connections as shown in Fig. 4. The structure of these connections is tuned based on experience, enabling neural networks to adapt to inputs and develop learning capabilities. ANNs exhibit diverse structures and functionalities, including radial basis functions, backpropagation, recurrent networks, feed-forward, etc. The optimal structure depends on the specific problem under examination.

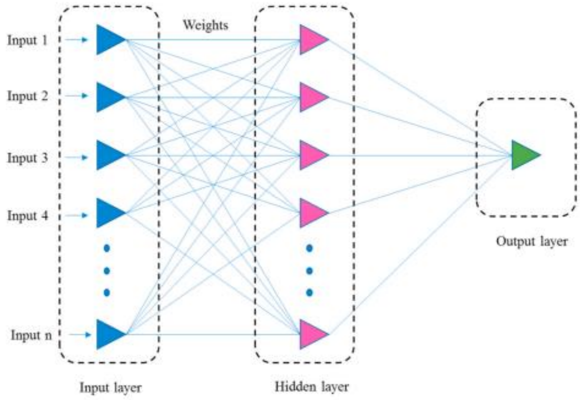

Fig. 4. Artificial Neural Network architecture.

Selecting the optimal number of neurons in the hidden layer for optimal network performance lacks a systematic approach. Researchers commonly employ a trial-and-error method to determine the appropriate number of neurons in the hidden layers, recognizing the importance of customization based on the specific problem at hand.

The present study used a multilayer perception with a single hidden layer as the artificial neural network (ANN) model. Several training algorithms were examined and reviewed to determine the most suitable one for addressing the fouling phenomena and achieving optimal performance. As a result of this evaluation, the Keras training method was selected [28]. The artificial neural network (ANN) model used in this study consisted of three layers: an input layer, a hidden layer, and an output layer. In addition, the use of the sigmoid transfer function was observed in the output layer, specifically to accommodate the prediction of the thermal resistance of the fouling. Conversely, the hyperbolic tangent transfer function was chosen for both the input and hidden layers. The input layer consisted of seven neurons that represented (Tdw, Tdi, Ta, Thwi, Pa, Rh, Flow.

Several examples were explored and assessed by altering the number of hidden layer neurons from 3 to 12 with randomly initialized weights to find the ideal one and prevent overfitting. To optimize performance, the ANN model was trained and assessed 10 times for each hidden layer neuron count[29]. The best-performing ANN model with 10 neurons in the hidden layer was utilized to generate model outputs. The dataset had 80% for training, 10% for validating, and 10% for testing.

Furthermore, the accuracy level and performance of the created model were assessed using four primary statistical error indices: Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), and regression coefficient (R2). The statistical formulae for these indicators may be found in the references cited as [30]. Optimal model performance is attained when these errors approach zero, hence yielding a high level of accuracy, and when the R2 parameter approaches 1. The dataset used in this study included observations taken each minute for one month, while the totaling 44640 instances. These observations were employed in the current model to forecast the outlet hot water temperature T_{hwo}, while considering the operating and the environmental factors.

The findings from the employed artificial neural network (ANN) model highlight a robust correlation

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with the dataset, explaining approximately 81% of the variance (MAE=0.054256 , MSE=0.004109, RMSE= 0.064105, R^2 = 0.724, $p < 0.05$). This underscores the ANN model's capacity to comprehensively understand the interactions among input variables, leading to more accurate predictions of daily Thwo with diminished biases compared to the multiple linear regression (MLR) model. Additionally, the ANN model demonstrates a substantial reduction of over 40% (R^2=0.724) in comparison to the MLR model, as evidenced by the lower root mean square error (R^2 = 0.507).

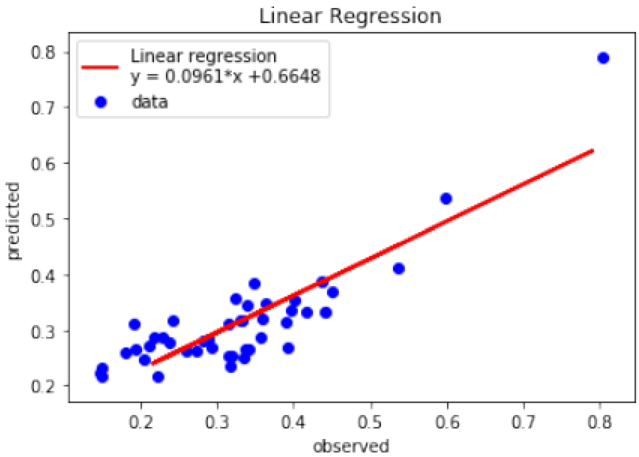

Fig. 5 illustrates the regression plots of the proposed model, showcasing the capabilities of the Artificial Neural Network (ANN) model in terms of rapid processing and superior accuracy. The results offer a comparative analysis with linear models, emphasizing that ANNs serve as potentially effective tools for resolving complex scenarios and achieving high R^2 values. However, the establishment of a robust ANN structure, along with crucial steps such as pre-processing techniques, dataset augmentation, and incorporation of relevant features, is vital. Attention to these criteria is essential to develop a highly accurate model while preventing overfitting, requiring the implementation of suitable strategies and techniques.

Fig. 5. Regression plots of the proposed ANN model for All data.

CONCLUSION

In conclusion, this study utilized three distinct models, namely Multiple Linear Regression (MLR), MATLAB-based Artificial Neural Networks (ANN), and Python-based ANN with the Keras framework, to predict hot water outlet temperature (Thwo) in cooling tower systems. The MLR model, serving as a benchmark, explored both simple and multiple linear regression with interaction (MLRWI), highlighting the significance of interactions with a higher R^2 (0.507). Key influencers on Thwo included deluge water temperature (Tdw), ambient temperature (Ta), and relative humidity (Rh). The MATLAB-based ANN, an 8-10-1 two-layer feed-forward network, demonstrated a strong regression relationship (R = 0.92982) with Thwo_5, using the Levenberg-Marquardt algorithm and 10 hidden layer neurons. Meanwhile, the Python-based ANN with Keras, optimized with varying hidden layer neurons, outperformed MLR with an R^2 of 0.724. These ANN models showcased a robust ability to comprehend interactions among input variables, resulting in accurate predictions and a remarkable 40% reduction in R^2 compared to MLR. The study underscores the effectiveness of ANN models, particularly when implemented with Python and Keras, as powerful tools for predicting hot water outlet temperature in cooling tower systems, emphasizing their potential in complex scenario resolution and achieving high R^2 values. To conclude, the comparison of modeling approaches—MLR, MLRWI, RSM, and ANN—demonstrated that the Artificial Neural Network (ANN) significantly outperformed the other models in predicting fouling behavior. This can be attributed to ANN's ability to capture complex, non-linear relationships between variables, which are prevalent in fouling dynamics. Unlike MLR and RSM, which are limited by their linear assumptions, ANN's flexibility and adaptability allow it to model intricate patterns and interactions more effectively. Consequently, ANN provides more accurate and robust predictions, highlighting its advantages for addressing the non-linear and multifaceted nature of fouling in hybrid cooling towers.

NOMENCLATURE

A Area m^2
Cp Specific heat of hot water, kJ/ (kg K)
Q Heat transfer rate, W
R Thermal resistance, m2 K/W
T Temperature, °C

Subscript

h hot
o outer
i inlet
d deluge
w water
f fouling

REFERENCES

[1] "World Energy Assessment: Energy and the Challenge of Sustainability | UNDP." Accessed: May 23, 2018. [Online]. Available: http://www.undp.org/content/undp/en/home/librarypage/environment-energy/sustainable_energy/world_energy_assessmentenergyandthechallengeofsustainability.html

[2] D. G. Kröger, *Air-cooled heat exchangers and cooling towers*. Tulsa, Okl: Penwell Corp, 2004.

ISBN: 978-0-9984188-3-4; Published online www.heatexchanger-fouling.com

[3] J. Maulbetsch and M. DiFilippo, “Advanced hybrid cooling systems: Technology review,” 2012.

[4] M. Kanoğlu and Y. Cengel, “Improving the performance of an existing air-cooled binary geothermal power plant: a case study,” *Journal of energy resources technology*, vol. 121, no. 3, pp. 196–202, 1999.

[5] R. D. Mitchell, “Survey of water-conserving heat rejection systems,” Electric Power Research Inst., Palo Alto, CA (USA); Sierra Pacific Power Corp., Reno, NV (USA), 1989.

[6] R. Ritter, “Fundamentals of corrosion in cooling water systems. AIChE preprint 7, fouling: the major unresolved problem in heat transfer. Parts I and II,” 1972.

[7] M. Owen and D. Kröger, “A Hybrid Dephlegmator for Incorporating into an Air-cooled steam condenser,” 2013.

[8] A. Zaza, N. E. Laadel, E. G. Bennouna, Y. E. Hammami, and M. T. Janan, “Numerical study of the fouling effect on wet cooling towers designed to CSP plants,” *Energy Procedia*, vol. 157, pp. 1230–1240, Jan. 2019, doi: 10.1016/j.egypro.2018.11.289.

[9] C. Shen, C. Cirone, and X. Wang, “A method for developing a prediction model of water-side fouling on enhanced tubes,” *International Journal of Heat and Mass Transfer*, vol. 85, pp. 336–342, 2015.

[10] C. Shen, L. Wang, S. E. Ford, C. Zhang, and X. Wang, “A novel fouling measurement system: Part I. design evaluation and description,” *International Journal of Heat and Mass Transfer*, vol. 110, pp. 940–949, 2017.

[11] R. Webb, “Principles of Enhanced Heat Transfer. New York: John Wiley&Sons,” 1994.

[12] R. L. Webb and W. Li, “Fouling in enhanced tubes using cooling tower water: Part I: long-term fouling data,” *International journal of heat and mass transfer*, vol. 43, no. 19, pp. 3567–3578, 2000.

[13] I. M. Tubman, “An analysis of water for water-side fouling potential inside smooth and augmented copper alloy condenser tubes in cooling tower water applications,” 2003.

[14] M. Sannad, Y. Mehdi, A. Zaza, Y. El Hammami, Y. Idihya, and O. Benkortbi, “A numerical simulation under milk fouling in a plate heat exchanger in the presence of a porous medium,” *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, vol. 91, no. 1, pp. 1–17, 2022, Accessed: Sep. 03, 2024. [Online]. Available: https://semarakilmu.com.my/journals/index.php/fluid_mechanics_thermal_sciences/article/view/118

[15] T. R. Bott, *Fouling of Heat Exchangers*. Elsevier, 1995.

[16] M. K. Peddojula *et al.*, “Synergetic integration of machining metal scrap for enhanced evaporation in solar stills: A sustainable novel solution for potable water production,” *Thermal Science and Engineering Progress*, vol. 51, p. 102647, Jun. 2024, doi: 10.1016/j.tsep.2024.102647.

[17] G. Zdaniuk, L. Chamra, and P. Mago, “A survey of cooling tower water quality for condenser tube fouling potential,” *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*, vol. 222, no. 1, pp. 111–122, 2008.

[18] A. Zaza, E. G. Bennouna, A. Iranzo, and Y. El Hammami, “Identifying fouling mechanism in a novel hybrid cooling tower’s bundles: Application in concentrated solar power (CSP) plant,” *International Communications in Heat and Mass Transfer*, vol. 149, p. 107139, Dec. 2023, doi: 10.1016/j.icheatmasstransfer.2023.107139.

[19] T. Rabas, C. Panchal, D. Sasscer, and R. Schaefer, “Comparison of power-plant condenser cooling-water fouling rates for spirally-indented and plain tubes,” Argonne National Lab., IL (United States), 1991.

[20] X. Wu and L. Cremaschi, “Thermal and chemical analysis of fouling phenomenon in condensers for cooling tower applications,” 2012.

[21] A. Zaza, N. E. Laadel, H. Agalit, E. G. Bennouna, and Y. E. Hammami, “Experimental Study of Fouling in Hybrid Cooling Tower Used in CSP Plants: A Prototype Scale Preliminary Test Feedback,” in *Proceedings of the 1st International Conference on Electronic Engineering and Renewable Energy*, in Lecture Notes in Electrical Engineering. Springer, Singapore, Apr. 2018, pp. 664–671. doi: 10.1007/978-981-13-1405-6_76.

[22] A. Zaza, N. E. Laadel, E. G. Bennouna, and Y. E. Hammami, “The influence of the cooling system fouling on the thermal performance of a CSP plant: Recent research updated,” *AIP Conference Proceedings*, vol. 2307, no. 1, p. 020061, Dec. 2020, doi: 10.1063/5.0032965.

[23] A. Zaza, N. E. Laadel, H. Agalit, E. G. Bennouna, and Y. E. Hammami, “Fouling mitigation on different heat exchanging surfaces materials used in the hybrid cooling tower test facility,” *AIP Conference Proceedings*, vol. 2126, no. 1, p. 080007, Jul. 2019, doi: 10.1063/1.5117602.

[24] A. Zaza, E. G. Bennouna, N. E. Laadel, and Y. El Hammami, “Experimental Study of Fouling in Hybrid Cooling Tower Used in CSP Plants: Effects of the Polymer and galvanized steel tubes,” *Thermal Science and Engineering Progress*, vol. 25, p. 101005, Oct. 2021, doi: 10.1016/j.tsep.2021.101005.

[25] A. Zaza, E. G. Bennouna, A. Iranzo, Y. El Hammami, and F. J. Pino, “Optimizing sustainability in hybrid cooling towers: Investigating fouling resistance, water quality correlations, modeling, and cleaning strategies for thermal power plants,” *Journal of Cleaner Production*, vol. 462, p. 142706, Jul. 2024, doi: 10.1016/j.jclepro.2024.142706.

[26] A. Benyekhlef, B. Mohammedi, D. Hassani, and S. Hanini, “Application of artificial neural network (ANN-MLP) for the prediction of fouling resistance in heat exchanger to MgO-water and CuO-water nanofluids,” *Water Science and Technology*, vol. 84, no. 3, pp. 538–551, Jun. 2021, doi: 10.2166/wst.2021.253.

[27] B. Van Rooyen, “Performance and fouling prediction model for finned-tube heat exchangers,” Thesis, North-West University (South Africa), 2020. Accessed: Jan. 24, 2024. [Online]. Available: https://repository.nwu.ac.za/handle/10394/36224

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[28] "Géron: Hands-on machine learning with Scikit-Learn,... - Google Scholar." Accessed: Jan. 17, 2024. [Online]. Available: https://scholar.google.com/scholar_lookup?title=Hands-On%20Machine%20Learning%20with%20Scikit-Learn%2C%20Keras%2C%20and%20TensorFlow%3A%20Concepts%2C%20Tools%2C%20and%20Techniques%20to%20Build%20Intelligent%20Systems&author=A.%20G%C3%A9ron&publication_year=2019

[29] F.-V. Gutierrez-Corea, M.-A. Manso-Callejo, M.-P. Moreno-Regidor, and M.-T. Manrique-Sancho, "Forecasting short-term solar irradiance based on artificial neural networks and data from neighboring meteorological stations," *Solar Energy*, vol. 134, pp. 119–131, Sep. 2016, doi: 10.1016/j.solener.2016.04.020.

[30] E. Davoudi and B. Vaferi, "Applying artificial neural networks for systematic estimation of degree of fouling in heat exchangers," *Chemical Engineering Research and Design*, vol. 130, pp. 138–153, Feb. 2018, doi: 10.1016/j.cherd.2017.12.017.

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