EUROPEAN MECHANICAL SCIENCE

Research Article

e-ISSN: 2587-1110

Optimisation of design parameters of the finned tube heat exchanger by numerical simulations and artificial neural networks for the condensing wall hang boilers

Hasan Avcı[1]*, Dilek Kumlutaş[1], Özgün Özer[2], Utku Alp Yücekaya[1]

[1]Dokuz Eylül University, Department of Mechanical Engineering, Turkey
[2]The University of Manchester, Department of Mechanical, Aerospace and Civil Engineering, Manchester, United Kingdom

Orcid: H. Avcı (0000-0002-3297-1229), D. Kumlutaş (0000-0002-0778-785X), Ö. Özer (0000-0003-4130-2323), U. A. Yücekaya (0000-0003-0934-5593)

Abstract: This research investigates the use of computational fluid dynamics (CFD) and artificial neural networks (ANNs) to be optimized the design of finned tube heat exchangers for use in condensing wall-mounted boilers (WHBcs). Fin height, thickness, and distance are selected as the input design parameters, and the internal volume of the heat engine is modelled using the CFDHT (CFD and heat transfer) method. Different ANN structures are trained and tested on the resulting data to identify the optimal training process. The trained ANN is then used to predict various output parameters, including total heat transfer on the inner surface of the tube, maximum temperature on the fins, total heat transfer per unit volume of the heat exchanger, and pressure drop between the inlet and outlet of the internal volume. The optimal design scenarios are evaluated based on design criteria, and the ANN is found to have good statistical performance, with an average accuracy of 1.00018 and a maximum relative error of 9.16%. The ANN is able to accurately estimate the optimal design case.

Keywords: Heat Exchanger, Computational Fluid Dynamics, Artificial Neural Networks, Boilers

1. Introduction

Individual heating systems provide the needed heat for domestic hot water generation and residential heating of a single house. The wall hang heating appliances are part of individual heating systems, and they became widespread in Turkey and Europe due to the natural gas infrastructure.

With increasing concern about environmental changes, emissions and costs for clients, the condensing technology offers an efficient heating solution for various applications. Nowadays, the number of regulations about the energy efficiency of appliances used for heating the residence space is increasing to fight against climate change. Since September 2015, the ErP (Energy-related Products) directive has enforced the use of condensing technology when using natural gas in both newly built and refurbished houses in European countries. Due to the increase in demand for condensing wall hang heating appliances, new designs are needed with low-cost and high thermal performance.

Heat exchangers used in combustion units play an essential role in the thermal performance of condensing wall-hang heating appliances. The total heat transferred from the burnt gas medium, known as flue gas, to water varies with the heat exchanger design. The finned tube-type heat exchangers made of aluminium material are recently used in condensing heat engines instead of stainless-steel heat exchangers. Many numerical and experimental studies were seen for the thermal performance of finned tube heat exchangers with various fin types in literature [1-7]. These studies usually belong to heat transfer applications outside the combustion units. There are a few studies in the literature which are related to the investigation of condensing wall-hang heating appliances via numerical and experimental methods [8,9].

Numerical methods are suitable for investigating the effects of a few design parameters on the outputs of thermal systems. Furthermore, Numerical methods should be used together with prediction techniques to evaluate the effects of a wider range of design parameters and decrease the analysis time. Generally, many thermal problems are solved by the correlations of input and output parameters. These relations of the independent variables are complex

* Corresponding author.
Email: hasanavci35@hotmail.com

European Mechanical Science (2023), 7(3): 160-171
https://doi.org/10.26701/ems.1298839
Received: May 18, 2023 — Accepted: July 19, 2023

and non-linear problems. In such cases, artificial intelligence (AI) can be a useful tool for efficiently estimating the outputs and optimizing them. Artificial intelligence has many applications in the field of design and optimisation as well as heat exchangers, multi-phase fluid flows and combustion systems [10, 11, 12 and 13]. The artificial neural network (ANN) is one of the AI methods.

ANN applications for thermal analysis of heat exchangers are reviewed by Mohanraj et al [14]. ANN methods were used for modelling the finned tube heat exchangers to assume the temperatures, heat transfer rate and pressure variance of control volumes in the literature. These exchangers are widely used for refrigeration, air conditioning and heat pump applications [15, 16, and 17].

The ANN method is used for the heat exchanger modelling and optimization of studies in the literature [18, 19, 20 and 21]. Xie et. al. optimized the design parameters of the vortex generator used for fin and tube heat exchangers via artificial neural networks [20]. Zhang et al. used the CFD simulation and artificial neural networks methods to optimize heat transfer performance and pressure drop in terms of the inlet air velocity and design parameters of the fin and tube heat exchanger [21]. There is not any study about the design parameters of condensing wall hang boilers' heat engines that have been investigated through the heat transfer and performance outputs using the ANN method in the literature.

In this study, CFD and ANN methods are used together to be optimized the design parameters of the condensing wall hang boiler with the aluminium finned and tube heat exchanger. The numerical studies were performed to obtain data sets for the development of the ANN model. The ANN model has been used for predicting the output values of the internal volume of a condensing heat engine. The optimum design cases are evaluated parametrically in terms of design criteria, and the ANN estimates the optimum design case.

2. Numerical Study

A schematic representation of the heat engine unit of a condensing wall hang boiler (WHBc) is given in Figure 1. Since CO and CO_2 emissions must be limited by the standards, flammable gas (natural gas) and fresh air are mixed in certain proportions in the mixer. The gas-air mixture is burned on the burner. The heat energy from the combustion reaction is transferred from the heat exchanger to the water through conduction, convection, and radiation. When the water vapour in the flue gas loses its latent heat, it becomes the liquid phase at the condensation point. This water returns to the liquid phase is called condensing water. The condensing water is drained from the heat engine unit's drainage. The flue gas is finally sent to the atmosphere by the flue gas pipe.

The main component of the condensing heat engine is the helical finned tube heat exchanger. It provides heat transfer between the water domains and flue gas. The internal volume of the heat engine given in Figure 2 is modelled numerically in three dimensions in order to determine the total heat transfer from the heat exchanger to the water, in other words, the capacity of the heat exchanger. This volume consists of the part where the flue gas formed in the burner passes over the heat exchanger and goes to the outlet. The top cross-section view is given in Figure 2. The repeated fins are illustrated on the tube pipe as dot lines. The investigated symmetrical area is modelled numerically in 3D.

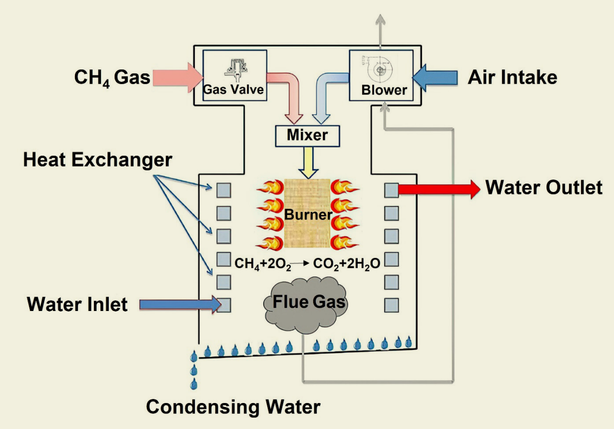

Figure 1. Schematic representation of the working principle of the heat engine unit of a condensing wall hang heating appliance [22]

In the numerical model given in Figure 3, "flue gas" as the fluid domain and "finned tube heat exchanger" is modelled as the solid domain, and the water domain in the heat exchanger is defined as the boundary condition.

The aluminium heat exchanger has a helical coil tube in real condition. Therefore, the literature investigated to determine the calculation of the heat transfer coefficient for the helical coil pipe inner flow. Seban and Mclaughlin performed an experimental study to determine the heat transfer coefficient in helical coil tubes [23]. According to this study, Equation 1 provides to calculate the heat transfer coefficient for turbulent flow.

$$\frac{hd}{k}\left(\frac{\upsilon}{\alpha}\right)^{-0.4}=\frac{f}{8}\frac{U_m\,d}{\upsilon} \tag{1}$$

"d" is the tube inside diameter and "D_h" is the coil diameter to the tube centre. All numerical models have the same d value (30 mm). D_h for the helical coil tube is modelled to provide small coil acceptance [23], and all numerical models have the same D_h value. According to the EN15502 standard, the performance of the condensing wall hang boilers is tested for 80 ˚C - 60 °C and 50 °C - 30 °C operating conditions [24]. The film temperature of the water inside the tube coil is calculated as 55 °C (average temperature of operating conditions). This film temperature of the water is used to determine the thermal conductivity (k), thermal diffusivity (α) and kinematic viscosity (ν) [25]. The mean velocity (U_m) is calculated according to the inner diameter of the heat exchanger and the water flow rate

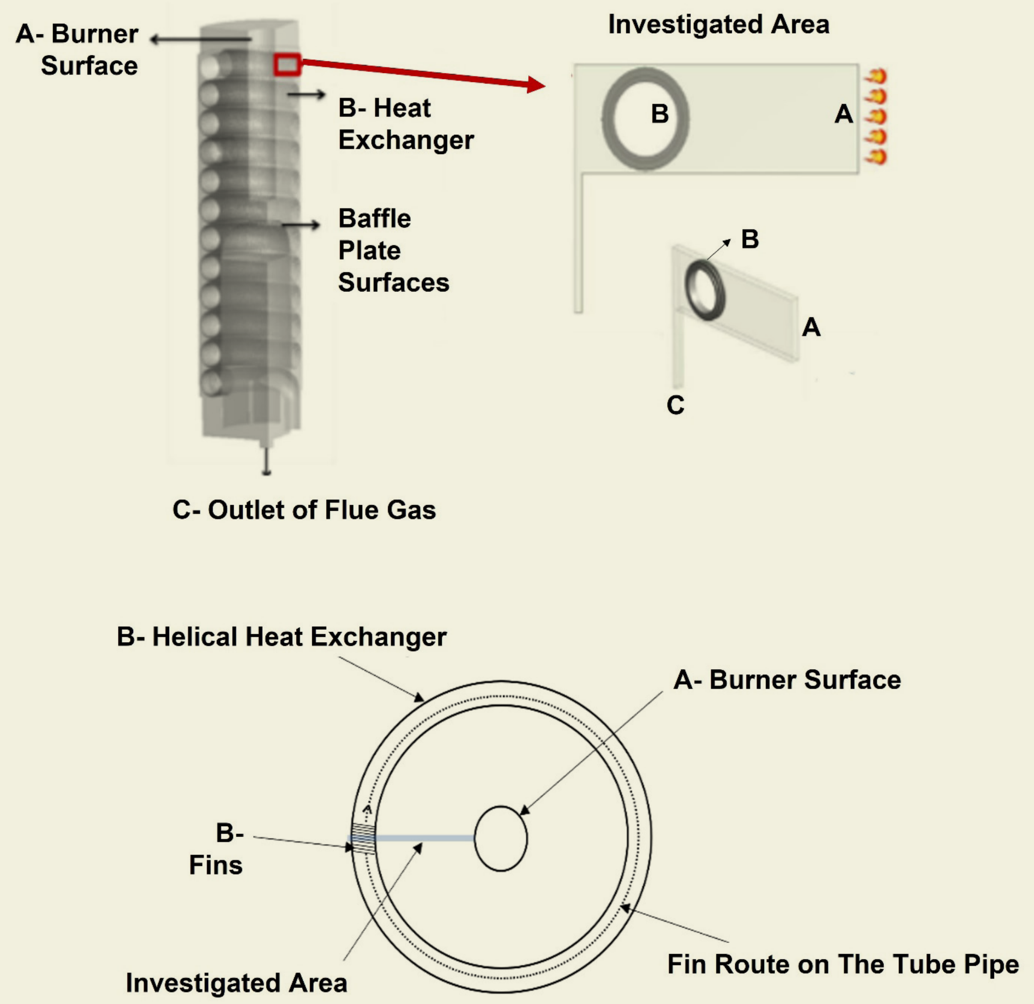

Figure 2. The modelled internal volume of the heat engine

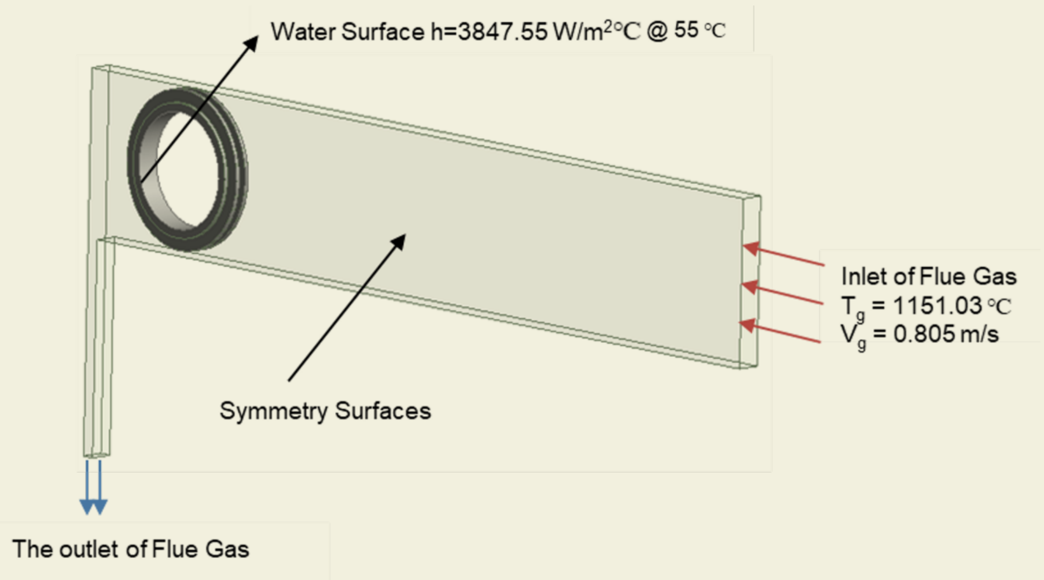

Figure 3. Numerical model and boundary conditions

Table 1. The composition of the combustion gases @ G20 (100% CH_4) & Phi =0.75

Combustion Gas	O_2	N_2	CO_2	H_2O	CO	NO	H	H_2	O	OH
Mass Fraction %	4.705	73.139	7.426	14.274	0.023	0.300	0.001	0.011	0.008	0.114

passed inside the tube. The water flow rate is selected as 17 lt/min. The Weisbach friction factor (f) is determined from the graph of Reynolds number – friction factor according to the turbulent flow and small coil criteria [23].

Finally, the new heat transfer coefficient (h) of the water-side is calculated as 3847.55 W/m²K for the below conditions:

- Water temperature 55 °C
- Water flow rate 17 lt/min
- D_h/d= 17; small coil acceptance [23]

As it is mentioned before, the flue gas is modelled as a fluid domain according to the combustion gas mixture. The mass fraction of the combustion gases is used from the previous study [25]. This prediction of mass fractions is made for 100 % methane gas (G20) and an air-gas equivalent ratio (phi) 0.75. Table 1. gives the composition of the combustion gases.

The temperature of flue gas is calculated as 1151.03 °C with a program [26], which was created in the master thesis based on the equations and formulations inside the NASA report SP-3001 [27]. The temperature of flue gas is calculated according to the CO_2 mass fraction inside the combustion gases. The assumption of the ideal combustion is taken into consideration, and the base equation is given below.

$$\frac{C_p^{\circ}(T)}{R} = a_1T^{-2} + a_2T^{-1} + a_3 + a_4T + a_5T^2 + a_6T^3 + a_7T^4 \quad (2)$$

The investigated condensing heat engine has a premix combustion unit. This unit provides the gas/air mixture, which can be adjusted to the desired value. It consists of a radial fan, pneumatic gas valve, venture, and stainless-steel multi-hole burner. This gas/air mixture passes through multi-holes of the burner. The average velocity of the flue gas created after the combustion process is equal to the gas/air mixture. The average velocity of the flue gas is calculated according to the gas/air volumetric flow and the lateral area of the stainless-steel multi-hole burner. When the 24 kW input load is attained from the heat engine used with methane gas (G20), a 55.65 m³/h volumetric flow of gas-air mixture is needed in terms of 0.75 air-gas equivalent ratio (phi). The lateral area of the burner of the heat engine is 0.0192 m² for that input load. Consequently, the velocity of flue gas is obtained as 0.805 m/s for the boundary condition of the numerical model.

The selected design parameters of the aluminium heat exchanger are fin height (h_f), fin thickness (t_f), and fin spacing (s). The values of these parameters are given in Table 2. All values for design parameters are selected according to manufacturing conditions. The inner pipe diameter and thickness are kept the same for all models.

According to the combination of design parameters' values, 350 different numerical models are created.

Table 2. The variation of design parameters

Design Parameter (Input Parameter)	Values [mm]
Fin Height (h_f)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Fin Thickness (t_f)	0.5, 1, 1.5, 2, 2.5
Fin Spacing (s)	1, 1.5, 2, 2.5, 3, 3.5, 4

The next step for the numerical analysis is the meshing process. Using different meshing techniques together, optimized meshing structures for numerical models have been created. The number of mesh elements of numerical models varies according to the model between 550733 and 1128369.

During the numerical solution, 167 W/m°C thermal conductivity coefficient and 0.42 emissivity coefficient values of 6000 series aluminium material at room temperature conditions were entered for the heat exchanger solid model [28].

According to the literature research and experiences gained from our previous studies, in the solution of our numerical model; continuous regime, radiation effects, natural convection caused by gravity, forced convection caused by fan effect and turbulent flow type conditions were taken into consideration.

Each numerical analysis took an hour for model preparation, meshing and defining boundary conditions and solving 350 different design cases within 15 days to obtain data set for parametric study and ANN modelling.

Total heat transfer (Q_T) on the inner surface of the tube, the maximum temperature on the fins (T_{max}), the pressure drop (ΔP) between the inlet and outlet of internal volume and the total heat transfer ($\bar{Q}_T$) per unit volume of the heat exchanger are selected and calculated as numerical results. These are also used as output parameters for parametric study and ANN modelling.

3. Modelling With ANN

Because of the complicated nature of the fluids, many thermal problems that include fluids are solved by experimentally obtained correlations between the input and the output parameters. These relations of the independent variables are complex and non-linear. Artificial neural networks are models for predicting the performance and generalisations of these complex systems in a short time. To predict the effect of the determined design parameters on the output parameters of the finned tube heat exchanger for condensing wall hang boilers with high precision, several ANN configurations should be developed, and the optimal ANN structure should be selected.

In the current study, the backpropagation algorithm was used to train the ANNs. This is the most widely used

ANN algorithm method for engineering applications. The estimations of the values of outputs were performed with a feed-forward backpropagation network, a tangent sigmoid activation function for the hidden layer and a linear transfer activation function for the output layer. While the network is being trained, the weighting coefficients are determined using the Levenberg-Marquardt algorithm. The ANN model's performance is dependent on the topology of a network (hidden layer numbers, neuron numbers of each hidden layer, and so on). The performance of an ANN model depends on the characteristics of the network, such as the number of hidden layers and the number of neurons in each of these layers. Therefore, the selection of these numbers is a trial-and-error process that may be changed if the performance of the neural network during the training is not good enough. The number of input and output parameters, the size of dataset and past experiences were important role to select neurons numbers for each hidden layer. The relative error of each estimated output was specified using the method proposed by Kreith and Wang. [29,30].

$$Er = \frac{|A^t - A^p|}{A^t} \times 100\% \tag{3}$$

The predicted results of the ANN (A^p) were compared to the target data (A^t). The root-mean-square (RMS) values of the outputs were defined during the training process of the ANN to evaluate the network performance. [29,30]. The neural network is trained using N data sets.

$$rms = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{A^t - A^p}{A^t}\right)^2} \tag{4}$$

The network topology and size effect on prediction performance. Large networks can learn complex problems but require more effort to solve them. Therefore, the selection process of the ANN structure is comprised of principles that minimize the prediction error. The performance of the trained network is evaluated by comparing its prediction with the data sets aside for testing. The calculated data sets from the numerical studies were divided into the training and the testing sets to model the ANN for the internal volume of the heat engine. The data sets consist of 345 input-output pairs, as listed in Table 3. While 95% of the data set was randomly assigned as the training set, the remaining 5% was used for the testing and the validation of the network.

Seven different network topologies were implemented via the MATLAB program, as detailed in Table 4. The standard deviation of the relative error in predictions (σ)

Table 3. The dataset for modelling network

No.	h_f (mm)	t_f (mm)	s (mm)	Q_T (W)	T_{max} (°C)	$\bar{Q}_T$ (W/mm³)	ΔP (Pa)
1	1	0.5	1	19.87	79.33	30.69	5.24
2	1	1.0	1	24.43	76.98	26.26	6.05
3	1	1.5	1	29.51	75.95	24.32	6.76
4	1	2.0	1	34.13	75.04	22.82	7.12
5	1	2.5	1	38.81	74.45	21.82	7.45
6	1	0.5	1.5	23.59	76.95	28.43	4.06
7	1	1.0	1.5	28.20	75.54	25.34	4.64
8	1	1.5	1.5	33.00	74.79	23.65	5.15
9	1	2.0	1.5	37.70	74.24	22.46	5.52
10	1	2.5	1.5	42.28	73.70	21.56	5.84
11	1	0.5	2	27.63	75.75	27.30	3.55
12	1	1.0	2	32.00	74.60	24.71	3.91
...	...	...	...	...	...	...	...
334	10	2.0	3.0	107.29	101.65	15.38	0.81
335	10	2.5	3.0	115.73	99.58	13.71	0.91
336	10	0.5	3.5	90.00	122.71	32.77	0.52
337	10	1.0	3.5	95.45	108.21	22.64	0.59
338	10	1.5	3.5	103.67	103.02	18.23	0.66
339	10	2.0	3.5	111.60	99.94	15.59	0.73
340	10	2.5	3.5	120.00	98.03	13.91	0.81
341	10	0.5	4.0	95.64	121.52	32.66	0.50
342	10	1.0	4.0	100.71	106.88	22.89	0.55
343	10	1.5	4.0	108.43	101.60	18.47	0.62
344	10	2.0	4.0	115.78	98.47	15.78	0.68
345	10	2.5	4.0	123.97	96.65	14.07	0.75

and the average accuracy of predictions (R) are specified in [29, 30] and are useful for evaluating the ANN performances. Upon examining Table 4, the best topology 3-6-12-8-4 was selected for testing based on its small value of σ=0.01285 and R=1.00018, as well as a maximum relative error of approximately 9.16% with the majority of errors being less than 2% (Figure 4).

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N}\frac{A^t}{A^p} \tag{5}$$

$$\sigma = \sqrt{\sum_{i=1}^{N}\frac{(R - R_i)^2}{N}} \tag{6}$$

The best topology of ANN has four layers. It is schematically illustrated in Figure 5. Fin height, fin thickness and fin spacing are defined as input parameters for ANN structure. Their manufacturing values are given in Table 2. Three hidden layers are created. The first one has six, the second one has twelve, and the third one has eight neurons. According to the numerical results, the network structure has four output parameters.

4. Result and Discussion

4.1. Parametric Results

350 design points obtained by numerical analyses are used for parametric study. This parametric study aims to investigate the effects of design parameters on the output parameters and find the relationships between them. In the end, the optimal design parameters are found in this study.

The maximum temperature is the most important output parameter in terms of the robustness of the aluminium heat exchanger inside the combustion regions. When the heating and cooling cycle of the heat engine is, thermal stress affects the lifetime of the fins on the heat exchanger. If the maximum temperature of the melting point exceeds the aluminium fin tips, the permanent deformation of the heat exchanger becomes unavoidable. For that reason, the maximum temperature on the fin tips is desired below 200 °C. These are the key criteria to start the evaluation of the results of the calculated 350 design cases. All design cases have the maximum temperature on fins below the key temperature criteria.

After the selection of robustness criteria of the heat exchanger, designers and researchers can evaluate other criteria on heat exchangers' performance like heat transfer, less material usage and pressure drop. If they need the maximum heat transfer from the heat exchanger to the water domain, they should use the fin thickness of 2.5 mm (according to Table 5). Besides the heat transfer criteria, pressure drop or material weight could be considered as additional criteria. Table 5 can guide them to the starting point to evaluate which fin thickness could be used.

The next evaluation is that the optimum design cases are determined for each output parameter's target value. Table 6 summarises the optimum design cases and their output values in terms of selected target criteria.

The heat transfer from the heat exchanger to the water domain maximises with a 10 mm – 2.5 mm – 4.0 mm (h_f- t_f- s) design case. Although the heat transfer maximises for this case, the total heat transfer ($\bar{Q}_T$) per unit volume of the heat exchanger is found as 14.1 W/mm³. This value is approximately 34.5 % of the maximised value of $\bar{Q}_{T.}$ The consumption of material is another essential criterion when the design phase of the heat exchanger is ongoing. It is related directly to the cost of the heat exchanger.

Table 4. The Comparison of performance by different ANN topologies

Topology	Error in the training process		Error in the test process	
	Er (%)	rms	R	σ
3-3-4	125.16	0.28136	0.97793	0.21220
3-6-4	70.06	0.11330	1.01211	0.16805
3-9-4	41.94	0.06619	1.00486	0.07081
3-12-4	38.34	0.07149	1.00346	0.07410
3-12-8-4	23.47	0.02252	1.00011	0.02319
3-3-6-8-4	16.35	0.02716	1.00043	0.02724
3-6-12-8-4	9.16	0.01263	1.00018	0.01285

Note: The Er (%) is the maximum value among the errors of the two output variables.

Table 5. Sort of design cases in terms of the fin thickness and their maximum and minimum values of output parameters

T_f (mm)	T_{max} (°C)		Q_T (W)		$\bar{Q}_T$ (W/mm³)		ΔP (Pa)	
	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
0.5	73.2	161.2	19.9	95.6	24.9	40.9	0.50	5.24
1.0	72.5	137.0	24.4	100.7	22.1	26.3	0.55	6.05
1.5	72.3	123.4	29.5	108.4	17.5	24.3	0.62	6.76
2.0	72.2	117.7	34.1	115.8	15.0	22.8	0.68	7.12
2.5	72.0	114.0	38.8	124.0	13.4	21.8	0.75	7.45

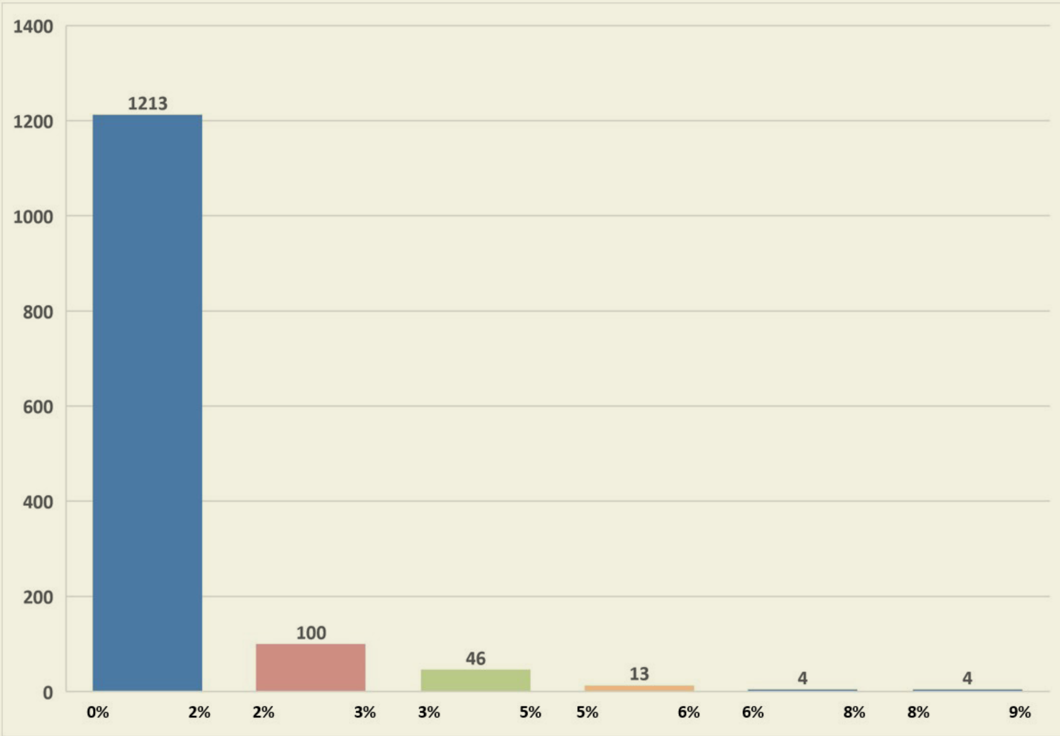

Figure 4. The histogram graph of relative errors in the training of the network

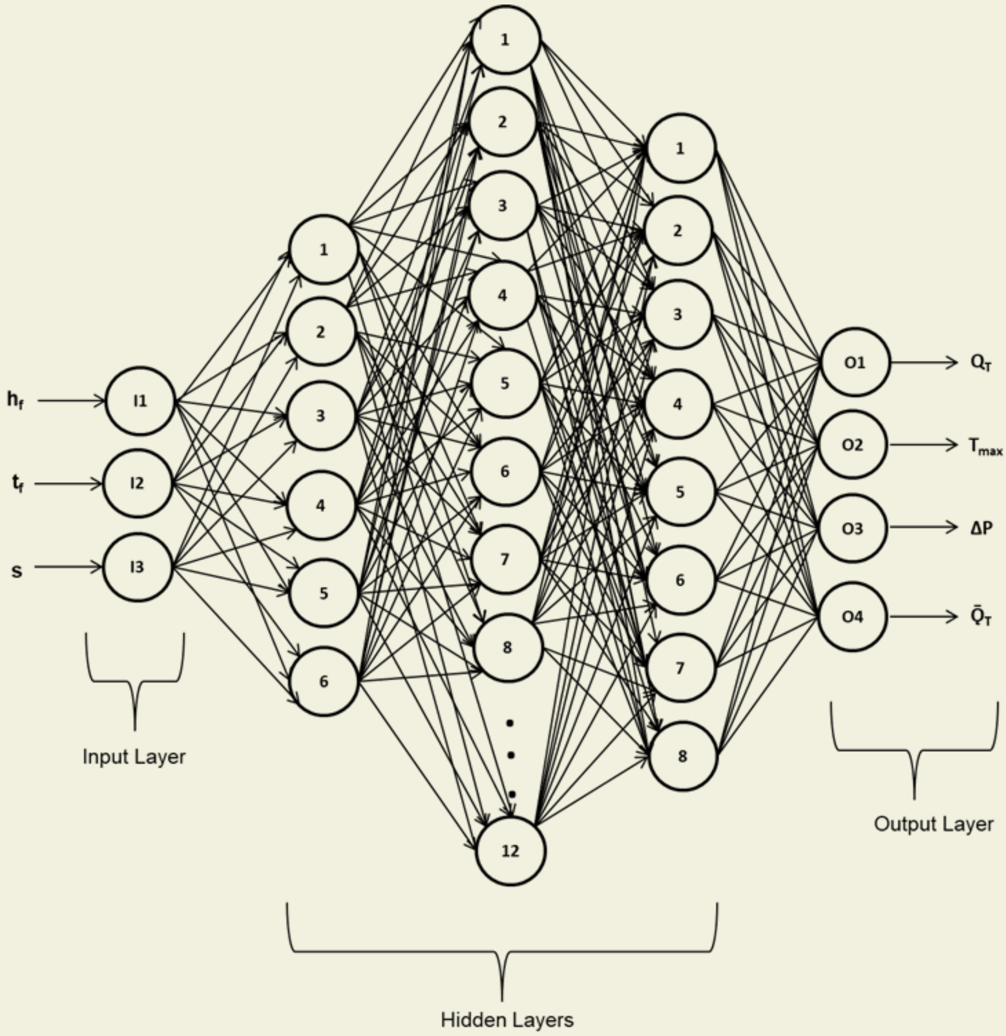

Figure 5. The selected structure for ANN modelling

Therefore, $\bar{Q}_T$ shows a good performance indicator for selecting the optimum total heat transfer (Q_T). Maximised $\bar{Q}_T$ is available with a 10 mm – 0.5 mm – 1.0 mm (h_f - t_f - s) design case, according to Table 3. But the total heat transfer decreased to 75.1 W in that case. It is not enough to use this criterion to be optimized the design of the heat exchanger. When the two parameters maximise simultaneously, the convenient heat transfer rate could enable the fit material consumption. The maximum temperature on the fin tips is obtained at the maximised $\bar{Q}_T$ design case. When the $\bar{Q}_T$ increases, the temperature on the fin tip also increases for every design case due to the usage of less material.

The pressure drop is one of the other criteria to determine or select the correct fan type or power for combustion heat engines. This value is demanded to keep a minimum level in order to use smaller fan types and operating costs. Therefore, the pressure drop (ΔP) between the inlet and outlet of internal volume could minimise with a 10 mm – 0.5 mm – 4 mm (h_f - t_f - s) design case.

Finally, the optimal design case is found to reach the target status of each output parameter simultaneously. Table 7 shows the optimum design case and its output values.

4.2. ANN Results

The ANN method aims to quickly estimate the output parameters of the condensing wall hang boilers.

After the training and validation of the network, it is ready to use the estimation of new outputs for different design cases. Five design cases aren't used for training the network process, so the network never knows those data sets. The input values of the estimation dataset are shown in Table 8.

The ANN model was able to produce all results within seconds, whereas if numerical studies had been employed to compute the outputs, it would have taken a minimum of 7 hours.

Table 9 presents a comparison between ANN predictions and numerical results for the total heat transfer (Q_T) on the inner surface of the tube. 0.58 W is found as the maximum absolute difference of Q_T. And its maximum relative error is less than 1.10%. The deviation range of its relative errors and the deviation range of its prediction accuracy are respectively 0.09-1.08% and 0.99590 – 1.01099. Figure 6 shows the scatter plot of the comparison between numerical and ANN results for Q_T. There are three lines highlighted in different colours. Black line indicates faultless estimation. The purple and red lines represent a ±15% band of error. R, MRE and mean absolute difference are determined respectively 1.00283, 0.48% and 0.29 W by the optimal network topology.

Table 10 compares ANN predictions and numerical results for the maximum temperature on the fins (T_{max}). 0.31 °C is found as the maximum absolute difference of

Table 6. Optimised design cases in terms of their target criteria

Optimised Parameter	Target	Inputs			Outputs			
		h_f (mm)	t_f (mm)	s (mm)	Q_T (W)	T_{max} (°C)	$\bar{Q}_T$ (W/mm³)	ΔP (Pa)
Q_T	Maximise	10	2.5	4.0	124.0	96.6	14.1	0.75
$\bar{Q}_T$	Maximise	10	0.5	1	75.1	161.2	40.9	1.04
ΔP	Minimise	10	0.5	4.0	95.6	121.5	32.66	0.50

Table 8. The input values of estimation dataset

Estimation Data	h_f [mm]	t_f [mm]	s [mm]
Set 1	1	2.0	2.5
Set 2	4	0.5	1.5
Set 3	5	2.5	3.5
Set 4	6	1.5	4.0
Set 5	10	1.0	2.0

Table 7. Optimum design case (Q_T, $\bar{Q}_T$ max.; ΔP min.)

h_f (mm)	t_f (mm)	s (mm)	Q_T(W)	T_{max} (°C)	$\bar{Q}_T$(W/mm³)	ΔP (Pa)
10	0.5	3.5	90.0	122.7	32.8	0.52

Table 9. The comparison of results for total heat transfer (Q_T) on the inner surface of the tube

Q_T of Estimation Data	Numerical Result	ANN Result	Absolute Difference	Er	R
Set1	45.13 W	45.09 W	0.04 W	0.10 %	1.00097
Set2	37.82 W	37.41 W	0.41 W	1.08 %	1.01096
Set3	83.84 W	83.91 W	0.07 W	0.09 %	0.99912
Set4	83.27 W	83.62 W	0.34 W	0.41 %	0.99590
Set5	81.04 W	80.47 W	0.58 W	0.71 %	1.00718

T_{max}. And its maximum relative error is less than 0.33%. The deviation range of its relative errors and the deviation range of its prediction accuracy are respectively 0.03 – 0.32% and 0.99797 – 1.00321. Figure 7 shows the scatter plot of the comparison between numerical and ANN results for T_{max}. R, MRE and mean absolute difference are determined respectively 1.00018, 0.13% and 0.12 °C by the optimal network topology.

Table 11 compares ANN predictions and numerical results for the total heat transfer ($\bar{Q}_T$) per unit volume of the heat exchanger. 0.28 W/mm^3 is found as the maximum absolute difference of $\bar{Q}_T$. And its maximum relative error is less than 0.90%. The deviation range of its relative errors and the deviation range of its prediction accuracy are respectively 0.10 – 0.87% and 0.99534 – 1.02268. Figure 8 shows the scatter plot of the comparison between numerical and ANN results for $\bar{Q}_T$. R, MRE and mean absolute difference are determined respectively 1.00123, 0.44% and 0.11 W/mm^3 by the optimal network topology.

Table 12 gives the comparison of estimation and numerical result for the pressure drop (ΔP) between the inlet and outlet of internal volume. 0.03 Pa is found as the maximum absolute difference of ΔP. And its maximum relative error is less than 2.60%. The deviation range of its relative errors and the deviation range of its prediction accuracy are respectively 0.02 – 2.56% and 0.97501- 1.02268. Figure 9 shows the scatter plot of the comparison between numerical and ANN results for ΔP. R, MRE and mean absolute difference are determined respectively 1.00152, 1.65% and 0.02 Pa by the optimal network topology.

Finally, the optimal values of the design case are found with the parametrical method and estimated via the selected network topology. Table 13 gives the comparison of the ANN estimation and parametric result for the optimum design case. The maximum relative error is less than 0.40% for output values of the optimum design.

5. Conclusions

The influence of design variables on the output characteristics of an aluminium heat exchanger used in a condensing wall-mounted boiler is examined. Optimal design scenarios are determined based on design criteria, and the feasibility of using artificial neural networks (ANNs) to model the finned tube heat exchanger of such boilers is demonstrated. An ANN structure is developed to predict various output parameters of the heat exchanger's inter-

Table 10. The comparison of results for the maximum temperature on the fins (T_{max})

T_{max} of Estimation Data	Numerical Result (°C)	ANN Result (°C)	Absolute Difference	Er	R
Set1	73.14	73.11	0.03	0.04 %	1.00040
Set2	95.51	95.20	0.31	0.32 %	1.00321
Set3	83.14	83.16	0.02	0.03 %	0.99973
Set4	87.90	88.08	0.18	0.20 %	0.99797
Set5	115.76	115.81	0.05	0.04 %	0.99958

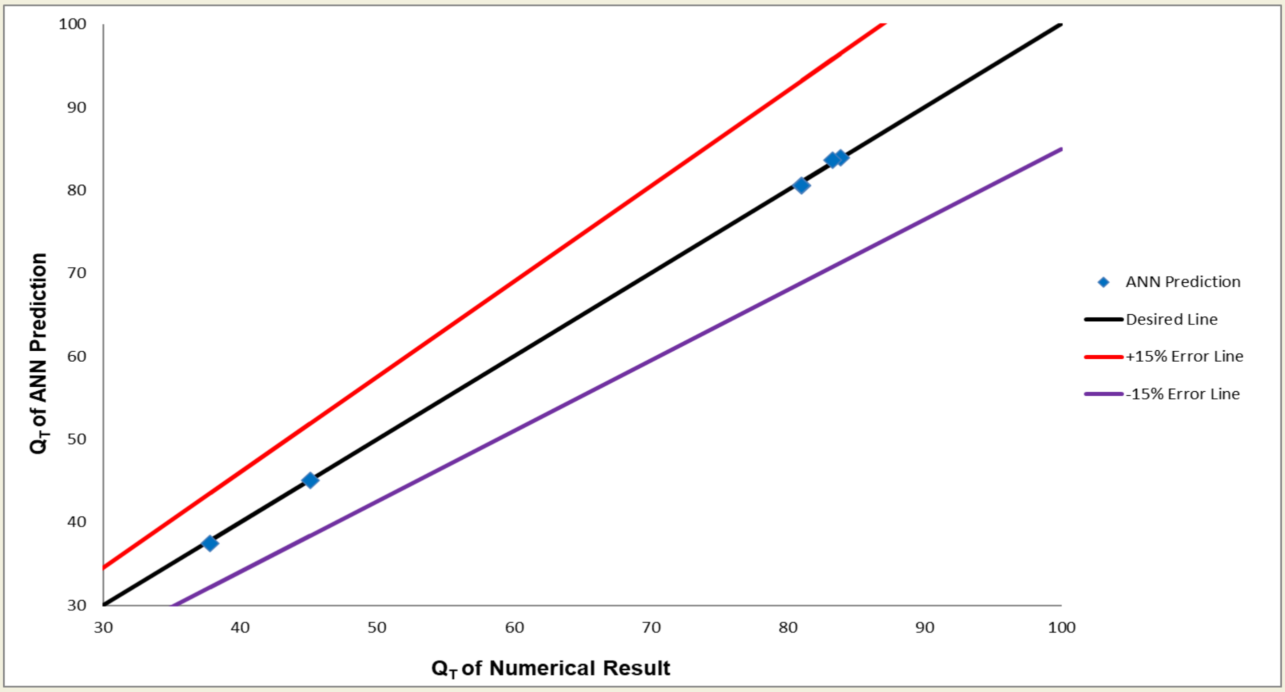

Figure 6. The scatter plot of the total heat transfer (Q_T) on the inner surface of the tube

Table 11. The comparison of results for the total heat transfer ($\bar{Q}_T$) per unit volume of heat exchanger

$\bar{Q}_T$ of Estimation Data	Numerical Result	ANN Result	Absolute Difference	Er	R
Set1	22.09 W/mm^3	22.11 W/mm^3	0.02 W/mm^3	0.10 %	0.99901
Set2	32.35 W/mm^3	32.07 W/mm^3	0.28 W/mm^3	0.87 %	1.00875
Set3	16.72 W/mm^3	16.76 W/mm^3	0.04 W/mm^3	0.22 %	0.99781
Set4	20.32 W/mm^3	20.42 W/mm^3	0.10 W/mm^3	0.47 %	0.99534
Set5	22.08 W/mm^3	21.97 W/mm^3	0.12 W/mm^3	0.52 %	1.00525

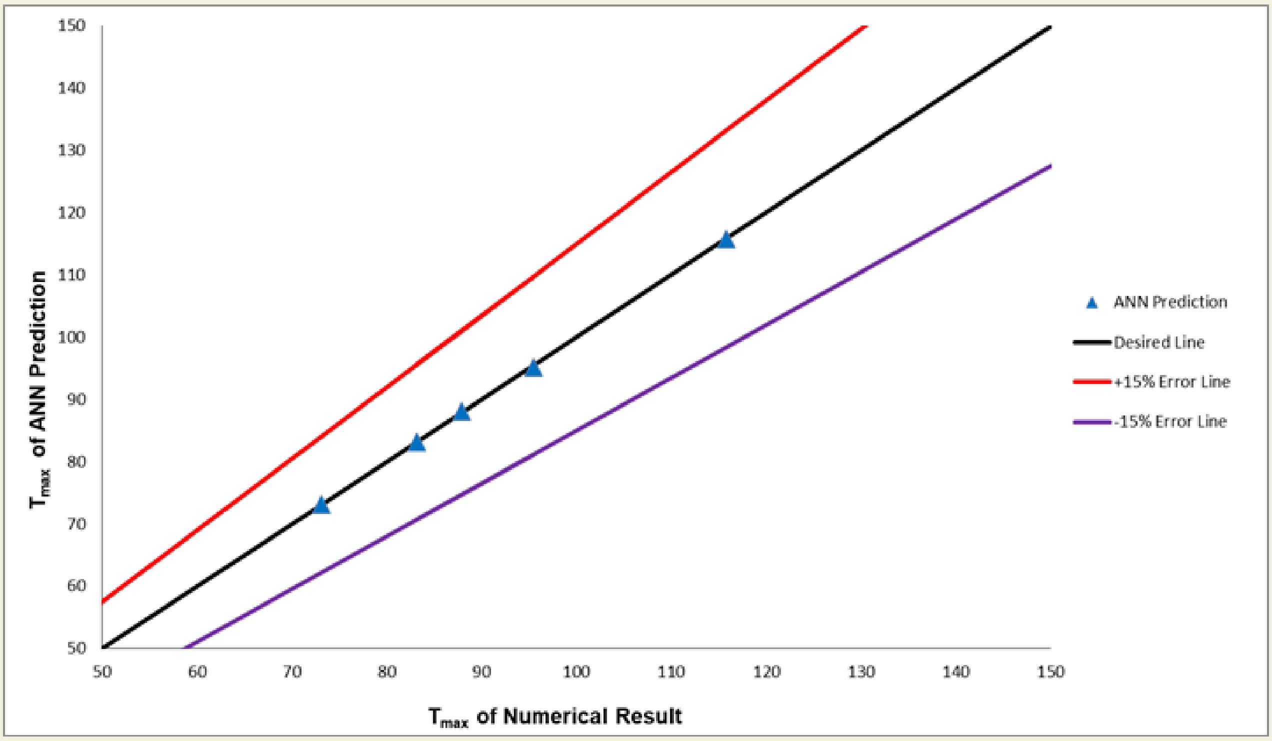

Figure 7. The scatter plot of the maximum temperature on the fins (T_{max})

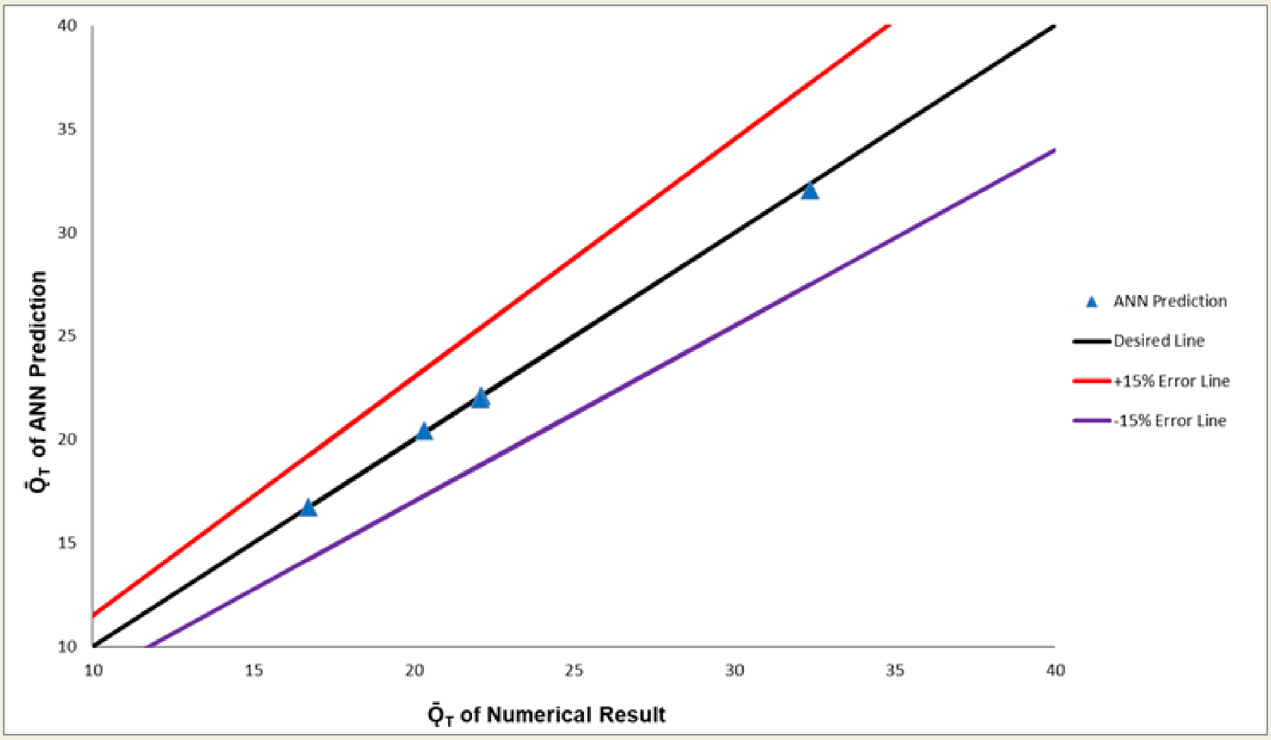

Figure 8. The scatter plot of the total heat transfer ($\bar{Q}_T$) per unit volume of the heat exchanger

nal volume, and the effects of selected design parameters on these output parameters are analyzed using a commercial simulation program. The resulting data is then used to train and validate the ANN model. The performance of the ANN model for predicting the internal volume of the heat exchanger in a condensing wall-mounted boiler is found to be satisfactory, with an average accuracy of 1.00018 and a maximum relative error of 9.16%.

This study has significant implications in the field of heat exchanger design and analysis. By combining numerical simulation and ANN techniques, it presents a method for predicting the performance of finned tube heat exchangers used in condensing wall-mounted boilers. This method has the potential to improve the design process, making it faster and more cost-effective. It may also be used to optimize the performance of these heat exchangers, ultimately leading to improved efficiency and effectiveness in the overall heat engine system.

In summary, this work demonstrates that thermal designers and engineers can utilize the parametric approach and ANN prediction method presented in this study as a tool in the research and development process. In the future, the performance of the condensing wall hang boiler could be predicted by using experimental study results and ANN methods to optimize them for real conditions.

6. Acknowledgements

The Scientific and Technological Research Council of Turkey partially supported this study (as projects grant no: TUBITAK-TEYDEB 5180092 & 3130798). We gratefully acknowledge this support.

Table 12. The comparison of results for the pressure drop (ΔP) between the inlet and outlet of internal volume

ΔP of Estimation Data	Numerical Result	ANN Result	Absolute Difference	Er	R
Set1	4.14 Pa	4.13 Pa	0.01 Pa	0.24 %	0.99980
Set2	1.34 Pa	1.31 Pa	0.03 Pa	2.19 %	1.02243
Set3	1.13 Pa	1.14 Pa	0.01 Pa	1.25 %	0.98767
Set4	0.74 Pa	0.73 Pa	0.02 Pa	2.22 %	1.02268
Set5	0.80 Pa	0.83 Pa	0.02 Pa	2.56 %	0.97501

Table 13. Comparison of the parametric result evaluated numerically and using ANN model for best design case

Optimum Design Case	Parametric Result	ANN Estimation	Absolute Difference	Er %
Q_T (W)	90.00	90.01	0.01	0.01
T_{max} (°C)	122.70	122.67	0.03	0.02
$\bar{Q}_T$ (W/mm³)	32.80	32.82	0.02	0.07
ΔP (Pa)	0.520	0.522	0.002	0.39

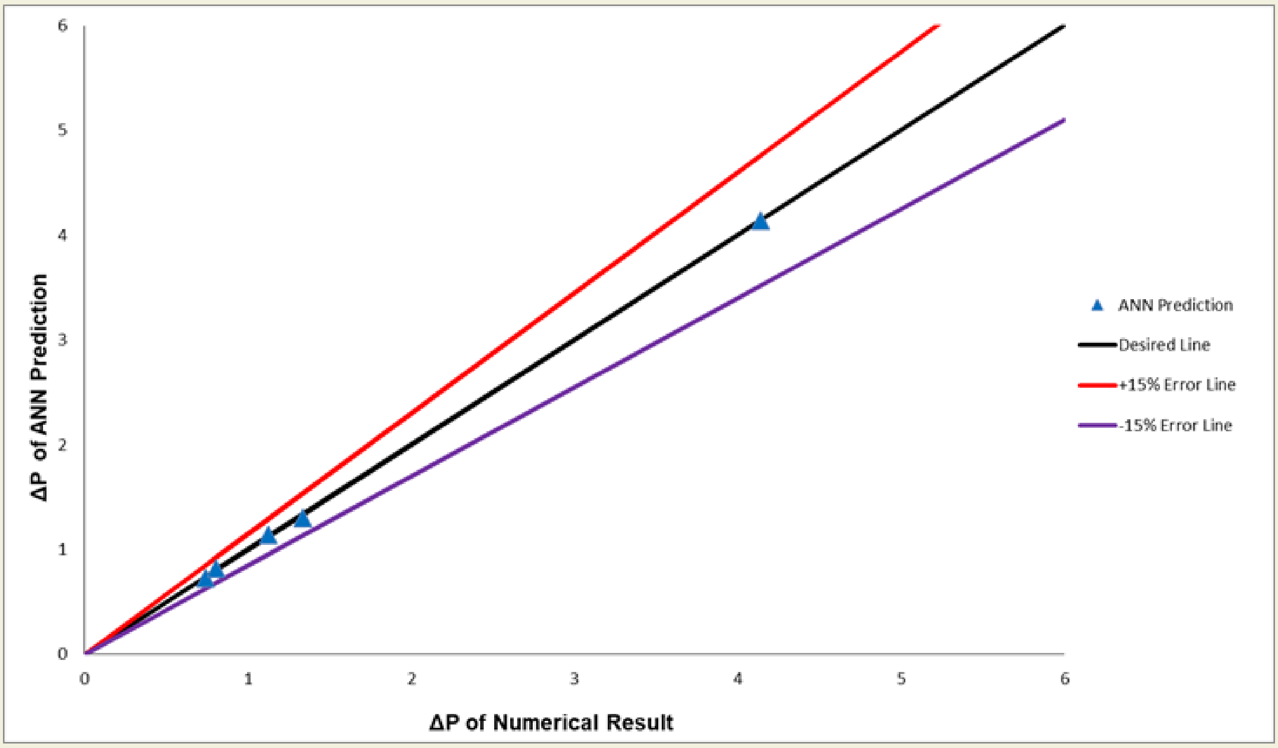

Figure 9. The scatter plot of the pressure drops (ΔP) between the inlet and outlet of the internal volume

References

[1] Wais, P. (2010). Fluid flow consideration in fin-tube heat exchanger optimization. Archives of Thermodynamics, 31: 87–104. doi:10.2478/v10173-010-0016-7.

[2] Bilirgen, H., Dunbar S., Levy E. K. (2013). Numerical modelling of finned heat exchangers. Applied Thermal Engineering, 61: 278-288. doi:10.1016/j.applthermaleng.2013.08.002

[3] Kim, N. H., Youn B., Webb R. L. (1999). Air side heat transfer and friction correlations for plain fin and tube heat exchangers with staggered tube arrangements. ASME Transaction, 121. doi:10.1115/1.2826030.

[4] Tutar, M., Akkoca A. (2004). Numerical analysis of fluid flow and heat transfer characteristics in three-dimensional plate fin and tube heat exchanger. Numerical Heat Transfer, Part A: Applications, 46:3, 301-321. doi:10.1080/10407780490474762

[5] Wang, C. C., Lee, W. S., Sheu, W. J. (2001). A comparative study of compact enhanced fin and tube heat exchangers. International Journal of Heat and Mass Transfer, 44(18): 3565-3573. doi:10.1016/S0017-9310(01)00011-4.

[6] Du, Y. J., Wang, C. C. (2000). An experimental study of the air side performance of superslit fin and tube heat exchangers. International Journal of Heat and Mass Transfer, 43(24) : 4475-4482. doi: 10.1016/S0017-9310(00)00082-X.

[7] Perrotin, T., Clodic, D. (2003). Fin efficiency calculation in enhanced fin and tube heat exchanger in dry conditions. 21st International Congress of Refrigeration: Serving the Needs of Mankind. ISBN: 2913149324.

[8] Antonescu, N., Stanescu, P.D. (2017). Computational model for a consensing boiler with finned tubes heat exchanger. Energy Procedia, 112 : 555-562. doi:10.1016/j.egypro.2017.03.1116.

[9] Balanescu, D. T., Homutescu V.M. (2017). Experimental study on the combustion system optimization in the case of a 36 kW condensing boiler. Procedia Engineering, 181 : 706-711. doi:10.1016/j.proeng.2017.02.453.

[10] Vidyadhar H. I., Mahesh S., Malpani R., Sapre M., Kulkarni A. J. (2019). Adaptive range genetic algorithm: A hybrid optimization approach and its application in the design and economic optimization of shell-and-tube heat exchanger. Engineering Applications of Artificial Intelligence, 85 : 444-461. doi:10.1016/j.engappai.2019.07.001.

[11] Zoebiry N., Humfeld K.D. (2021). A physics-informed machine learning approach for solving heat transfer equation in advanced manufacturing and engineering applications. Engineering Applications of Artificial Intelligence. 101: 104232. doi:10.1016/j.engappai.2021.104232.

[12] Shang Z. (2005). Application of artificial intelligence CFD based on neural network in vapor-water two-phase flow. Engineering Applications of Artificial Intelligence. 18 : 663-671. doi: 10.1016/j.engappai.2005.01.007.

[13] Cheng Y., Huang Y., Pang B., Zhang W. (2018). ThermalNet: A deep reinforcement learning-based combustion optimization system for coal-fired boiler. Engineering Applications of Artificial Intelligence. 74 : 303-311. doi: 10.1016/j.engappai.2018.07.003.

[14] Mohanraj M., Jayaraj S., Muraleedharan C. (2015). Applications of artificial neural networks for thermal analysis of heat exchangers – A review. International Journal of Thermal Sciences. 90 : 150-172. doi:10.1016/j.ijthermalsci.2014.11.030.

[15] Singh V., Aute V., Radermacher R. (2009). A heat exchanger model for air-to-refrigerant fin-and-tube heat exchanger with arbitrary fin sheet. International Journal of Refrigeration. 32 : 1724-1735. doi:10.1016/j.ijrefrig.2009.05.011.

[16] Pacheco-Vega A., Diaz G., Sen M., Yang K. T., Mcclain R. L. (2001). Heat rate predictions in humid air-water heat exchangers using correlations and neural networks. Journal Heat Transfer. 123 : 348-354. doi:10.1115/1.1351167.

[17] Wu Z.G., Zhang J.Z., Tao Y.B., He Y.L., Tao W.Q. (2008). Application of artificial neural network method for performance prediction of Gas cooler in a CO2 heat pump. International Journal of Heat Mass Transfer. 51 : 5459-5464. doi:10.1016/j.ijheatmasstransfer.2008.03.009.

[18] Kamsuwan C., Wang X., Seng L.P., Xian C.K., Piemjaiswang R., Piumsomboon P., Pratumwal Y., Otarawanna S., Chalermsinsuwan B., (2023). Simulation of nanofluid minro-channel heat exchanger using computational fluid dynamics integrated with artificial neural network. Energ Reports. 9: 239-247. doi: 10.1016/j.egyr.2022.10.412.

[19] Giannetti N., Redoo M.A., Sholahudin, Jeong J., Yamaguchi S., Saito K., Kim H. (2020). Prediction of two-phase flow distribution in microchannel heat exchangers using artificial neural network. International Journal of Refrigeration. 111: 53-63. doi: 10.1016/j.ijrefrig.2019.11.028.

[20] Xie C., Yan G., Ma Q., Elmasry Y., Singh P. K., Algelany A.M., Wae-hayee M. (2022). Flow and heat transfer optimization of a fin-tube heat exchanger with vortex generators using response surface methodology and artificial neural network. 39: 102445. doi: 10.1016/j.csite.2022.102445.

[21] Zhang T., Chen L., Wang J. (2023). Multi-objective optimization of elliptical tube fin heat exchangers based on neural networks and genetic algorithm. Energy. 269: 126729. doi: 10.1016/j.energy.2023.126729.

[22] Satyavada H., Baldi S. (2018). Monitoring energy efficiency of condensing boilers via hybrid first-principle modelling and estimation. Energy.142: 121-129. doi: 10.1016/j.energy.2017.09.124.

[23] Seban R.A., McLaughlin E.F. (1963). Heat transfer in tube coils with laminar and turbulent flow. International Journal of Heat and Mass Transfer. 6 : 387-395. doi:10.1016/0017-9310(63)90100-5.

[24] EN 15502 -1:2012+A1:2015, (2015). Gas-fired heating boilers Part 1: General requirements and tests-TC109 (Issue February), European Committee for Standardization.

[25] Yılmaz, S., Kumlutaş, D., Yücekaya, U. A., Cumbul, A. Y. (2021). Prediction of the equilibrium compositions in the combustion products of a domestic boiler. Energy. 233 : 121-123. doi: 10.1016/j.energy.2021.121123.

[26] Cumbul A.Y., (2018). Evaluation of energy efficiency of a power-plant using energy analysis. (Msc), Dokuz Eylül University, Turkey. https://tez.yok.gov.tr/UlusalTezMerkezi/TezGoster?key=hcgrYffRbz0Z44UJEuLtwQ0CunVOm65XkkDQY2Js-7LjW7oYNRQDI9MV4BbWX-H3L.

[27] NASA report SP-3001, (accessed date: 22 June2018). https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19630013835.pdf

[28] Incropera, F.P., Dewitt, D.P. (1996). Fundamentals of Heat and Mass Transfer, John Wiley&Sons.

[29] Kreith K. (2000). The CrcHandbook of Thermal Engineering, Crc Press, Boca Raton.

[30] Wang. B.X. (2000). Heat Transfer Science and Technology, Higher Education Press.