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Comparison between an artificial neural network and Poppe's model for wet cooling tower performance prediction in CSP plants

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Abstract:

The efficiency of a Concentrated Solar Power (CSP) plant strongly depends on the temperature at what the steam is condensed. To date, the conventional systems used to remove the heat from CSP plants are either water (wet) or air-cooled (dry). The use of wet cooling in CSP plants results in the best plant performance. This efficiency increase, however, comes at a high cost: huge water use. This fact is crucial since CSP plants are, in general, located in arid areas where water is scarce. Dry cooling eliminates the water use but suffers from lower efficiency when ambient air temperature is high. Those hot periods are often the periods of peak system demand and higher electricity sale price. A combined cooling system (combination of dry and wet cooling) offers the advantages of each process in terms of lower water consumption and higher electricity production. The ultimate goal of this research is to model and optimise the performance of a CSP plant operating alongside with a combined cooling system in terms of water consumption and net power generation. This paper focuses on the wet cooling tower modelling validated with experimental data from a pilot plant. In this sense, two different models are compared: the Poppe model and an artificial neural network (ANN). Both models are compared in terms of performance prediction (water outlet temperature and water use), experimental requirements and applications. Although both models are reliable (for outlet water temperature, R^2 = 0.97 and RMSE= 1.01°C with the ANN, and $R^2 \approx 1$ and RMSE$<$ 0.36°C for with the Poppe model), it was found that depending on the variable, each model had its strengths and weaknesses.

Keywords:

Concentrated solar power, Combined cooling systems, Cooling tower, Neuronal networks, Poppe model

1. Introduction

Concentrated Solar Power (CSP) plants use mirrors to concentrate the sun's energy to drive steam turbines that create electricity. This technology currently represents a minor part of renewable energy generation in Europe. Only approximately 5 GW are installed globally (of which 2.3 GW in Europe, concentrated in Spain). However, the potential for growth is significant given the capability of CSP to provide renewable electricity when needed, unlike other technologies that are dependent on the availability of the energy source. This dispatchability is possible thanks to in-built energy storage and enables plants to respond to peaks in demand, continue production even in the absence of sunlight, and provide ancillary services to the grid. According to the International Energy Agency forecasts, CSP has a huge potential in the long term, ranging from the 986 TWh by 2030 up to 4186 TWh by 2050 according to the Sustainable Development hi-Ren scenario (Energy Technology Perspectives 2014), meaning CSP will account for 11% of the electricity generated worldwide and 4% in Europe. As the technological leader in the sector, the EU has much to gain from such expansion. To remain a global leader, the European industry needs to stay ahead with more advanced, competitive technologies. CSP plants are, in general, located in arid areas, where water is scarce. The efficiency of these plants strongly depends on the temperature at what the steam is condensed. To date, the conventional systems used to remove the heat from CSP plants are either water (wet) or air-cooled (dry). The lowest attainable condensing temperature is the wet-bulb temperature (wet system). This efficiency increase comes at a high cost: huge water use. Dry cooling eliminates the water use but suffers from lower efficiency when ambient air temperature is high. Those hot periods are often the periods of peak system demand and higher electricity sale price.

There are different types of innovative cooling systems that can reduce the water consumption: those that integrate the dry and wet cooling systems into the same cooling device, which are called hybrid cooling systems [1–3] and those that combine a dry and a wet cooling system, which are called combined systems. In the last case, different configurations can be found.The most proposed in the literature is the one considering an Air

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Cooled Condenser (ACC) in parallel with a Wet Cooling Tower (WCT) [4, 5]. In this case, the exhaust steam from the turbine is condensed either through the ACC or through a surface condenser coupled with the WCT. Another configuration, recently proposed in Palenzuela et al. [6] is a wet and a dry cooling tower (type air cooled heat exchanger) sharing a surface condenser. In this case, the exhaust steam from the turbine is condensed through the surface condenser and the heated cooling water is cooled either through the WCT or through the dry cooling tower. Combined systems are the most suitable option for a flexible operation as a function of the ambient conditions, allowing to select the best operation strategies to achieve an optimum water and electricity consumption [7]. To optimise the operation of this kind of refrigeration systems, modelling each one of its components is required as a first step.

Regarding WCT modelling, two kind of models can be distinguished: those based on physical equations and black-box model such as artificial neuronal networks (ANN). The analysis of wet cooling towers through modelling (physical equations) has its origin in [8], where the theory for the performance evaluation of wet cooling towers was developed. The author proposed a model based on several critical assumptions to reduce the solution of heat and mass transfer in wet-cooling towers to a simple hand calculation. Because of these assumptions, however, the Merkel method does not accurately represent the physics of the heat and mass transfer process in the cooling tower. Bourillot [9] stated that the Merkel method is simple to use and can correctly predict cold water temperature when an appropriate value of the coefficient of evaporation is used. In contrast, it is insufficient for the estimation of the characteristics of the warm air leaving the fill and for the calculation of changes in the water flow rate due to evaporation. These quantities are important to estimate water consumption and to predict the behaviour of plumes exiting the cooling tower. Jaber and Webb [10] developed the equations necessary to apply the effectiveness-NTU method directly to counterflow or crossflow cooling towers. This approach is particularly useful in the latter case and simplifies the method of solution when compared to a more conventional numerical procedure. The effectiveness-NTU method is based on the same simplifying assumptions as the Merkel method. Poppe and Rögener [11] developed the Poppe method. They derived the governing equations for heat and mass transfer in a wet cooling tower and did not make any simplifying assumptions as in the Merkel theory. Predictions from the Poppe formulation result in values of evaporated water flow rate that are in good agreement with full scale cooling tower test results. In addition, the Poppe method predicts the water content of the exiting air accurately.

Although the theoretical analysis of WCT has demonstrated successful results with not excessive complexity, black box models based on experimental data are also available in the literature. Numerous authors have designed ANN models for WCT with different objectives, such as performance prediction, simulation and optimisation. One of the first works in this area is the one described in [12] where an ANN model was developed to predict the performance of a forced-counter flow cooling tower at lab scale. In this case, the input variables were the dry bulb temperature, relative humidity of the air stream entering the tower, the temperature of the water entering the tower, the air volume flow rate and the water mass flow rate. The outputs of this model were the heat rejection rate at the tower, the mass flow rate of water evaporated, the temperature of the water at the tower outlet and the dry bulb temperature and relative humidity of the air stream leaving the tower. The results obtained with a 5-5-5[1] ANN demonstrated that cooling towers at lab-scale can be modelled using ANNs within a high degree of accuracy. At lab-scale there are also ANN models for Natural Draft Counter-flow Wet Cooling Towers (NDWCT) such as the one proposed by [13]. In this case, the authors used a 4-8-6 ANN structure and considered some additional variables, such as air gravity, wind velocity, heat transfer coefficients and efficiency as outputs. All these works at lab-scale can be useful to validate the model development methodology but may fail predicting the performance of WCT at larger scale. In this sense, special attention deserves the study carried out by [14] where an 8-14-2 ANN model was proposed to predict the performance (the cooling number and the evaporative loss proportion) of NDWCTs at commercial scale. The model is based on 638 sets of field experimental data collected from 36 diverse NDWCTs used in power plants. It is a very challenging work since it covers samples from a wide range of tower sizes and capacities but the results show that the Mean Relative Error (MRE) is below 5%. From the ANN models found in the literature, it can be concluded that these computational models are able to predict WCT performance with satisfactory results, but it is necessary to deepen and reflect when it is convenient to develop models of this type or to use others, either based on experimental data or based on physical equations. In the literature, comparisons between ANN and Response Surface Methodology (RSM) models for WCT can also be found [15], such as the case of where ANN model is compared with one obtained with the RSM. Although the results obtained show that ANN model predictions are better than RSM model, the study is based on data from a WCT lab-scale system, with only one output (the cooling temperature) and no ambient conditions variability.

Based on the previous discussion, the ultimate goal of this research is to optimise the operation of combined cooling systems integrated into CSP plants in terms of water consumption avoiding a penalty in the plant performance . This paper presents a comparison between the Poppe model (based on physical equations) and

[1]The notation n_1-...-n_l represents the architecture of the ANN model, where l is the number of layers and n_i are the nodes in each one of the layers.

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a model based on an ANN for performance evaluation of wet cooling towers. For the calibration of the physical model and for the development of the neural network model, experiments have been performed in a 200 kW$_{th}$ WCT integrated into a combined cooling system pilot plant, located at Plataforma Solar de Almería (PSA). The comparison between models not only evaluates the outputs accuracy obtained with both models, but also discusses other aspects such as required inputs/outputs and parameters, minimal number of experiments and possibility of applying these models for different purposes.

This paper is organised as follows: section 2. contains the description of the experimental facility, the mathematical modelling, and the experimental procedure for the performance tests. Next, the results obtained in the tests are presented and discussed in section 3. Finally, the the most important findings of the research are summarised in section 4.

2. Methodology

2.1. Description of the pilot plant

The pilot plant of combined cooling systems located at PSA (see the layout in Figure 1) consists of three circuits: cooling, exchange and heating. In the cooling circuit (see a picture in Figure 2), refrigeration water circulating inside the tube bundle of a Surface Condenser (SC) can be cooled through a Wet Cooling Tower and/or a Dry Cooling Tower (type Air Cooled Heat Exchanger), both with a designed thermal power of 204 kW$_{th}$. In the exchange circuit, a saturated steam generator of 80 kWth (on the design point), generates steam at different pressures (in the range between 82 and 200 mbar), which is in turn condensed in the surface condenser that has a thermal power at design conditions of 80 kW$_{th}$. In this way, the steam transfers its latent heat of condensation to the refrigeration water, that is heated. Finally, in the heating circuit, a solar field with a thermal power of 300 kW$_{th}$ at the design point, provides the energy source required by the steam generator, in the form of hot water. It is a unique, very flexible, fully instrumented and versatile facility, able to operate in different operation modes: series and parallel mode, conventional dry-only mode (all water flow is cooled through the dry cooling tower) and wet-only mode (all water flow is cooled through the wet cooling tower). For this work, the wet-only operation mode has been used, in which the cooling water (FT-003) is pumped by Pump 1 from the basin of the WCT to the surface condenser, circulating through Valve 2 position I up to the entrance of the WCT where water is sprayed. The velocity of air going through the tower is regulated by variable frequency drive (SC-001). The water losses by evaporation in the tower are replaced by demineralised water (FT-004) when the basin level decreases. The sensors used in this operation mode and their characteristics in terms of errors are shown in Table 1.

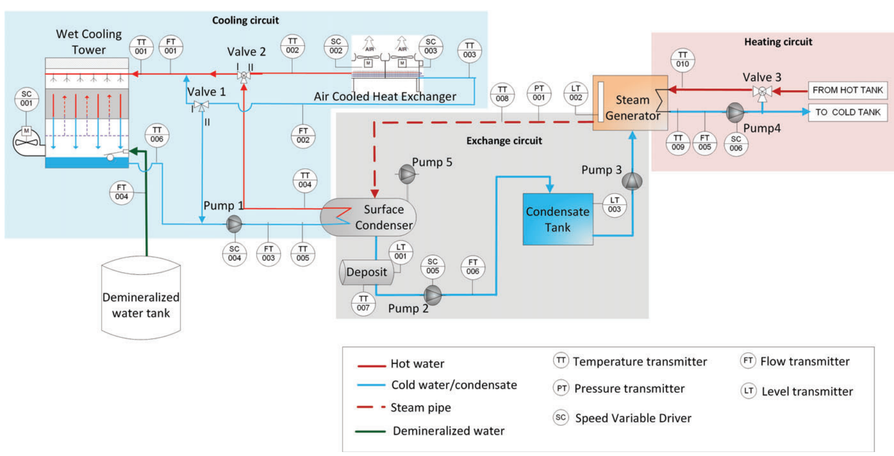

Figure 1: Layout of combined cooling systems pilot plant at PSA.

2.2. Experimental campaign

As mentioned in section 1., two models have been developed for performance evaluation of a WCT: the Poppe model (based on physical equations) and ANN (based on experimental data). With the aim of calibrating and validating both models, 19 experimental tests were performed at the combined cooling pilot plant located at PSA. The physical model focuses on the calculation of the Merkel number, which according to the literature depends on the water-to-air mass flow ratio ($\dot{m}_w/\dot{m}_a$). Therefore, the experimental camping has been designed to cover different water-to-air mass flow ratios. This criterion is also valid with the neural network model, since varying $\dot{m}_w/\dot{m}_a$ allows obtaining different operating points, which helps in collecting information from different

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Figure 2: Picture of the cooling circuit in the combined cooling pilot plant at PSA.

Table 1: Characteristics of instrumentation (^{a} value of the temperature in °C, ^{b} of reading, ^{c} full scale, ^{d} mean value).

Measured variable	Instrument	Range	Measurement uncertainty
Water temperature, TT-001, TT-006	Pt100	0 - 100°C	$0.3 + 0.005 \cdot T^a$
Cooling water flow rate, FT-001	Vortex flow meter	9.8 - 25 m^3/h	± 0.65% o.r.^{b}
Water flow rate, FT-004	Paddle wheel flow meter	0.05 - 2 m^3/h	± 0.5% of F.S^c + 2.5% o.r
Ambient temperature	Pt1000	-40 - 60°C	± 0.4 @20°C
Relative humidity	Capacitive sensor	0 - 98%	± 3 % o.r @20°C
Air velocity	Impeller anemometer	0.1-15 m/s	± 0.1 m/s + 1.5% m.v.^{d}

scenarios that can occur in tower. At the experimental facility, $\dot{m}_w/\dot{m}_a$ can be modified in two ways, with Pump 1 ($\dot{m}_w$) and with the fan frequency SC-001 ($\dot{m}_a$). Both variables were varied within the allowable range for plant operation. In the case of the water flow, it ranged from 8 to 22 m^3/h. The air mass flow rate was modified by changing the frequency from 12.5 to a maximum of 50 Hz. Therefore, the experimental values of $\dot{m}_w/\dot{m}_a$ obtained were in the range 0.5-5. The thermal load was $\approx$ 170 kW_{th} in all tests conducted.

The standards UNE 13741 "Thermal performance acceptance testing of mechanical draught series wet cooling towers" [16] and CTI "Acceptance Test Code for Water Cooling Towers" [17] were taken as a reference to evaluate that stationary conditions were achieved during the tests, in which it is established that the duration of the test should not be less than one hour. During the test, the maximum deviation of circulating (or cooling) water flow rate, heat load and range cannot be more than 5%. For the wet-bulb temperature and dry-bulb temperature, the linear least-squares trends should not exceed 1°C and 3°C, respectively. Both variables shall not have a deviation greater than ±1.5°C and ±4.5°C, respectively. Finally, it must be verified that the average wind velocity did not exceed 4.5 m/s throughout the test and punctually (for a minute) the 7 m/s.

2.3. Modelling

The models presented in this section have been developed to predict two main outputs, the water temperature at the outlet of the WCT, $T_{wct,out}$, and the water consumption, $\dot{m}_{wct,lost}$. As inputs, both models require five variables: the cooling water flow rate ($\dot{m}_w$), inlet water temperature ($T_{wct,in}$), ambient temperature (T_∞), ambient relative humidity (ϕ_∞) and the frequency level of the fan (f_{fan}) (or the air mass flow rate[2] ($\dot{m}_a$).

2.3.1. Poppe model

The well-known Merkel number is accepted as the performance coefficient of a wet cooling tower, [18]. This dimensionless number is defined in Equation 1, and it measures the degree of difficulty of the mass transfer processes occurring in the exchange area of a cooling tower.

[2] ANN uses as input f whereas Poppe's model uses $\dot{m}_a$.

$$\text{Me} = \frac{h_D a_v V}{\dot{m}_w}, \tag{1}$$

where the variables and parameters involved are described in the Nomenclature Section.
The Merkel number can be calculated using the Merkel and Poppe theories for performance evaluation of cooling towers. The Merkel theory [8] relies on several critical assumptions, such as the Lewis factor (Le) being equal to 1, the air exiting the tower being saturated with water vapour and neglecting the reduction of water flow rate by evaporation in the energy balance. For this reason, the Poppe theory [11] is usually preferred. In this theory, the authors derived the governing equations for heat and mass transfer in the transfer region of the cooling tower (control volume shown in Figure 3, one dimensional problem). The detailed derivation process and simplification of the previously-mentioned governing equations can be found in [18]

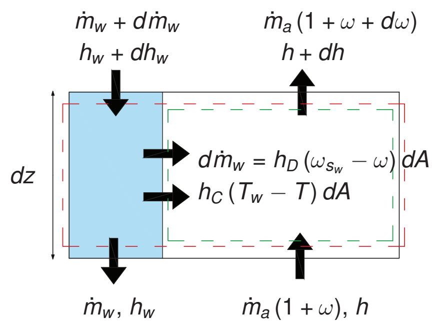

Figure 3: Control volume in the exchange area of a wet cooling tower for counterflow arrangement.

According to the Poppe theory, the major following equations for the heat and mass transfer are obtained:

$$\frac{d\omega}{dT_w} = \frac{c_{p_w}\frac{\dot{m}_w}{\dot{m}_a}(\omega_{s_w}-\omega)}{(h_{s_w}-h) + (\text{Le}-1)\left[(h_{s_w}-h) - (\omega_{s_w}-\omega)\,h_v\right] - (\omega_{s_w}-\omega)\,h_w} \tag{2}$$

$$\frac{dh}{dT_w} = c_{p_w}\frac{\dot{m}_w}{\dot{m}_a}\left[1 + \frac{(\omega_{s_w}-\omega)\,c_{p_w}T_w}{(h_{s_w}-h) + (\text{Le}-1)\left[(h_{s_w}-h) - (\omega_{s_w}-\omega)\,h_v\right] - (\omega_{s_w}-\omega)\,h_w}\right] \tag{3}$$

$$\frac{d\,\text{Me}}{dT_w} = \frac{c_{p_w}}{(h_{s_w}-h) + (\text{Le}-1)\left[(h_{s_w}-h) - (\omega_{s_w}-\omega)\,h_v\right] - (\omega_{s_w}-\omega)\,h_w} \tag{4}$$

where Me in Equation 4, is the Merkel number according to the Poppe theory. The above described governing equations can be solved by the fourth order Runge-Kutta method. Refer to [18] for additional information concerning the calculation procedure.

2.3.2. Neural Network model

Machine learning algorithms are unique in their ability to obtain models and extract patterns from data, without being explicitly programmed to do so. They are more effective with large volumes of data but can also be applied for steady state modelling with fewer information. Artificial neural networks are part of this set of algorithms and, as the name suggests, have a behaviour similar to biological neurons. Its structure is formed by a succession of layers, each one composed by nodes (or neurons) and receiving as input the output of the previous layer. With this input a calculation is performed and its output is fed as the input for the subsequent layers.

The training process was done making use of the *Neural Network Toolbox* of MATLAB, using the Lavenberg-Marquardt BP algorithm [19]. Several ANN architectures were tested varying the number of hidden layers between 1 and 2 and the number of neurons in each layer between 1 and 10. The transfer function adopted in the hidden layers was the *logsig*, whereas the one employed in the output layer was the *purelin*. The optimal architecture was selected according to the performance function (Mean Square Error, MSE).

2.4. Procedure

Figure 4 schematically depicts the steps taken to perform the comparison procedure. Different tests are carried out with a variety of values in the system inputs (mainly cooling water mass flow rate and fan speed), while the system timeseries outputs are monitored and stored. The processing of the experimental data is done

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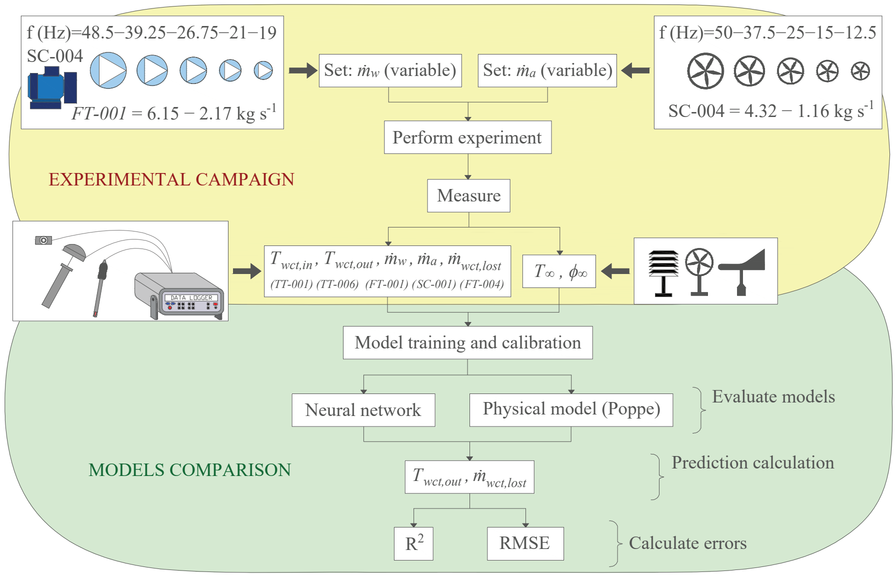

Figure 4: Methodology scheme for experimental procedure and model calibration and evaluation.

as mentioned in subsection 2.2., when the plant achieves steady state conditions according to UNE 13741 specifications.

Once the experimental campaign is done and the steady state operation points identified, different case studies are presented. Each case study takes the available operation points and divides them in two subsets: one is used for calibration/training of the modelling approaches and the second one for testing their performance. The case studies start with a low amount of points selected for training while the remaining are used for validation and increase up to a maximum, to have a minimum of 5 points for validation.

The performance metrics used to evaluate the fitness of the models to the experimental data are the Root Mean Square Error (RMSE) and R-squared (R^2). RMSE is a statistical measure of the difference between the values predicted by a model and the observed values. It is calculated as the square root of the mean of the squared differences between the predicted and observed values:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

where y_i is the measurement variable for the $i-th$ data point, $\hat{y}_i$ is the estimated value of the same variable and N is the number of data points.

R-squared [20] is a statistical measure that represents the proportion of the variance in the predicted variable that can be explained by the independent variable in a regression model, the measured output in this case, with value equal to 1 indicating the best fit. It is calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2},$$

where $\bar{y}$ is the mean value of the experimental values.

3. Results and discussion

Table 2 shows the average values of the variables required by both models, which were obtained from the experimental campaign described in subsection 2.2.. As can be observed, the range of air and water mass

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flow rates are 1.16-4.32 kg/s and 2.17-6.15 kg/s, respectively. Regarding the environmental conditions, these were quite similar for all tests: high ambient temperatures (ranging between 32°C and 41°C), and low ambient relative humidities (between 13% and 40%) since it was carried out during the summer season. The table also lists the output variables: $T_{wct,out}$ and $\dot{m}_{wct,lost}$.

Table 2: Averaged values in the experimental test runs.

Test	Q_{pump} (m^3/h)	f_{fan}(%)	T_∞ (°C)	ϕ_∞ (%)	T_{wb_∞} (°C)	$T_{wct,in}$ (°C)	$T_{wct,out}$ (°C)	$\dot{m}_a$ (kg/s)	$\dot{m}_w$ (kg/s)	$\dot{m}_{wct,lost}$ (kg/s)
1		12.5	33.31	39.58	22.53	48.88	34.79	1.193	2.173	0.050
2	≈8	15	35.05	32.38	22.16	46.87	32.95	1.481	2.176	0.081
3		50	36.02	29.94	22.23	43.74	25.43	4.248	2.170	0.091
4		25	36.76	14.76	18.39	42.56	26.74	2.636	2.449	0.073
5	≈9	37.5	36.59	17.43	19.11	39.58	23.74	3.668	2.445	0.080
6		50	34.77	18.46	18.30	39.15	22.26	4.248	2.445	0.092
7		12.5	40.50	13.11	19.97	46.85	36.94	1.157	3.263	0.058
8		25	39.75	12.97	19.50	40.30	28.42	2.588	3.272	0.075
9	≈12	37.5	36.93	22.39	20.79	38.13	26.25	3.648	3.266	0.097
10		50	35.79	16.13	18.24	35.34	23.32	4.319	3.268	0.087
11		50	34.40	23.07	19.32	35.82	23.79	4.312	3.267	0.084
12		12.5	34.69	32.55	21.94	46.53	39.44	1.177	4.895	0.058
13	≈18	25	33.57	27.24	19.83	38.37	30.15	2.619	4.914	0.071
14		37.5	35.66	25.14	20.71	35.39	27.57	3.637	4.942	0.075
15		50	33.53	29.29	20.30	34.50	26.27	4.292	4.940	0.086
16		12.5	32.84	38.77	21.99	46.25	40.57	1.186	6.096	0.057
17	≈22	25	34.25	16.50	17.42	36.41	29.81	2.596	6.127	0.072
18		37.5	35.99	16.91	18.59	33.54	27.04	3.651	6.133	0.078
19		50	35.80	14.73	17.83	31.30	24.87	4.302	6.147	0.085

3.1. Poppe model

Figure 5 shows the variation of the Merkel number as a function of the water-to-air mass flow ratio ($\dot{m}_w/\dot{m}_a$) for two case studies. It can be seen that the expected trend is observed: decreasing Me for increasing $\dot{m}_w/\dot{m}_a$ values (linear trend on log-log scale).

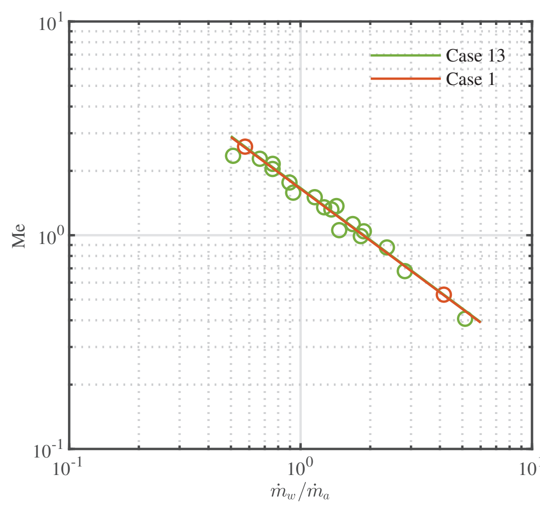

Figure 5: Experimental results for the Me number as a function of $\dot{m}_w/\dot{m}_a$.

The model based on the physical equations (Merkel number) can be obtained by correlating the values of Me with the water-to-air mass flow ratio as an independent variable, described by an equation of the form Me = $c\,(\dot{m}_w/\dot{m}_a)^{-n}$. Constants c and n in the previous equation have been calculated for the different case studies. In the Case 1, only 2 tests are considered for the fit (solid red line in Figure 5). Subsequently, more

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Table 3: Comparison of results and parameters for each case study between an ANN model and a physical model based on Poppe equations.

Case studies	Train set size	Test set size	ANN					Poppe					
			Topology	$T_{wct,out}$		$\dot{m}_{wct,lost}$		Params		$T_{wct,out}$		$\dot{m}_{wct,lost}$	
				RMSE (°C)	R^2	RMSE (l/min)	R^2	c	n	RMSE (°C)	R^2	RMSE (l/min)	R^2
1	2	17	5-4-2	5.23	-0.19	0.73	-0.01	1.663	-0.806	0.33	1.00	0.75	-0.06
2	3	16	5-2-2	5.35	-0.19	0.77	-0.06	1.651	-0.817	0.29	1.00	0.78	-0.09
3	4	15	5-5-2	2.11	0.83	0.47	0.62	1.595	-0.850	0.30	1.00	0.84	-0.19
4	5	14	5-5-2	2.03	0.85	0.56	0.50	1.618	-0.823	0.29	1.00	.085	-0.14
5	6	13	5-2-2	1.13	0.95	0.61	0.43	1.631	-0.802	0.31	1.00	0.84	-0.10
6	7	12	5-3-2	1.45	0.93	0.43	0.67	1.631	-0.802	0.32	1.00	0.75	0.00
7	8	11	5-10-2	1.67	0.91	0.46	0.66	1.629	-0.803	0.33	1.00	0.78	0.01
8	9	10	5-2-2	1.74	0.91	0.46	0.65	1.635	-0.790	0.35	1.00	0.76	0.06
9	10	9	5-10-2	1.69	0.91	0.49	0.62	1.640	-0.786	0.37	1.00	0.77	0.06
10	11	8	5-10-2	2.01	0.88	0.54	0.36	1.652	-0.769	0.41	1.00	0.81	-0.43
11	12	7	5-5-2	2.41	0.85	0.44	0.62	1.648	-0.776	0.32	1.00	0.55	0.40
12	13	6	5-5-2	2.72	0.81	0.47	0.59	1.636	-0.793	0.32	1.00	0.51	0.51
13	14	5	5-10-2	1.01	0.97	0.25	0.85	1.647	-0.804	0.36	1.00	0.55	0.31

tests are progressively added for the fit, up to a total of 14 tests in Case 13 (green series). These data are presented in Table 3.

As can be seen in the Figure 5 and in Table 3, the fit is practically the same for cases 1 and 13. This suggests that not much tests will be needed to get a reliable model of the tower. To evaluate the goodness of the correlation, the differences between the data calculated with these correlations and those measured experimentally for the outlet water temperature and water consumption of the tower can be verified. The results of the comparison for both models is presented in subsection 3.3..

3.2. ANN

In Table 3 - Topology column, the configuration of the best obtained networks for each case study are shown. In the first case study, the data available for training the neural network were too sparse to obtain significant results, but it was still done to show the strengths of the model based on the first principle. More interesting results are obtained for the latter case studies that make use of more data for its training, even though better results could be obtained with a more extensive campaign and thus obtaining more points to work with. For all of them, one hidden layer was always the best design, which is in accordance with results from literature [12–15] since there is not enough data to adjust a more complex ANN. Also, the number of neurons tends to be low, though the most performant networks make use of a higher number of neurons in the hidden layer (10). As expected, the optimal network, considering as optimal the one that performs best with the available data, is the one using the maximum amount of available data for training, while leaving enough points for testing. A high error is obtained for the scarce available data networks.

Detailed parameters for the best obtained model are shown at Table 4. It is composed of five inputs, one hidden layer containing ten neurons, and two outputs. It is a feedforward neural network (FFNN) that can be described as 5-10-2 and its predicted output expression is: $\hat{Y} = \Phi_{(2)}(LW_{(1)}\Phi_{(1)}\left(IW_{(1)}x + b_{(1)}\right) + b_{(2)})$, where Φ_i is the layer i transfer function, b the bias matrices, LW and IW are the layer weight matrices (output and input respectively), x is the network input and $\hat{Y}$. The subscripts corresponds with the notation used in the table.

3.3. Comparison between both approaches: prediction, abilities and requirements

3.3.1. Prediction

Table 3 shows the results obtained with both models. Each row shows a case study, which corresponds to a number of data used for the training (or calibration) of the models. As one progresses through the case studies, the number of data used for calibration increases. For each case the performance metrics (*RSME* and R^2) are calculated. Looking at the case of study with the best results (case study 16), the error obtained in the prediction of the water outlet temperature ($T_{wct,out}$) is almost null using the Poppe model ($R^2 \approx 1$ and RMSE = 0.36°C) whereas the error with ANN model is slightly higher (R^2 = 0.97 and RMSE = 1.01°C). This comparison is also observed in Figure 6 (b), where the perfect fit is depicted together with the results obtained with both models. On the contrary, in the case of the water consumption, the results with the ANN model are better than those provided by Poppe's model, being the RMSE with ANN model less than half that obtained with Poppe's model (0.25 to 0.55 l/min). This is because Poppe's model predicts the water lost by evaporation during the process, but it does not consider the water lost as drift (emission of droplets into the atmosphere) nor other losses such as windage , splash-out, leaks or overflow.

Table 4: Best performing network parameters.

Input weight matrix	$IW_{(1)}^{(10x5)} = \begin{pmatrix} 0.0016 & 0.0418 & 0.1239 & 0.1353 & -0.1324 \\ 0.0011 & -0.0348 & -0.1022 & -0.1104 & 0.1098 \\ 0.0064 & -0.0066 & -0.0297 & -0.0294 & 0.0334 \\ -0.0015 & 0.0252 & 0.0697 & 0.0740 & -0.0748 \\ -0.0056 & 0.0109 & 0.0389 & 0.0394 & -0.0430 \\ 0.0035 & 0.0454 & 0.1362 & 0.1494 & -0.1452 \\ 0.2361 & 0.1815 & 0.4889 & 0.3339 & -0.4397 \\ 0.0209 & 0.0641 & 0.1763 & 0.1930 & -0.1823 \\ -0.0079 & -0.0505 & -0.1457 & -0.1602 & 0.1539 \\ 0.0024 & -0.0319 & -0.0953 & -0.1023 & 0.1026 \end{pmatrix}$
Hidden layer bias vector	$b_{(1)} = \begin{pmatrix} 0.0041 \\ -0.0062 \\ -0.0040 \\ 0.0064 \\ 0.0048 \\ 0.0022 \\ -0.2480 \\ -0.0086 \\ -0.0001 \\ -0.0066 \end{pmatrix}$
Output layer weight matrix	$LW_{(1)}^{(2x10)^T} = \begin{pmatrix} 0.1648 & -0.1636 \\ -0.1349 & 0.1351 \\ -0.0335 & 0.0430 \\ 0.0922 & -0.0908 \\ 0.0467 & -0.0540 \\ 0.1814 & -0.1799 \\ 0.6502 & -0.5160 \\ 0.2428 & -0.2231 \\ -0.1969 & 0.1897 \\ -0.1246 & 0.1265 \end{pmatrix}$
Output layer bias vector	$b_{(2)} = \begin{pmatrix} -0.0051 \\ -0.1031 \end{pmatrix}$

3.3.2. Experimental requirements

As previously mentioned, Table 3 shows the results obtained varying the number of training experimental points. Regarding the water outlet temperature ($T_{wct,out}$), it can be seen that the error is almost null for the Poppe model even using the lowest number of train points ($R^2 \approx 1$ and RMSE = 0.33°C), whilst is not the case for the ANN one ($R^2 = -0.19$ and RMSE = 5.23°C), as expected. This is reflected in Figure 6 (a), there is not enough information to adjust the weights and biases in the network and therefore it is unable to capture the system dynamics. By increasing the available information during training, the results get better obtaining the best results explained in subsubsection 3.3.1.. In the case of the ANN model, this trend is similar for ($\dot{m}_{wct,lost}$) predictions; increasing the training point, the results improve (RMSE decreases more than 80% and R^2 changes from being negative to approaching 1). With the Poppe model and the $\dot{m}_{wct,lost}$ predictions, it can be observed that, increasing the number of tests, the prediction improvement is low (RMSE decreases less than 27 % and R^2 changes from being negative to 0.31). Therefore, while the ANN model benefits from as much data as possible, the Poppe model is already able to produce satisfactory results with just two properly selected points. These two points are easy to identify in advance because they are related to the maximum and minimum $\dot{m}_w/\dot{m}_a$ ratio. In the practice, to minimise the error prediction, ≈5 points are often used.

Regarding the instrumentation, Poppe's model requires measurement of the air flow rate at the outlet of the WCT, while the ANN model uses as input the frequency of the WCT fan. In addition, to improve the water consumption estimations provided by Poppe's model, it would be necessary to carry out an experimental campaign to measure the water losses due to drift.

3.3.3. Scalability, operating and weather conditions

One important advantage of the Poppe model is its adaptability to large scale systems, as long as the system configuration remains the same. This allows to study and analyse pilot scale plants and extrapolate the results to industrial sized plants. In addition, the model obtained is also capable of accurately predicting the behaviour of the WCT in conditions that have not been tested (different environmental conditions or inlet water temperatures). It would even be valid for unknown $\dot{m}_w/\dot{m}_a$, although the reliability of the model will be lower if this ratio moves away from those experimentally used for calibration. This is not the case for ANN models that are only applicable to the system and operating ranges they are trained for. Even though there are techniques to create new ANN models from previously trained ones [21], this is not as straightforward, requires expertise and additional experimental data.

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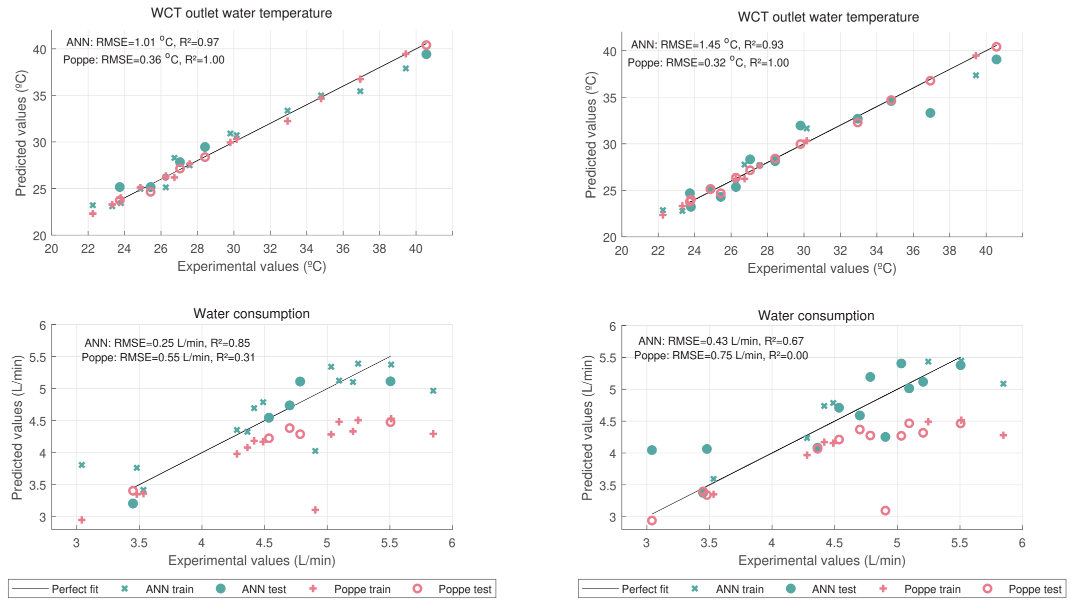

(a) Larger set for training. Case study: 13

(b) Scarce train data. Case study: 6

Figure 6: Models performance comparison with different dataset distribution.

3.3.4. Implementation

In the recent years and due to the increase popularity of artificial intelligence, there are many libraries of easy access for most common programming languages, which makes the development and implementation of ANN models achievable by non experts or specialised teams. The need of extensive data can be mitigated if an online steady-state identification is implemented [22], which allows updating the model with a growing dataset. In the case of the Poppe model, although the number of tests is not a problem, it is necessary to know the governing equations described in the subsubsection 2.3.1.. Solving the system of differential equations requires a non linear solver, which nowadays it is not a problem since there is a wide variety of software tools and packages available to face it.

3.3.5. Execution time

The execution time in the case of the ANN model is very low (in the order of milliseconds) and independent of the input conditions. This is not the case for the Poppe model because it depends on the non-linear solver used. This issue can have an impact in optimisation applications, such as the determination of optimal operating conditions to minimise the water consumption of combined cooling systems for CSP plants.

4. Conclusions

In this study, a comparison between an artificial neural network and Poppe model for wet cooling tower performance prediction in CSP plants has been performed. The results obtained during the investigation can be summarised as follows:

Both models reported good results predicting the outlet water temperature, since the errors were quite low (R^2 = 0.97 and RMSE= 1.01°C for the best case with the ANN, and $R^2 \approx 1$ and RMSE$<$ 0.36°C for all cases with the Poppe model). However, the Poppe model reached confidence levels with only 2 tests, while the ANN needed the maximum number of points available.

For the measurements of water consumption, it was shown that the Poppe model does not accurately predict this magnitude (R^2 = 0.51 and RMSE= 0.51 l/min for the best case), since it does not account for the water lost by drift or other losses. On the other hand, the ANN does present good results in this aspect (R^2 = 0.85 and RMSE= 0.25 l/min for the best case), since it only depends on the results measured in similar tests.

The strengths and weaknesses of each model have also been compared. As for the Poppe model, it is capable of predicting the operation of the tower, regardless of the tested conditions. It is also possible to adapt it to large-scale systems, as long as the system configuration remains the same. Unlike the ANN model that can only be used for the conditions and the tower for which it was developed.

As for the ANN model, it has the advantage of being able to be developed and implemented by non expert or specialised teams (who do not know the physical process that takes place in a cooling tower). Another advantage is in the execution time, the ANN model is faster and more constant independently of the input conditions (in the order of milliseconds for simple networks like the ones presented in this work).

As future lines of work, drift measurements could be carried out on the tower so that the prediction of $\dot{m}_{wct,lost}$ can be improved for the Poppe model. Another way could be to parameterise and adjust this model output to reduce the error. Other possible lines of work would consist of checking other output variables ($\phi_{a,o}$ and $T_{a,o}$) or evaluating the models under different conditions (other seasons). Finally, these models will be used for optimisation purposes in combined cooling systems for CSP plants.

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Nomenclature

a_V	surface area of exchange per unit of volume (m^2/m^3)
c_p	specific heat (J/kg K)
f	frequency level (Hz)
h	enthalpy (J/kg)
h_C	heat transfer coefficient (W/m^2 K)
h_D	mass transfer coefficient (kg/m^2 s)
Le	Lewis number (= $h_C / \left(h_D c_{p_{ma}}\right)$)
$\dot{m}$	mass flow rate (kg/s)
Me	Merkel number (= $h_D a_V V / \dot{m}_w$)
N	number of data points
R^2	R-squared
T	temperature (K)
T_{wb}	wet bulb temperature (°C)
V	volume of the transfer region (m^3)
y_i	measurement variable for the $i - th$ data point
$\hat{y}_i$	estimated value of variable y_i
$\bar{y}$	mean value of the experimental values
z	height (m)
Greek symbols	
ϕ	relative humidity (%)
ω	humidity ratio (kg/kg)
Subscripts and superscripts	
a	air
∞	ambient
fan	fan
i	inlet
$lost$	consumption
o	outlet
s	saturated
v	vapour
w	water
Abbreviations	
ACC	Air Cooled Condenser
ANN	Artificial Neural Network
CSP	Concentrated Solar Power
NDWCT	Natural Draft Counter-flow Wet Cooling Towers
PSA	Plataforma Solar de Almería
RMSE	Root Mean Square Error
WCT	Wet Cooling Tower

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References

[1] Rezaei E, Shafiei S, Abdollahnezhad A. Reducing Water Consumption of an Industrial Plant Cooling Unit Using Hybrid Cooling Tower. Energy Conversion and Management. 2010 Feb;51(2):311-9.

[2] Asvapoositkul W, Kuansathan M. Comparative Evaluation of Hybrid (Dry/Wet) Cooling Tower Performance. Applied Thermal Engineering. 2014 Oct;71(1):83-93.

[3] Hu H, Li Z, Jiang Y, Du X. Thermodynamic Characteristics of Thermal Power Plant with Hybrid (Dry/Wet) Cooling System. Energy. 2018 Mar;147:729-41.

[4] Barigozzi G, Perdichizzi A, Ravelli S. Wet and Dry Cooling Systems Optimization Applied to a Modern Waste-to-Energy Cogeneration Heat and Power Plant. Applied Energy. 2011 Apr;88(4):1366-76.

[5] Barigozzi G, Perdichizzi A, Ravelli S. Performance Prediction and Optimization of a Waste-to-Energy Cogeneration Plant with Combined Wet and Dry Cooling System. Applied Energy. 2014 Feb;115:65-74.

[6] Palenzuela P, Roca L, Asfand F, Patchigolla K. Experimental Assessment of a Pilot Scale Hybrid Cooling System for Water Consumption Reduction in CSP Plants. Energy. 2022 Mar;242:122948.

[7] Asfand F, Palenzuela P, Roca L, Caron A, Lemarié CA, Gillard J, et al. Thermodynamic Performance and Water Consumption of Hybrid Cooling System Configurations for Concentrated Solar Power Plants. Sustainability. 2020;12(11).

[8] Merkel F. Verdunstungskühlung. VDI Zeitschriff Deutscher Ingenieure, Berlin, Alemania. 1925:123-8.

[9] Bourillot C. Hypotheses of Calculation of the Water Flow Rate Evaporated in a Wet Cooling Tower. 1983 Aug.

[10] Jaber H, Webb RL. Design of Cooling Towers by the Effectiveness-NTU Method. Journal of Heat Transfer. 1989 Nov;111(4):837-43.

[11] Poppe M, Rögener H. Berechnung von Rückkühlwerken. VDI wärmeatlas. 1991:Mi 1.

[12] Hosoz M, Ertunc HM, Bulgurcu H. Performance Prediction of a Cooling Tower Using Artificial Neural Network. Energy Conversion and Management. 2007 Apr;48(4):1349-59.

[13] Gao M, Shi Yt, Wang Nn, Zhao Yb, Sun Fz. Artificial Neural Network Model Research on Effects of Cross-Wind to Performance Parameters of Wet Cooling Tower Based on Level Froude Number. Applied Thermal Engineering. 2013 Mar;51(1):1226-34.

[14] Song J, Chen Y, Wu X, Ruan S, Zhang Z. A Novel Approach for Energy Efficiency Prediction of Various Natural Draft Wet Cooling Towers Using ANN. Journal of Thermal Science. 2021 May;30(3):859-68.

[15] Ramakrishnan R, Arumugam R. Optimization of Operating Parameters and Performance 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.

[16] UNE. Thermal Performance Acceptance Testing of Mechanical Draught Series Wet Cooling Towers [Manual]; 2004.

[17] CTI. Code Tower, Standard Specifications. Acceptance Test Code for Water Cooling Towers [Manual]; 2000.

[18] Navarro P, Ruiz J, Hernández M, Kaiser AS, Lucas M. Critical Evaluation of the Thermal Performance Analysis of a New Cooling Tower Prototype. Applied Thermal Engineering. 2022;213:118719.

[19] Beale MH, Hagan MT, Demuth HB. Neural Network Toolbox. User's Guide, MathWorks. 2010;2:77-81.

[20] Chicco D, Warrens MJ, Jurman G. The Coefficient of Determination R-squared Is More Informative than SMAPE, MAE, MAPE, MSE and RMSE in Regression Analysis Evaluation. PeerJ Computer Science. 2021;7:e623.

[21] Zhuang F, Qi Z, Duan K, Xi D, Zhu Y, Zhu H, et al. A Comprehensive Survey on Transfer Learning. Proceedings of the IEEE. 2020;109(1):43-76.

[22] Pérez-Sánchez B, Fontenla-Romero O, Guijarro-Berdiñas B. A Review of Adaptive Online Learning for Artificial Neural Networks. Artificial Intelligence Review. 2018;49:281-99.

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