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Research Article

Performance Evaluation and Parametric Optimization of Coal-Fired Water Tube Boiler Using the Grey-Taguchi Method

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Industries, district heating companies, and public institutions that use boilers for heating, processing, or power production find it challenging to run at peak efficiencies due to rising fuel prices. Insufficient heat energy production and distribution through boilers contribute to an overall increase in energy expenditure. The performance of a boiler is affected by various controlling parameters, including specific fuel consumption capacity, load, and heat losses. The current study was conducted to evaluate the performance of the coal-fired water tube boiler at D.G. Khan Cement Company Limited, Pakistan. The experimental results were validated with artificial neural network- (ANN-) based predictions, which were observed to have an error of 14% in the regression plot. In this study, the performance parameters of the boiler, including steam temperature (ST), steam pressure (SP), and specific steam flow rate (SSFR), were optimized against fuel consumption (FC) and load using the Grey-Taguchi method. The best-performing parameters, with the best criteria, were observed at an overall grey relational grade (OGRG) of 0.891 and a load of 66%. The findings indicated that the overall performance of the boiler was optimized with an FC of 3.09 kg/s, a load of 66%, ST of 532°C, SP of 9.93 MPa, and SSFR of 21.38 kg/s.

1. Introduction

In the late 1700s and early 1800s, the kettle-type boiler, which simply boiled water into steam, paved the way for the steam-generating boiler [1]. By placing the water above a firebox, it was converted into steam. The steam-generating industry did not begin until the convection boiler was invented in 1867 [2]. Although it is uncertain who invented the first steam-generating boiler, George Babcock and Steven Wilcox are widely recognized as two founders of the boiler. In 1867, they were the first to patent their boiler design, which created steam through tubes within a firebrick building. In 1891, they founded Babcock & Wilcox Company in New York City [3]. Initially, small-sized boilers were produced. These boilers were manually fired with lump coal to generate steam. The unit's robust firebrick walls were essential to expedite the combustion process by reradiating heat back into the furnace.

The Stirling boiler was founded by O.C. Barber in 1891 [4]. The H-type Stirling boiler featured a brick setting pattern [5]. Unlike Babcock & Wilcox's boiler, the Stirling boiler was much bigger, with three drums to aid in the circulation of water and steam [6]. It remained the most popular boiler for steam generation until the late 1800s [7]. High-quality Stoker boilers, with complete brick walls, used screw-type structures to feed the fuel [8], resulting in homogeneous circulation of heat throughout the boiler. The E-stoker boiler, developed in 1912 through a merger of two American companies, marked a significant engineering advancement.

There are three modes of heat transfer in a boiler, including conduction, convection, and radiation [9]. The heat loss occurring through these three modes might cause a decrease in the boiler's efficiency [10]. Boilers can be broadly categorized into two main types based on their design: fire tube boilers and water tube boilers [11].

Table 1: Input and output parameters.

Sr. no.	Input		Output		
	FC (kg/s)	Load (%)	ST (°C)	SP (MPa)	SSFR (kg/s)
1	1.44	33.00	545.00	10.01	17.52
2	1.49	34.00	544.00	9.89	26.38
3	1.54	35.00	543.00	9.92	22.71
4	1.59	36.00	542.00	10.06	22.22
5	1.64	37.00	556.00	10.15	19.72
6	1.69	38.00	547.00	10.03	20.27
7	1.74	39.00	548.00	10.15	20.27
8	1.79	40.00	553.00	9.98	27.71
9	1.84	41.00	542.00	10.25	25.27
10	1.89	42.00	544.00	10.23	19.71
11	1.94	43.00	544.00	10.02	17.22
12	1.99	44.00	555.00	10.03	21.38
13	2.04	45.00	553.00	10.01	20.83
14	2.09	46.00	536.00	9.99	21.11
15	2.14	47.00	546.00	10.19	27.70
16	2.19	48.00	535.00	9.92	18.81
17	2.24	49.00	543.00	10.03	21.38
18	2.29	50.00	537.00	9.79	16.11
19	2.34	51.00	539.00	10.05	23.88
20	2.39	52.00	543.00	10.29	18.33
21	2.44	53.00	542.00	10.01	20.83
22	2.49	54.00	542.00	10.02	28.05
23	2.54	55.00	534.00	10.11	22.71
24	2.59	56.00	544.00	10.04	21.66
25	2.64	57.00	540.00	9.91	21.94
26	2.69	58.00	543.00	10.12	21.66
27	2.74	59.00	544.00	10.26	20.27
28	2.99	64.00	542.00	10.06	22.77
29	3.04	65.00	552.00	10.31	26.11
30	3.09	66.00	532.00	9.93	21.38
31	3.14	67.00	541.00	9.98	20.83
32	3.19	68.00	537.00	10.05	19.16
33	3.24	69.00	537.00	9.93	19.72
34	3.29	70.00	538.00	9.86	13.61
35	3.34	71.00	539.00	9.86	20.55
36	3.39	72.00	531.00	9.84	26.66
37	3.44	73.00	537.00	10.04	19.44
38	3.49	74.00	551.00	9.93	20.11
39	3.54	75.00	543.00	10.07	19.44
40	3.59	76.00	538.00	9.69	20.01
41	3.64	77.00	537.00	9.87	13.72
42	3.69	79.00	538.00	9.90	20.83

Additionally, boilers can be further classified according to their fuel consumption, such as coal fuel-fired boilers, gas-fired boilers, electric boilers, and nuclear-fired boilers. Among these, gas-fired boilers are known for their cost-effectiveness and higher efficiency compared to other types of boilers [12]. Despite the advantages of gas-fired boilers, running any boiler at peak efficiency can be challenging for industries and heating companies, especially considering the constant rise in fuel prices [13]. The insufficient heat energy production and distribution lead to an increase in energy production cost. To address this issue effectively, it is essential to evaluate the current infrastructure and identify

Table 2: Validation of experimental vs. predicted results.

Sr. no.	ST Exp (°C)	ST pred (°C)	SP Exp (MPa)	SP Pred (MPa)	SSFR Exp (kg/s)	SSFR Pred (kg/s)
1	0.9820	0.9835	0.9730	0.9723	0.6240	0.6488
2	0.9800	0.9845	0.9610	0.9774	0.9400	0.7947
3	0.9780	0.9851	0.9640	0.9798	0.8090	0.8468
4	0.9770	0.9855	0.9780	0.9807	0.7920	0.8538
5	1.0020	0.9858	0.9860	0.9810	0.7030	0.8455
6	0.9860	0.9860	0.9750	0.9812	0.7230	0.8309
7	0.9870	0.9860	0.9860	0.9811	0.7230	0.8160
8	0.9960	0.9860	0.9700	0.9810	0.9880	0.8014
9	0.9770	0.9858	0.9960	0.9807	0.9010	0.7865
10	0.9800	0.9854	0.9940	0.9803	0.7020	0.7737
11	0.9800	0.9848	0.9730	0.9797	0.6130	0.7618
12	1.0000	0.9839	0.9730	0.9788	0.7620	0.7500
13	0.9960	0.9828	0.9720	0.9778	0.7430	0.7400
14	0.9660	0.9813	0.9710	0.9765	0.7530	0.7311
15	0.9840	0.9794	0.9900	0.9749	0.9880	0.7231
16	0.9640	0.9774	0.9640	0.9735	0.6700	0.7177
17	0.9780	0.9756	0.9750	0.9724	0.7620	0.7154
18	0.9680	0.9743	0.9510	0.9724	0.5740	0.7180
19	0.9710	0.9741	0.9770	0.9738	0.8510	0.7262
20	0.9780	0.9749	1.0000	0.9765	0.6530	0.7393
21	0.9770	0.9762	0.9720	0.9799	0.7430	0.7552
22	0.9770	0.9770	0.9740	0.9824	1.0000	0.7675
23	0.9620	0.9770	0.9830	0.9837	0.8090	0.7754
24	0.9800	0.9763	0.9720	0.9840	0.7720	0.7792
25	0.9730	0.9753	0.9630	0.9835	0.7820	0.7799
26	0.9780	0.9743	0.9830	0.9828	0.7720	0.7790
27	0.9800	0.9733	0.9970	0.9821	0.7230	0.7775
28	0.9770	0.9704	0.9720	0.9791	0.8120	0.7756
29	0.9950	0.9700	1.0010	0.9783	0.9310	0.7772
30	0.9590	0.9695	0.9650	0.9771	0.7620	0.7766
31	0.9750	0.9689	0.9700	0.9752	0.7430	0.7670
32	0.9680	0.9682	0.9770	0.9716	0.6830	0.7264
33	0.9680	0.9677	0.9620	0.9664	0.7020	0.6333
34	0.9690	0.9680	0.9580	0.9608	0.4850	0.5314
35	0.9710	0.9695	0.9580	0.9606	0.7330	0.7187
36	0.9570	0.9724	0.9560	0.9659	0.9500	0.9463
37	0.9680	0.9755	0.9760	0.9680	0.6930	0.8418
38	0.9930	0.9763	0.9650	0.9658	0.7130	0.7197
39	0.9780	0.9755	0.9790	0.9624	0.6930	0.6881
40	0.9690	0.9743	0.9420	0.9593	0.7130	0.6948
41	0.9680	0.9732	0.9590	0.9569	0.4890	0.7122
42	0.9690	0.9722	0.9620	0.9547	0.7430	0.7346

areas for improvement. Therefore, conducting an analysis of boiler efficiency becomes crucial, as it significantly contributes to increasing energy generation and lowering production cost [14].

Moreover, understanding the impact of accurate modelling and simulation of power plant components allows for informed decision-making in areas such as training, strategic planning, maintenance, techno-economic choices, and ongoing plant operation monitoring [15]. For these reasons, both boiler efficiency analysis and precise modeling are essential for optimizing power plant performance and cost-effectiveness. The demand for user-friendly modeling and

Table 3: Taguchi-based normalization.

Sr. no	Input		Outputs		
	FC (kg/s)	Load (%)	ST (°C)	SP (MPa)	SSFR (kg/s)
1	1.440	33.000	0.561	0.767	0.276
2	1.490	34.000	0.520	0.567	0.906
3	1.540	35.000	0.480	0.767	0.645
4	1.590	36.000	0.441	0.483	0.611
5	1.640	37.000	1.000	0.933	0.434
6	1.690	38.000	0.640	0.900	0.473
7	1.740	39.000	0.681	0.533	0.473
8	1.790	40.000	0.883	0.533	1.001
9	1.840	41.000	0.441	0.517	0.828
10	1.890	42.000	0.520	0.500	0.432
11	1.940	43.000	0.520	0.833	0.255
12	1.990	44.000	0.961	0.383	0.551
13	2.040	45.000	0.883	0.567	0.512
14	2.090	46.000	0.201	0.167	0.532
15	2.140	47.000	0.600	0.600	1.002
16	2.190	48.000	0.160	1.000	0.368
17	2.240	49.000	0.481	0.517	0.551
18	2.290	50.000	0.241	0.550	0.177
19	2.340	51.000	0.320	0.700	0.729
20	2.390	52.000	0.481	0.517	0.335
21	2.440	53.000	0.440	0.367	0.512
22	2.490	54.000	0.441	0.717	1.025
23	2.540	55.000	0.120	0.950	0.645
24	2.590	56.000	0.521	0.517	0.571
25	2.640	57.000	0.361	1.017	0.591
26	2.690	58.000	0.484	0.400	0.571
27	2.740	59.000	0.521	0.483	0.473
28	2.990	64.000	0.440	0.600	0.650
29	3.040	65.000	0.842	0.350	0.887
30	3.090	66.000	0.045	0.283	0.551
31	3.140	67.000	0.421	0.283	0.512
32	3.190	68.000	0.244	0.250	0.394
33	3.240	69.000	0.240	0.583	0.432
34	3.290	70.000	0.281	0.400	0.000
35	3.340	71.000	0.321	0.633	0.493
36	3.390	72.000	0.000	0.000	0.926
37	3.440	73.000	0.242	0.300	0.414
38	3.490	74.000	0.821	0.350	0.454
39	3.540	75.000	0.483	0.153	0.414
40	3.590	76.000	0.281	0.267	0.454
41	3.640	77.000	0.241	0.764	0.008
42	3.690	79.000	0.284	0.345	0.512

Table 4: Taguchi quality loss function.

Sr. no	Input		Outputs		
	FC (kg/s)	Load (%)	ST (°C)	SP (MPa)	SSFR (kg/s)
1	1.440	33.000	0.440	0.250	0.749
2	1.490	34.000	0.480	0.450	0.119
3	1.540	35.000	0.520	0.250	0.381
4	1.590	36.000	0.560	0.533	0.414
5	1.640	37.000	0.030	0.083	0.591
6	1.690	38.000	0.360	0.117	0.542
7	1.740	39.000	0.320	0.483	0.552
8	1.790	40.000	0.120	0.483	0.025
9	1.840	41.000	0.560	0.500	0.197
10	1.890	42.000	0.480	0.517	0.593
11	1.940	43.000	0.480	0.183	0.772
12	1.990	44.000	0.040	0.633	0.474
13	2.040	45.000	0.120	0.450	0.513
14	2.090	46.000	0.800	0.850	0.493
15	2.140	47.000	0.410	0.417	0.025
16	2.190	48.000	0.840	0.017	0.657
17	2.240	49.000	0.520	0.500	0.474
18	2.290	50.000	0.760	0.467	0.848
19	2.340	51.000	0.680	0.317	0.296
20	2.390	52.000	0.520	0.500	0.691
21	2.440	53.000	0.560	0.650	0.513
22	2.490	54.000	0.560	0.300	0.001
23	2.540	55.000	0.880	0.067	0.385
24	2.590	56.000	0.480	0.500	0.454
25	2.640	57.000	0.640	0.000	0.434
26	2.690	58.000	0.520	0.617	0.454
27	2.740	59.000	0.480	0.533	0.552
28	2.990	64.000	0.560	0.417	0.375
29	3.040	65.000	0.160	0.667	0.138
30	3.090	66.000	0.960	0.733	0.474
31	3.140	67.000	0.600	0.733	0.513
32	3.190	68.000	0.760	0.767	0.631
33	3.240	69.000	0.760	0.433	0.593
34	3.290	70.000	0.720	0.617	1.025
35	3.340	71.000	0.680	0.383	0.532
36	3.390	72.000	1.010	1.017	0.099
37	3.440	73.000	0.760	0.717	0.611
38	3.490	74.000	0.200	0.667	0.571
39	3.540	75.000	0.520	0.167	0.611
40	3.590	76.000	0.720	0.185	0.571
41	3.640	77.000	0.760	0.187	1.017
42	3.690	79.000	0.720	0.197	0.513

monitoring tools has multiplied in the last decade due to environmental concerns and deregulation of energy [16]. An example of such user-friendly modeling and monitoring tools is the online plant monitoring system. It continuously collects a significant amount of operational data from existing facilities to ensure appropriate operations [17]. This data is often stored only in databases and can be used to build ANN models that simulate plant operations. Many researchers have investigated the ANN modeling of various energy systems [18].

The use of ANN-based prediction has been explored in a few past studies [4, 5, 11, 16], to assess the performance

Table 5: Overall grey relational grade.

Sr. no	Input		Outputs			ORG
	FC (kg/s)	Load (%)	ST (°C)	SP (MPa)	SSFR (kg/s)	
1	1.440	33.000	0.532	0.630	0.738	0.604
2	1.490	34.000	0.510	0.486	0.845	0.608
3	1.540	35.000	0.490	0.630	0.738	0.603
4	1.590	36.000	0.472	0.443	0.883	0.104
5	1.640	37.000	1.000	0.836	0.624	0.324
6	1.690	38.000	0.581	0.785	0.649	0.567
7	1.740	39.000	0.610	0.468	0.861	0.435
8	1.790	40.000	0.806	0.468	0.861	0.507
9	1.840	41.000	0.472	0.459	0.869	0.843
10	1.890	42.000	0.510	0.451	0.876	0.341
11	1.940	43.000	0.510	0.699	0.695	0.645
12	1.990	44.000	0.926	0.402	0.924	0.321
13	2.040	45.000	0.806	0.486	0.845	0.000
14	2.090	46.000	0.385	0.333	1.000	0.312
15	2.140	47.000	0.556	0.505	0.829	0.346
16	2.190	48.000	0.373	0.962	0.570	0.721
17	2.240	49.000	0.490	0.459	0.869	0.672
18	2.290	50.000	0.397	0.477	0.853	0.702
19	2.340	51.000	0.424	0.573	0.777	0.603
20	2.390	52.000	0.490	0.459	0.869	0.342
21	2.440	53.000	0.472	0.395	0.931	0.532
22	2.490	54.000	0.472	0.586	0.767	0.432
23	2.540	55.000	0.362	0.864	0.611	0.654
24	2.590	56.000	0.510	0.459	0.869	0.345
25	2.640	57.000	0.439	1.000	0.556	0.245
26	2.690	58.000	0.490	0.408	0.918	0.145
27	2.740	59.000	0.510	0.443	0.883	0.801
28	2.990	64.000	0.472	0.505	0.829	0.657
29	3.040	65.000	0.758	0.389	0.937	0.835
30	3.090	66.000	0.342	0.367	0.961	0.891
31	3.140	67.000	0.455	0.367	0.961	0.654
32	3.190	68.000	0.397	0.357	0.973	0.576
33	3.240	69.000	0.397	0.495	0.837	0.456
34	3.290	70.000	0.410	0.408	0.918	0.345
35	3.340	71.000	0.424	0.526	0.812	0.765
36	3.390	72.000	0.333	0.295	1.048	0.754
37	3.440	73.000	0.397	0.372	0.955	0.675
38	3.490	74.000	0.714	0.389	0.937	0.752
39	3.540	75.000	0.490	0.718	0.684	0.753
40	3.590	76.000	0.410	0.697	0.696	0.654
41	3.640	77.000	0.397	0.694	0.698	0.632
42	3.69	79.00	0.410	0.683	0.704	0.765

parameters of boilers. However, none of these studies has yet optimized the results of boiler performance. The optimization of ANN-predicted boiler performance parameters using GTM remains an unexplored area. The performance of coal-fired boilers widely varies with specific fuel consumption, load, steam temperature, steam pressure, and specific steam flow rate. Optimizing the input and output parameters of the boiler using the Gray Taguchi Method (GTM) could prove to be cost-effective by supporting the economical operation of water tube boilers [19].

The aim of this study is to optimize boiler performance using GTM and validate the experimental results with

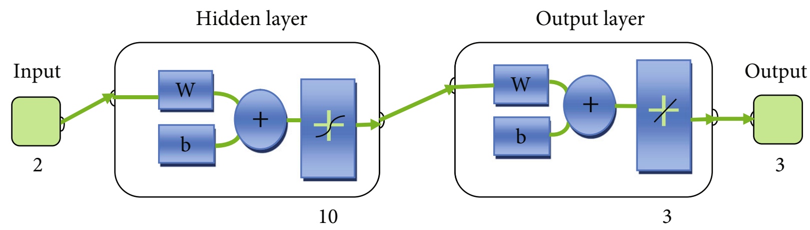

Figure 1: Fitting neural network.

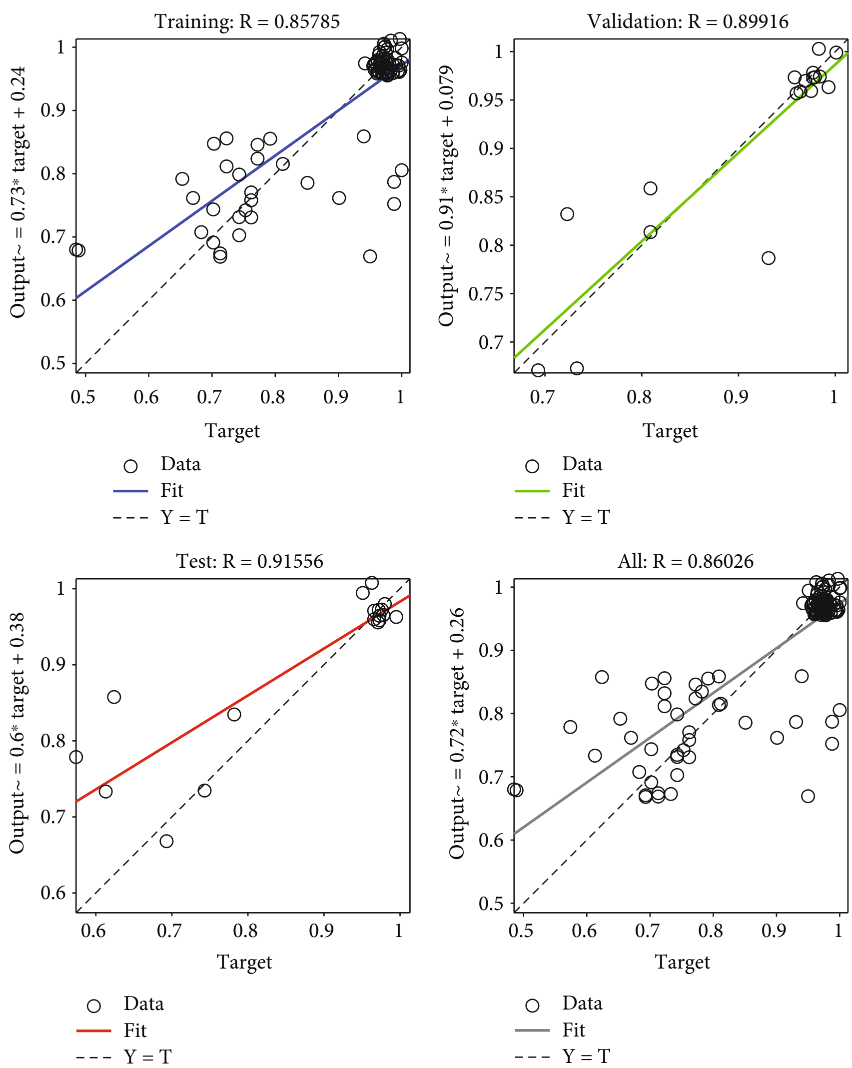

Figure 2: Fitting and validation using ANN.

ANN-predicted results under various loading conditions for the coal-fired boiler located at D.G. Khan Cement Company Limited, Pakistan.

2. Methods

The study was conducted to evaluate the performance of D.G. Khan Cement Company Limited's coal-fired boiler with a capacity of 30 MW. The input parameters included load and fuel consumption (FC), while the output parameters included steam temperature (ST), steam pressure (SP), and specific steam flow rate (SSFR). The set of experimental targets was normalized using Grey Relational Generation (GRG) with the "maximal the better" criteria for output parameters [20]. The experimental and GTM optimized results were then compared to the ANN projected results for validation. The input and output data used in the training of ANN and optimization using GTM are given in Table 1, while the experimental versus predicted values are mentioned in Table 2.

A total of forty-two samples were physically collected from D.G. Khan Cement Company Limited. After the

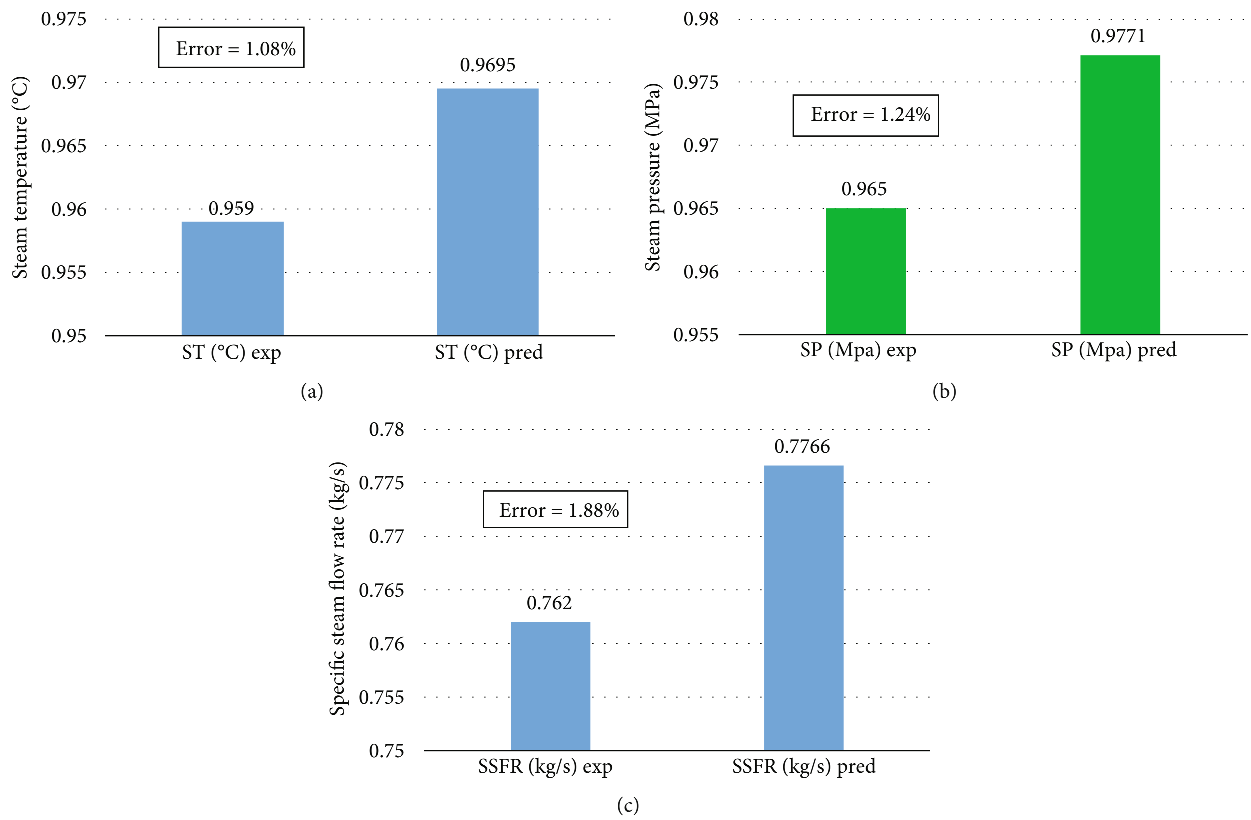

Figure 3: Convergence between experimental and predicted results of steam temperature (a), steam pressure (b), and specific steam flow rate (c).

collection of experimental data, it was normalized to make the results comparable to other studies [21]. In the current experimental analysis, ANN and GRG were used to study the output and performance responses, such as ST, SP, and SSFR, using the "larger the better" criteria. The coal-fired boiler performed very well under these conditions [17, 22].

$$Xi = \frac{\mathrm{Yi}(K) - \mathrm{MinYi}(K)}{\mathrm{MaxYi}(K) - \mathrm{minYi}(K)}, \tag{1}$$

$$\mathrm{Yi} = \frac{\mathrm{MaxYi}(K) - \mathrm{Yi}(K)}{\mathrm{MaxYi}(K) - \mathrm{minYi}(K)}, \tag{2}$$

where $\mathrm{Xi}(k)$ and $\mathrm{Yi}(k)$ are the gray relation-generation values in equations (1) and (2), min $\mathrm{Yi}(k)$ represents the smallest $\mathrm{Yi}(k)$ value for the kth response, and max $\mathrm{Yi}(k)$ represents the largest $\mathrm{Yi}(k)$ value for the kth response. The gray partnership generation sequences are shown in Tables 3–5. The optimal sequence for SP, ST, and SSFR is $x0(k)$ $(k = 1, 2, \cdots\cdots, 7)$ [23]. The grey relational grade description in the grey relational analysis demonstrates how the seven sequences ($x0(k)$ and $xi(k)$, if $= 1, 2$) are related to the grade, 7, k $= [1, 2, 7]$ [24].

$$\nabla_{\mathrm{om}} = [X^* - X_m(X, m = 1, 2, 3 \cdots .x)], \tag{3}$$

where ∇_{om} is Taguchi quality loss function, X_m represents the individual comparable data series from Table 4, X^* is the maximum value of the data series taken as 1, and x is the number of experiments [25]. The corresponding results of Taguchi quality loss functions for comparable data series are presented in Table 4 [26, 27].

$$\Psi m = \frac{\nabla \mathrm{min} + \zeta \times \nabla \mathrm{max}}{\nabla_{\mathrm{om}} + \zeta \times \nabla \mathrm{max}}, \tag{4}$$

$$\epsilon = \frac{1}{y} \sum_{m=1}^{y} (\beta_m) \times \Psi_m. \tag{5}$$

An average GRC for each response is determined by the overall gray relation grade (OGRG). In equation (4), Ψm is the grey relational coefficient, calculated by the model in equation (3) while keeping the value of coefficient $\zeta = [0, 1]$ as 0.5, an average of the two limits [28].

3. Results

The fitting tool was used to train the ANN via defined inputs and outputs for ANN prediction. The predicted results for a trained ANN algorithm can be visualized in Table 2. The results were predicted by the network using two input neurons, three output neurons, and ten to thirty adjustable neurons in the hidden layer (Figure 1). The deviation was 86%, and it converged towards the experimental results in the validation regression plot, showing deviations to both the negative and positive sides, as shown in Figure 2.

The bar chart in Figure 3 depicts the deviation of predicted output parameters from the experimental ones. The

Table 6: Optimization of performance factor.

Sr. no.	Input		Experimental results			Predicted results			OGRG
	Load (%)	FC (kg/s)	ST (°C)	SP (MPa)	SSFR (kg/s)	ST (°C)	SP (MPa)	SSFR (kg/s)	
1	33.0000	1.4400	0.9820	0.9730	0.6240	0.9835	0.9723	0.6488	0.6040
2	34.0000	1.4900	0.9800	0.9610	0.9400	0.9845	0.9774	0.7947	0.6080
3	35.0000	1.5400	0.9780	0.9640	0.8090	0.9851	0.9798	0.8468	0.6030
4	36.0000	1.5900	0.9770	0.9780	0.7920	0.9855	0.9807	0.8538	0.1040
5	37.0000	1.6400	1.0020	0.9860	0.7030	0.9858	0.9810	0.8455	0.3240
6	38.0000	1.6900	0.9860	0.9750	0.7230	0.9860	0.9812	0.8309	0.5670
7	39.0000	1.7400	0.9870	0.9860	0.7230	0.9860	0.9811	0.8160	0.4350
8	40.0000	1.7900	0.9960	0.9700	0.9880	0.9860	0.9810	0.8014	0.5070
9	41.0000	1.8400	0.9770	0.9960	0.9010	0.9858	0.9807	0.7865	0.8430
10	42.0000	1.8900	0.9800	0.9940	0.7020	0.9854	0.9803	0.7737	0.3410
11	43.0000	1.9400	0.9800	0.9730	0.6130	0.9848	0.9797	0.7618	0.6450
12	44.0000	1.9900	1.0000	0.9730	0.7620	0.9839	0.9788	0.7500	0.3210
13	45.0000	2.0400	0.9960	0.9720	0.7430	0.9828	0.9778	0.7400	0.4120
14	46.0000	2.0900	0.9660	0.9710	0.7530	0.9813	0.9765	0.7311	0.3120
15	47.0000	2.1400	0.9840	0.9900	0.9880	0.9794	0.9749	0.7231	0.3460
16	48.0000	2.1900	0.9640	0.9640	0.6700	0.9774	0.9735	0.7177	0.7210
17	49.0000	2.2400	0.9780	0.9750	0.7620	0.9756	0.9724	0.7154	0.6720
18	50.0000	2.2900	0.9680	0.9510	0.5740	0.9743	0.9724	0.7180	0.7020
19	51.0000	2.3400	0.9710	0.9770	0.8510	0.9741	0.9738	0.7262	0.6030
20	52.0000	2.3900	0.9780	1.0000	0.6530	0.9749	0.9765	0.7393	0.3420
21	53.0000	2.4400	0.9770	0.9720	0.7430	0.9762	0.9799	0.7552	0.5320
22	54.0000	2.4900	0.9770	0.9740	1.0000	0.9770	0.9824	0.7675	0.4320
23	55.0000	2.5400	0.9620	0.9830	0.8090	0.9770	0.9837	0.7754	0.6540
24	56.0000	2.5900	0.9800	0.9720	0.7720	0.9763	0.9840	0.7792	0.3450
25	57.0000	2.6400	0.9730	0.9630	0.7820	0.9753	0.9835	0.7799	0.2450
26	58.0000	2.6900	0.9780	0.9830	0.7720	0.9743	0.9828	0.7790	0.1450
27	59.0000	2.7400	0.9800	0.9970	0.7230	0.9733	0.9821	0.7775	0.8010
28	64.0000	2.9900	0.9770	0.9720	0.8120	0.9704	0.9791	0.7756	0.6570
29	65.0000	3.0400	0.9950	1.0010	0.9310	0.9700	0.9783	0.7772	0.8350
30	66.0000	3.0900	0.9590	0.9650	0.7620	0.9695	0.9771	0.7766	0.8910
31	67.0000	3.1400	0.9750	0.9700	0.7430	0.9689	0.9752	0.7670	0.6540
32	68.0000	3.1900	0.9680	0.9770	0.6830	0.9682	0.9716	0.7264	0.5760
33	69.0000	3.2400	0.9680	0.9620	0.7020	0.9677	0.9664	0.6333	0.4560
34	70.0000	3.2900	0.9690	0.9580	0.4850	0.9680	0.9608	0.5314	0.3450
35	71.0000	3.3400	0.9710	0.9580	0.7330	0.9695	0.9606	0.7187	0.7650
36	72.0000	3.3900	0.9570	0.9560	0.9500	0.9724	0.9659	0.9463	0.7540
37	73.0000	3.4400	0.9680	0.9760	0.6930	0.9755	0.9680	0.8418	0.6750
38	74.0000	3.4900	0.9930	0.9650	0.7130	0.9763	0.9658	0.7197	0.7520
39	75.0000	3.5400	0.9780	0.9790	0.6930	0.9755	0.9624	0.6881	0.7530
40	76.0000	3.5900	0.9690	0.9420	0.7130	0.9743	0.9593	0.6948	0.6540
41	77.0000	3.6400	0.9680	0.9590	0.4890	0.9732	0.9569	0.7122	0.6320
42	79.0000	3.6900	0.9690	0.9620	0.7430	0.9722	0.9547	0.7346	0.7650

results predicted by the network, using two inputs and ten neurons in the hidden layer, were found to converge towards the experimental results by 86% in the validation regression plot. These results exhibited convergence on both positive and negative sides. In the training regression plot, the values were accurate at 85%. To check the accuracy of training data samples, 16 sample test data were separated, and it was observed that 91% of the test results were accurate when compared with experimental values. Overall, the R^2 value was observed to be 86% for the experimental and predicted output parameters, with an error of more than 10%. The GTM concluded the optimization results in three steps, including Taguchi-based normalization, quality loss function, and overall grey relational grade.

The experimental and predicted results converged by 86% on both positive and negative sides, with an R value of 0.86026. The experimental results were then normalized using grey relational generation. The optimization of targets with input factors was obtained using an overall grey relation grade with the "larger the better" criteria. The optimized results through the overall grey relation grade, using the Grey-Taguchi method, were observed at run number 30 with a load of 66% and FC of 3.09 kg/s. The experimental outputs at 66% load were 0.959°C, 0.965 MPa, and 0.762 kg/s for ST, SP, and SSFR, respectively. Meanwhile, the predicted outputs were observed to be 0.9695°C, 0.9771 MPa, and 0.7766 kg/s for ST, SP, and SSFR, respectively, at an OGRG of 0.891. The best-performing output parameters were observed at an OGRG of 0.891, with an overall root mean square error of 14%.

4. Discussion

In the current study, functional fitting neural networks consisted of input, hidden, and output layers (Figure 1). There were two input parameters, including load percentage and specific FC. The second layer consisted of hidden neurons, which were adjustable between ten and thirty. The output layer consisted of three parameters: ST, SP, and SSFR. For network optimization, the number of hidden neurons depends on the number of input neurons, the number of output neurons, and the number of training data [29]. Thus, the choice of ten to thirty hidden neurons is justified in the current study and yielded reliable results.

The current study observed an 86% accuracy in results for boiler performance using ANN (Figure 2). In a study conducted in the past, the authors measured boiler performance using ANN and observed a 0.7% increase in efficiency [18]. Another research study measured boiler characteristics using ANN with the feed-back propagation algorithm and obtained 99% accuracy in results [4]. Thus, the observation of a 14% error in results in the current study is in agreement with the observations from the literature.

Furthermore, output parameters were optimized for experimental and ANN-predicted results using GTM, indicating that the findings are realistic and have practical implications. However, this error might be attributed to the fact that the data was collected from the hottest location in the country, where temperature variation (10-15°C) between morning and afternoon would be considerable, especially in summer. Such a wide range of temperature variation might affect the load and fuel consumption [30] of the plant, which could be reflected in the experimental data. On the other hand, the current ANN prediction did not consider the temperature variation within a day, which could contribute to an error of 14%.

The experimental values were observed to converge towards the predicted values of ST, SP, and SSFR, as shown in Figures 3(a)–3(c), respectively. The error was observed to be 1.08%, 1.23%, and 1.87% for ST, SP, and SSFR, respectively. The difference between experimental and predicted values indicated a deviation from the fitting line, which might be positive or negative [31]. The current study observed a higher number of negative residuals, which might be due to the limitation in data size. The data collection was restricted by the company due to scheduled maintenance and approval issues. A larger data size might yield a smaller value of the total residuals and reduce the overall error.

The GRG, which turns the original series of experimental data into comparable series, undergoes experimental data normalization in GTM. Figure 3 shows the comparison and validation of both experimental and ANN results at the best-predicted combination of outputs at 66% load. The results indicate that the overall performance of the boiler was optimized at a FC of 3.09 kg/s, load of 66%, ST of 532°C, SP of 9.93 MPa, and SSFR of 21.38 kg/s. The root mean square error was observed to be 14%, which is closer to a realistic setup.

The performance prediction and optimization process of the experimental setup are given in Table 6. Both experimental and ANN-predicted results were observed to be close to each other with an optimal arrangement of inputs. This suggests the suitability of the Grey-Taguchi technique for obtaining an optimal combination of output parameters. As a result, both the Grey-Taguchi approach and ANN were observed to be suitable for the optimization of coal-fired boiler parameters, providing the best possible combination of outputs.

5. Conclusion

The aim of this study was to optimize the boiler performance using GTM and validate the experimental results with ANN-predicted results under various loading conditions for a coal-fired boiler. The current study observed an 86% accuracy in results for boiler performance. The error of 14% might be attributed to the fact that the location of the plant for data collection experiences significant variations in temperature within the three shifts during 24 hours. As a result, the variation in ambient temperature might influence the plant efficiency. The experimental values were observed to converge towards the predicted values of ST, SP, and SSFR. The observation of a higher number of negative residuals in the current study could be due to the limitation in data size. Using a larger data size is suggested for future studies, as it may yield a smaller value of the total residuals, reducing the overall error and contributing to improved boiler performance. ANN offers an excellent alternative method for predicting boiler performance parameters. Thus, the current study has implications for the replacement of expensive boiler experiments with ANN. It also suggests the suitability of the Grey-Taguchi technique for obtaining an optimal combination of boiler performance parameters.

Data Availability

Data will be provided upon special request.

Conflicts of Interest

The authors declare no competing interests.

Authors' Contributions

All authors contributed equally to the article.

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