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Optimization of operating parameters and performance evaluation of forced draft cooling tower using response surface methodology (RSM) and artificial neural network (ANN) †

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Abstract

Optimization of cold water temperature in forced draft cooling tower with various operating parameters has been considered in the present work. In this study, response surface method (RSM) and an artificial neural network (ANN) were developed to predict cold water temperature in forced draft cooling tower. In the development of predictive models, water flow, air flow, water temperature and packing height were considered as model variables. For this propose, an experiment based on statistical five-level four factorial design of experiments method was carried out in the forced draft cooling tower. Based on statistical analysis, packing height, air flow and water flow were high significant effects on cold water temperature, with very low probability values (< 0.0001). The optimum operating parameters were predicted using RSM, ANN model and confirmed through experiments. The result demonstrated that minimum cold water temperature was optioned from the ANN model compared with RSM.

Keywords: Cooling tower; Optimization; Cold water temperature; Response surface methodology; Artificial neural network

1. Introduction

The cooling tower is a steady flow device that uses a combination of mass and energy transfer to cool water by exposing it as an extended surface to the atmosphere. The water surface is extended by filling, which presents a film surface or creates droplets. The air flow may be cross flow or counter flow and caused by mechanical means, convection currents or by natural wind. In mechanical draft towers, air is forced by one or more mechanically driven fans to provide a constant air flow. The function of the fill is to increase the available heat transfer surface in the tower, either by spreading the liquid over a greater surface or by retarding the rate of fall of the droplet surface through the apparatus. The fill should be strong, light and deterioration resistant. In this study, expanded wire mesh was used as the filling material. Its hardness, strength and composition guard against common cooling tower problems resulting from fire, chemical water treatment and deterioration.

The operating theory of cooling tower was first suggested by Walker et al. [1]. Simpson and Sherwood [2] studied the performance of forced draft cooling towers with a 1.05 m packing height consisting of wood slats**.** Kelly and Swenson [3] studied the heat transfer and pressure drop characteristics of splash grid type cooling tower packing. Barile et al. [4] studied the performance of a turbulent bed cooling tower. They correlated the tower characteristic with the water/air mass flow ratio. Bedekar et al. [5] studied experimentally the performance of a counter flow packed bed mechanical cooling tower, using a film type packing. Goshayshi and Missenden [6] studied experimentally the mass transfer and the pressure drop characteristics of corrugated packing, including smooth and rough surface corrugated packing in atmospheric cooling towers [6]. Much work has appeared in the literature describing the performance analysis of cooling tower using different type of packing and orientation of the packing with operating parameters [7-12]. In addition, various references have mentioned examples that illustrated the performance optimization of cooling towers under varying operating conditions [13-15]. In most of the literature surveys, optimization techniques have been developed as mathematical modeling and simulation using ANN, fuzzy, PSO, genetic algorithm etc., and that is being compared with already existing experimental work from the literature itself. This study presents an experimental investigation of performance analysis of cooling tower with optimization techniques using RSM and ANN model. From the ex-

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Table 1. Cooling tower operating parameters and their corresponding range.

Parameter	Range
Water flow (kg/hr)	100-200
Air flow (kg/hr)	100-200
Hot water (°C)	40-48
Packing height (m)	0-1.25

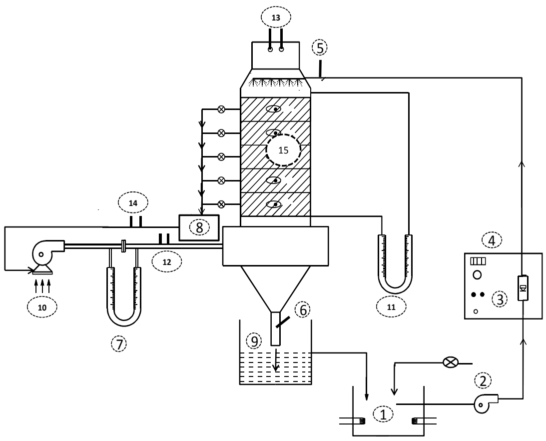


Fig. 1. Experimental setup of forced draft cooling tower.

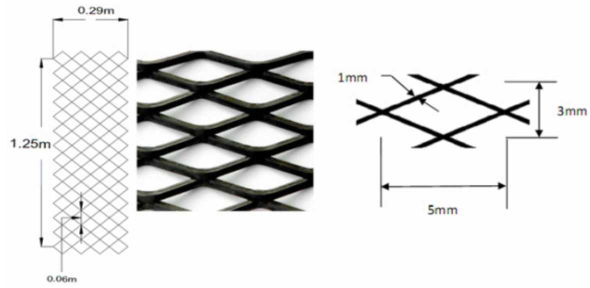
1. Water heater, 2. Pump, 3. Flow meter, 4. Temp. display and control unit, 5. Hot water thermometer, 6. Coldwater thermometer, 7. U-Tube manometer -- air flow, 8. Psychrometric gun, 9. Receiving tank, 10. Forced draft fan, 11. U-Tube manometer – packing differential pressure, 12. Air inlet temperature. (T_{DB1} T_{WB1}), 13. Air outlet temperature (T_{DB2} T_{WB2}), 14. Psychrometric gun temperature 15. Expanded wire mesh fill.

perimental study, cooling tower cold water temperature was identified with best optimum cooling tower operating parameters.

The results obtained from RSM and ANN models are compared with experimental results.

2. Experimental setup

A schematic diagram of the experimental apparatus is shown in Fig. 1. The main part of the installation is the cooling tower, 1.5 m in height and 0.3 m × 0.3 m in cross section. The tower structure is transparent and is made of acrylic plate of 5mm thickness. The water is directly distributed over the EWM packing, and the films of falling water were uniform across the whole surface of packing. The pressure drop at fill zone is measured by U-tube manometer. Chromel-alumel thermocouples were used to measure hot water (HW) and cold water (CW) temperatures and measure the water temperature in fill zone area. All thermocouples were connected to a 24 point digital temperature recorder. Both dry bulb and wet bulb temperature of air are measured at the inlet and exit of the cooling tower. The operating parameters and their corresponding ranges are given in Table 1.



(a) (b) (c)

Fig. 2. (a) Expanded Mire mesh packing in cooling tower; (b) Enlarged view of expanded wire mesh packing; (c) Wire mesh dimensions.

3. Expanded wire mesh

In the experimental study, expanded wire mesh was used as tower packing material. This type of wire mesh is considered as unique for film packing. The forming of wire meshes is made in such a way that each little aperture acts as directing vane on air, moving bulk of air alternately from one side to other. This action results in air travelling a distance of about 1.25 m through the total depth of packing. Compared with different solid packing, wire mesh provides the minimum restriction to the passage of air. The schematic arrangement of the packing is shown in Fig. 2(a-c). In one sq. inch area, 32 diamond shapes are present.

4. Experimental design and analysis

Experimental design of the process for optimum cold water (CW) temperature for the mechanical draft cooling tower was carried out using the RSM. The RSM is a collection of mathematical and statistical techniques. That is useful for the optimization of the industrial processes and chemical reactions, and is commonly used for experimental designs [16-20]. Here, RSM was used to assess the relationship between response (cold water (CW) temperature, (°C) and independent variables, as well as to optimize the relevant conditions of variables in order to predict the best value of responses. Experiments were designed on the basis of the experimental design technique that has been proposed by central composite design (CCD). CCD, which is the most widely used approach in RSM, was employed to determine the effect of operational variables on cold water (CW) temperature in a cooing tower. According to Guven et al. [19], CCD is ideal for sequential experimentation, as it allows reasonable amount of information to test lack of fit when a sufficient number of experimental values exist. CCD and RSM were established with the help of the Design Expert 8.0.6. The four significant independent variables considered in this study were water flow (WF), air flow (AF), hot water (HW) temperature, and packing height (PH), which are presented in Table 2. Each independent variable was varied over five levels between −2 and +2 at the determined ranges based

Table 2. Coding of process parameters and their corresponding range.

Level	Water flow (WF) kg/hr	Air flow (AF) kg/hr	Hot water (HW) °C	Packing height (PH) m
-2	100	100	40	0.00
-1	125	125	42	0.31
0	150	150	44	0.62
1	175	175	46	0.94
2	200	200	48	1.25

on some preliminary experiments [25, 27]. The total number of experiments for the four factors was 30 (= $2^k + 2k + 6$), where k is the number of factors (k = 4). As there are only five levels for each factor, the appropriate model is the quadratic model whose mathematical form [26, 28] is given in Eq. (1).

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \sum_{j=1}^{k} \beta_{jj} X_j^2 + \sum_i \sum_{<j=2}^{k} \beta_{ij} X_i X_j + e_i \tag{1}$$

where Y is the response; X_i and X_j are the variables; β_0 is a constant coefficient; β_j, β_{jj}, and β_{ij} are the interaction coefficients of linear, quadratic and second-order terms, respectively; k is the number of studied factors; and e_i is the error. The quality of the fit of polynomial model was expressed by the value of correlation coefficient (R^2). The main indicators demonstrating the significance and adequacy of the used model include the model F-value (Fisher variation ratio), probability value (Prob>F), and Adequate Precision [15, 21]. Instantaneous consideration of multiple responses involved the initial creation of a suitable response surface model, and subsequently, identifying a set of operational conditions that maximize or minimize targeted response [20, 22].

5. Artificial neural network (ANN)

The basic unit in the ANN is the neuron. Neurons are connected to each other by links known as synapses, and associated with each synapse there is a weight factor. The neural network modeling approach is explained in Ref. [23]. In this present study, the BP algorithm was used with a single hidden layer improved with numerical optimization technique [24].

The architecture of ANN used in this study is 4-121-1, with 4 corresponding to the input values, 12 to the number of hidden layer neurons and 1 to the output. The topology architecture of ANN-model used for prediction of cold water (CW) temperature is illustrated in Fig. 3. The neural network was trained for cold water (CW) temperature prediction. ANN was used to predict the cold temperature within the trained range. Statistical methods were used to compare the results produced by the network. Errors occurring at the learning and testing stages are called the root-mean square error (RMSE), absolute fraction of variance (R^2), and mean absolute error (MAE) percentage values. These are defined as follows, respectively:

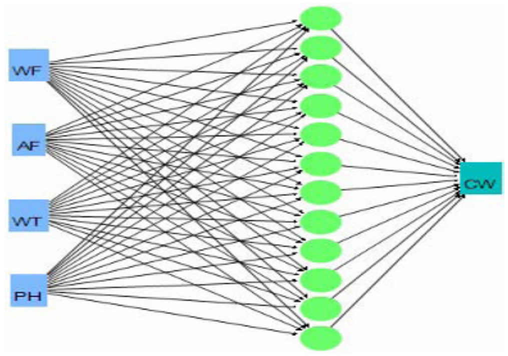


Fig. 3. Architecture of ANN-model used for prediction of cold water (CW) temperature.

$$RMS = \sqrt{\left(\frac{1}{p}\right) \sum (t_j - o_j)^2} \tag{2}$$

$$R^2 = 1 - \left[\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2}\right]^{\frac{1}{2}} \tag{3}$$

$$MAE = \left(\frac{1}{P}\right) \sum_j \frac{t_j - o_j}{t_j} \times 100 \tag{4}$$

where t_j the network (predicted) output from observation is, is O_j the experimental output from observation, and p is the total number of data observation.

6. Results and discussion

6.1 Response surface modeling (RSM)

A total of 30 runs of the CCD experimental design and response based on the experimental, RSM and ANN model runs are shown in Table 3. Table 4 shows the analysis of variance (ANOVA) of regression parameters of the predicted response surface quadratic model for cold water (CW) temperature. As can be seen from Table 4, the model F-value of 75.71 and a low probability value ($Pr > F < 0.0001$) indicate that the model was significant for cold water (CW) temperature. Values of $P > F$ less than 0.0500 indicate that model terms are significant, while values greater than 0.1000 indicate that the model terms are not significant [25]. The adequate precision measure signal to noise was computed by dividing the difference between the maximum predicted response and the minimum predicted response by the average standard deviation of all predicted responses. A ratio greater than 4 is desirable [21]. The "adequate precision" ratio of the model was 25.906, which is an adequate signal for the model [18]. PRESS stands for 'prediction error sum of square' and it is a measure of how well the model for the experiment is likely to predict the responses in a new experiment. In this case the value was 14.71.

The lack of fit F-test was statistically significant as the P values were less than 0.05. A significant lack of fit suggests that there may be some systematic variation unaccounted for in the hypothesized model.

This may due to the exact replicate values of the independent variable in the model that provide an estimate of pure error.

Table 3. Response values for different experimental conditions.

Run	Factor				Response cold water (CW)		
	WF	AF	HW	PH			
	kg/hr		°C	m	Exp	RSM	ANN
1	150	150	44	0.62	28.0	28.00	27.81
2	175	125	42	0.31	34.5	34.88	34.34
3	150	150	48	0.62	31.0	31.42	31.32
4	125	125	46	0.94	31.0	30.71	31.02
5	175	125	42	0.94	33.5	33.63	33.21
6	150	150	44	0.62	28.0	28.00	27.97
7	100	150	44	0.62	29.5	29.83	30.02
8	125	125	42	0.31	33.0	32.63	32.54
9	150	150	40	0.62	33.0	32.75	32.25
10	150	150	44	0.00	36.0	35.58	34.96
11	175	175	46	0.94	28.5	28.79	28.45
12	125	125	42	0.94	31.0	31.13	31.78
13	150	150	44	0.62	28.0	28.00	28.56
14	125	175	42	0.94	29.0	28.71	28.25
15	125	125	46	0.31	32.0	32.21	31.95
16	150	150	44	0.62	28.0	28.00	27.78
17	175	175	42	0.94	30.0	29.71	29.12
18	175	125	46	0.31	34.0	34.21	33.89
19	125	175	46	0.94	28.5	28.04	27.87
20	150	100	44	0.62	33.5	33.50	33.78
21	125	175	42	0.31	33.0	33.46	32.98
22	200	150	44	0.62	33.0	32.83	33.01
23	150	200	44	0.62	30.0	30.17	30.67
24	150	150	44	0.62	28.0	28.00	27.55
25	125	175	46	0.31	33.0	32.79	32.49
26	150	150	44	0.62	28.0	28.00	27.55
27	175	125	46	0.94	33.5	32.96	32.56
28	175	175	46	0.31	33.5	33.29	33.07
29	150	150	44	1.25	29.0	29.58	29.32
30	175	175	42	0.31	34.0	34.21	33.98

The value of correlation coefficient (R^2 = 99.11%) obtained in the present study for cold water (CW) temperature was higher than (R^2adj = 98.33%). High R^2 value illustrates good agreement between the calculated and observed results within the range of experiment. The R^2(pre) of 98.47% is in reasonable agreement with the R^2(adj) of 98.33%. In this case A, B, C, D, AB, BD, A^2, B^2, C^2, D^2 are significant model terms. Insignificant model terms, which have limited influence, such as AC, AD, BC and CD, were excluded from the study to improve the model. Based on results, the response surface model constructed in this study for predicting cold water (CW) temperature is considered to be reasonable. The final regression model, in terms of their coded factors, is expressed by the following second-order polynomial equation given below:

Table 4. ANOVA and adequacy of the quadratic model.

	Sum of squares	Degree of freedom	Mean square	F-value	Prob >F
Model	176.67	14	12.62	75.71	< 0.0001
A-WF	13.50	1	13.50	*81.00*	< 0.0001
B-AF	16.67	1	16.67	*100.00*	< 0.0001
C-HW	2.67	1	2.67	*16.00*	0.0012
D-PH	54.00	1	54.00	*324.00*	< 0.0001
AB	2.25	1	2.25	*13.50*	0.0023
AC	0.063	1	0.063	*0.37*	0.5495
AD	0.063	1	0.063	*0.37*	0.5495
BC	0.063	1	0.063	*0.37*	0.5495
BD	10.56	1	10.56	*63.37*	< 0.0001
CD	0.000	1	0.00	0.00	1.0000
A^2	19.05	1	19.05	*114.29*	< 0.0001
B^2	25.19	1	25.19	*151.14*	< 0.0001
C^2	28.58	1	28.58	*171.50*	< 0.0001
D^2	36.01	1	36.01	*216.07*	< 0.0001
Residual	2.50	15	0.17	R^2 = 99.11% R^2(pred) = 94.87% R^2(adj) = 98.33% Adeq Precision = 25.906 PRESS = 14.71 Std Dev. = 0.41	
Lack of fit	2.50	10	0.25		
Pure error	0.00	5	0.000		
Cor total	179.17	29			

$$CW = 28.00 + 0.75A - 0.83B - 0.33C - 1.50D - 0.37AB - 0.81BD + 0.83A^2 + 0.96B^2 + 1.02C^2 + 1.15D^2 \quad (5)$$

In terms of actual factors, an empirical relationship between cold water (CW) temperature and process variables can be expressed by the following second-order polynomial equation below:

$$\mathrm{CW} = 563.00 + 0.23\mathrm{WF} - 0.28\mathrm{AF} - 22.25\mathrm{HW} - 6.33\mathrm{PH} - 0.0006\mathrm{WFAF} - 0.13\mathrm{AFPH} + 0.0013\mathrm{WF}^2 + 0.0015\mathrm{AF}^2 + 0.25\mathrm{HW}^2 + 18.33\mathrm{PH}^2 \quad (6)$$

6.2 Model adequacy checking

Usually, it is necessary to check the fitted model to ensure that it provides an adequate approximation to the real system. Unless the model shows an adequate fit, proceeding with investigation and optimization of the fitted response surface likely gives poor or misleading results. The residuals from the least squares fit, which is defined by $e_i = y_i - \hat{y}_i$, $i = 1, 2, ..., n$, play an important role in judging model adequacy. By applying the diagnostic plots provided by the Design Expert 6.0.8 (Trial) software, such as normal probability plots of the studentized residuals, as well as the predicted versus actual value plots, the model adequacy can be judged.

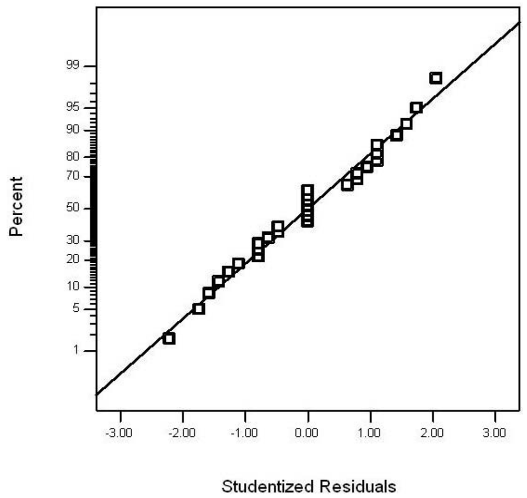


Fig. 4. Normal probability plot of the studentized residual for cold water (CW) temperature.

Fig. 4 shows the normal probability plots of the studentized residuals for cold water (CW) temperature. A normal probability plot indicates if the residuals follow a normal distribution, in which case the points will follow a straight line [26]. The data is normally distributed, since some scattering is expected even with the normal data, as shown in Fig. 4.

6.3 Optimizing parameters for cold water temperature

Contour plots show a distinctive circular shape which is an indicative of possible independence of factors with response. A contour plot is produced to visually display the region of optimal factor settings. For second-order response surfaces, such a plot can be more complex than the simple series of parallel lines that can occur with first-order models. Once the stationary point is found, it is usually necessary to characterize the response surface in the immediate neighborhood of the point by identifying whether the stationary point found is a maximum response or minimum response or a saddle point.

To classify this, the most straightforward way is to examine through a contour plot. Contour plots play a very important

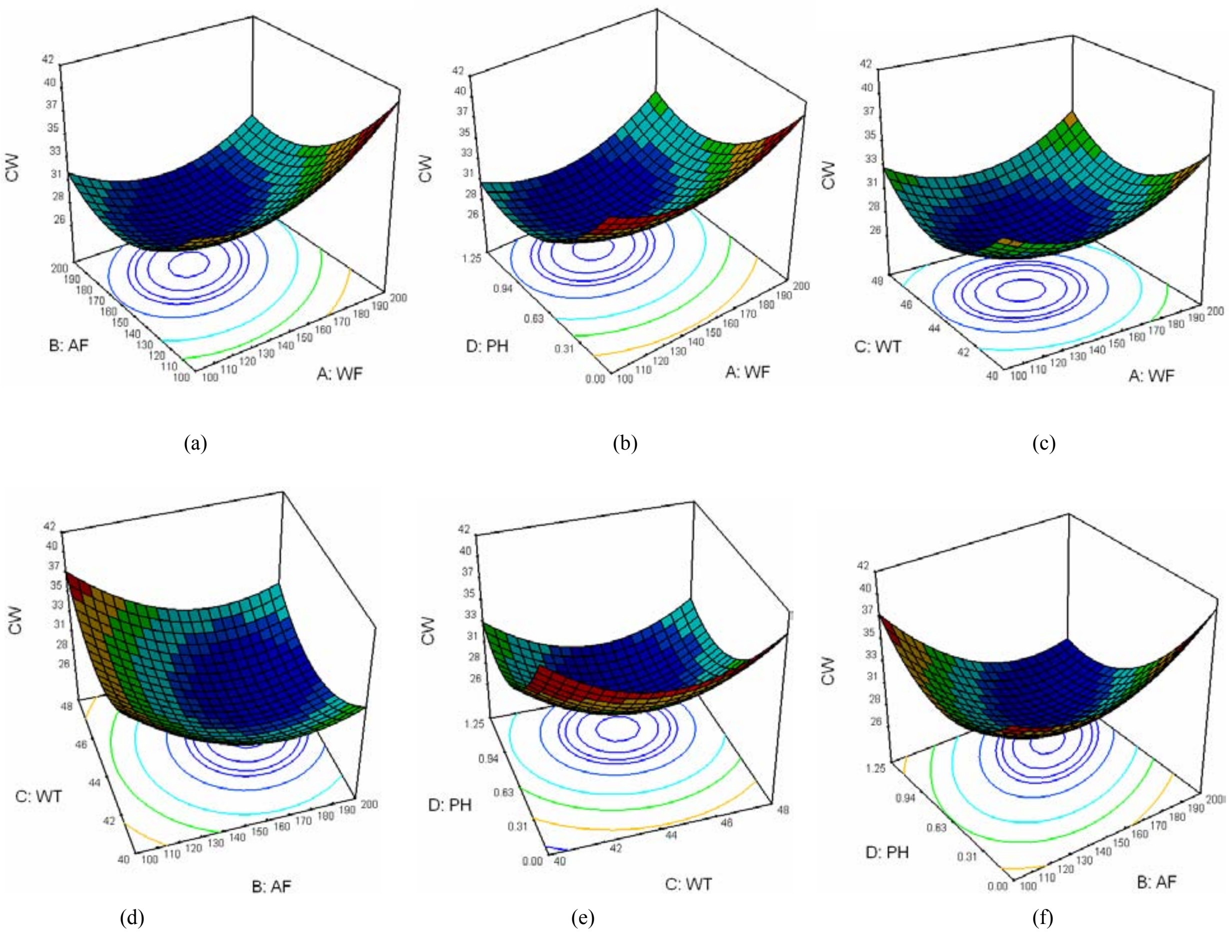


Fig. 5. Response surface of cold water temperature as a function of (a) WF and AF; (b) WF and HW; (c) WF and PH; (d) AF and HW; (e) AF and PH; (f) HW and PH.

role in the study of the response surface. By generating contour plots using software for response surface analysis, the optimum is located with reasonable accuracy by characterizing the shape of the surface. If a contour patterning of circular shaped contours occurs, it tends to suggest independence of factor effects while elliptical contours may indicate factor interactions [27]. Response surfaces have been developed for both the models, taking two parameters in the middle level and two parameters in the *X* and *Y* axis and response in *Z* axis.

The response surface graph is used to find the optimal set of process parameters that produce a maximum or minimum value of the response [29]. In the present investigation the process parameters corresponding to the minimum cold water (CW) temperature are considered as optimum (analyzing the contour graphs and by solving Eq. (6). Hence, when these optimized process parameters are used, then it will be possible to obtain the minimum cold water (CW) temperature. Fig. 5(a)-(f) presents three-dimensional response surface plots for the response cold water (CW) temperature obtained from the regression model. The optimum cold water (CW) temperature is exhibited by the apex of the response surface.

It shows almost a circular contour, which suggests independence of factor effect, namely WF, AF, HW and PH. From Fig. 5(a) the minimum cold water (CW) temperature was achieved at the maximum AF and minimum WF. Better heat transfer rate occurred and optimum cold water (CW) temperature was obtained at the WF to AR ratio of 0.8 to 0.95.

The interaction of WF and HW with respect to cold water (CW) temperature is shown in Fig. 5(b, d). At the higher and lower end of hot water (HW) temperature, there is no impact in cold water (CW) temperature. WT of 45°C obtained minimum cold water (CW) temperature. Better heat transfer rate between water and air was enhanced only by the packing. A packing height of 0 means there is no packing inside the cooling tower. In Fig. 5(c) the cold water (CW) temperature is at higher side between at the 0 to 0.2 m packing height. It represents that the heat transfer is very poor at lower packing height. When packing height is increased up to 0.92m, the cold water (CW) temperature is lowered to 27°C. Further increase in the packing height (PH) did not affect the cold water (CW) temperature. From this Fig. 5(c, e, f) the packing height was found to be optimum between 0.85 to 0.95 m.

6.4 Comparison of ANN and RSM models

The ANN and RSM models were compared and trained. The comparison was made on the basis parameters such as average % error and RMS. The test error for ANN and RSM model was about 1.56% and 2.45% respectively. The predicted values of ANN and RSM values are tabulated in Table 3. Fig. 6 shows the comparative parity plot for ANN and RSM predictions. The ANN model fitted the experimental data with an excellent accuracy. The RSM-based prediction shows greater deviation than ANN. Fig. 7 shows the independent variables on cold water (CW) temperature. The degree of impact of packing height (PH) is the most affecting variable with normalized importance of 100% followed by air flow (AF) with 76.7%, water flow (WF) with 45.9% and the hot water (HW) temperature with 42.8% of normalized importance. The response of the cold water (CW) temperature was achieved at 26.87 °C and 24.63 °C for RSM and ANN model, respectively, and it is tabulated in Table 5.

Table 5. Optimization process variables for cold water (CW) temperature through desirability function.

	Water flow (WF)	Air flow (AF)	Hot water (HW)	Packing height (PH)	Cold water (CW)	
					Exp	Pred
	kg/hr	kg/hr	°C	m	°C	°C
RSM	142.0	168.00	44.00	0.90	27.50	26.87
ANN	141.0	155.00	43.50	0.88	27.10	24.63

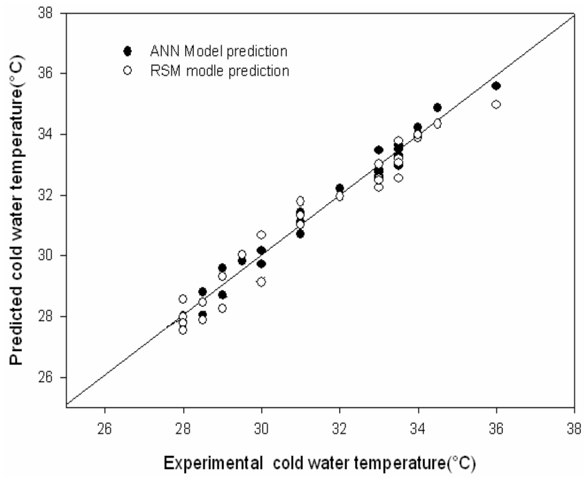


Fig. 6. RSM and ANN predicted vs Experimental for cold water (CW) temperature.

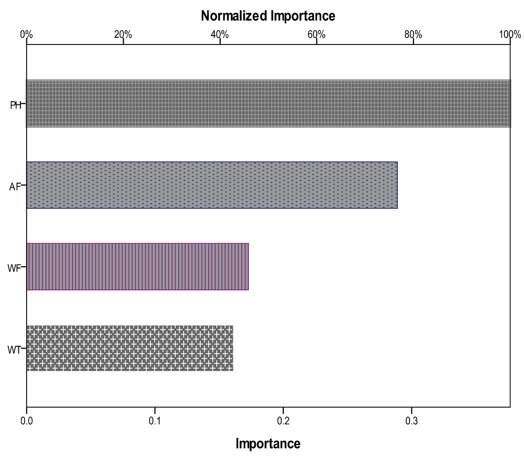


Fig. 7. Independent variables importance for cold water (CW) temperature.

7. Conclusion

RSM and ANN models were developed and operating parameters were optimized for forced draft cooling tower. Models were also compared, to predict cold water (CW) temperature accurately with a wide range of operating parameters based on design of experiment method. The model indicated that operating variables like packing height (PH), air flow (AF) and water flow (WF) were major influences for cold water (CW) temperature.

The response of cold water (CW) temperature was achieved at 26.87°C and 24.63°C using RSM and ANN model. Minimum cold water (CW) temperature was obtained in ANN model (24.63°C) and the related experimental run (27.10°C). By comparing experimental cold water (CW) temperature values, predicted from RSM model with those predicted ANN, the test errors were 2.45% and 1.56% respectively. ANN showed better accuracy and generalization capability than RSM.

The prediction accuracy of ANN was better than RSM, because RSM has structured nature and setting useful insight information of interaction between different variables of the system. ANN has also shown higher accuracy in finding optimum conditions and predicting optimum value. Thus, ANN has consistently performed better than RSM. The predictive ANN model was found to be capable of better prediction of minimum cold water (CW) temperature within the range that they had been trained. The results of the ANN model indicate that it is much more robust and accurate in estimating the values of minimum cold water (CW) temperature when compared with RSM model.

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