International Journal on "Technical and Physical Problems of Engineering" (IJTPE)
Published by International Organization of IOTPE
ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com
December 2021 | Issue 49 | Volume 13 | Number 4 | Pages 85-89

BOILER EFFICIENCY OPTIMIZATION USING ARTIFICIAL INTELLIGENCE AND RSM RESPONSE SURFACE METHOD

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Abstract- In the agroindustry, Boilers are widely used to heat water or produce steam, usually through the energy released by the combustion of a fuel, to power the facilities by steam (Figure 1). One of the main objectives to reduce energy consumption is the optimization and improvement of energy efficiency. The use of artificial intelligence allows today to improve the management of energy by optimizing the flows that is why companies want to integrate artificial intelligence to reap its benefits by decreasing their financial charges in several areas especially in energy. In this context, we suggest an approach to find the optimum between combustion temperature and fuel flow to find the maximum efficiency of the boiler. This result is obtained by making experimental measurements (temperature, steam flow and efficiency). To find this optimum point (temperature, flow and efficiency) we will show that the k-NN method is accurate and time efficient compared to the neural network method. This result is fundamental to optimize the energy consumption of this thermal system.

Keywords: Boiler, Energy, Artificial Intelligence, k-NN, RSM.

1. INTRODUCTION

A Boilers are pressurized devices widely used by the agroindustry to heat water or produce steam to supply the production processes. Generally, through the energy released by the combustion of a fuel, to power the installations with steam [1, 2].

One of the main objectives is to optimize and improve energy efficiency. [3, 4, 5]. In the literature [6, 7, 8], the indirect method is widely used to calculate the efficiency of a boiler, as it is more efficient and precise. The efficiency is defined as the ratio between the useful energy produced and the total energy input. It is expressed by the following relationship:

$$R = \text{Useful energy} / \text{Input energy} \quad (1)$$

We have performed experimental measurements on a thermal system. These measurements took place in a company operating in the beverage industry Figure 1.

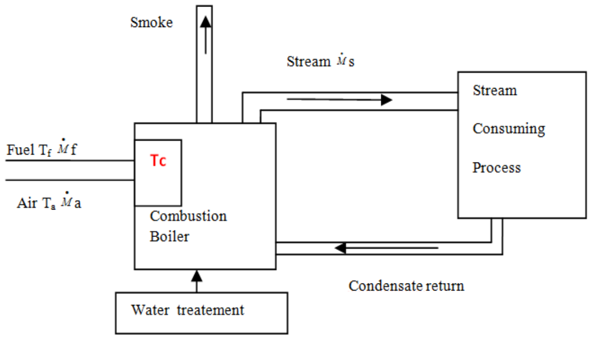

Figure 1. Industrial process

The studied boiler is a multi-tube smoke tube boiler with a capacity of 4 T/h working with fuel oil 2 as fuel (HCV: 9238, 55 Kcal/kg), with:
T_f: fuel temperature
$\dot{M}_f$: fuel flow
T_a: air temperature
$\dot{M}_a$: air flow

The steam produced is used in the manufacturing process and is measured by a flow meter where $\dot{M}_s$ is the flow rate of the steam. The temperature T_c of combustion is measured by a thermocouple.

We present in Figure 2 the temperature T (°C), steam mass flow rate $\dot{M}$ (kg/s) and efficiency R data for this measurement campaign.

2. OPTIMIZATION METHOD

As a first work, we used Neural Networks which are much more complex models than any other Machine Learning models in the sense that they represent mathematical functions with millions of coefficients (the parameters) [9, 10].

Table 1. The experimental data

$\dot{M}$	T (°C)	R	$\dot{M}$	T (°C)	R
7.28	169.67	74.91	11.82	220.22	66.59
10.72	209.56	73.42	9.12	212.73	66.83
11.73	214.13	76.09	13.47	247.14	69.76
12.64	181.23	73.14	17.42	224.57	66.69
9.49	180.26	73.85	12.30	240.20	66.00
8.32	163.24	76.74	9.32	216.73	67.16
16.19	177.74	74.84	10.30	219.85	65.34
11.92	207.94	73.94	9.86	239.13	67.55
10.78	203.95	76.97	16.41	214.82	68.95
16.35	180.76	72.91	13.35	198.03	67.41
8.45	197.02	75.43	15.10	219.54	68.87
12.34	188.38	75.71	15.40	209.55	68.89
12.79	170.76	73.80	14.16	200.36	67.45
9.97	167.12	75.59	14.72	222.26	68.30
11.47	222.89	76.08	17.14	213.99	67.57
13.89	211.63	76.44	15.04	221.47	69.13
16.12	214.93	76.66	17.21	204.59	69.30
13.41	212.12	73.28	13.15	190.30	66.88
8.52	205.87	75.50	9.85	195.50	64.83
10.54	217.97	74.65	8.73	216.75	69.12
11.64	234.61	76.33	14.80	168.71	67.56
16.38	178.80	75.00	10.85	176.30	69.67
13.79	203.58	74.07	14.61	193.17	69.54
11.25	191.99	76.37	14.20	197.12	68.72
14.02	191.10	75.53	12.98	171.04	68.84
12.88	177.29	76.67	14.81	203.15	67.03
16.95	178.24	76.09	12.76	215.56	68.79
17.30	200.91	76.44	12.80	173.78	69.39
16.17	182.30	76.29	12.76	191.36	69.87
14.72	197.87	74.48	16.95	184.08	66.56
15.05	221.75	75.39	11.72	221.79	66.53
16.57	209.63	72.43	10.26	201.42	67.61
8.46	207.36	72.57	11.25	183.29	68.90
11.09	222.36	71.70	14.46	176.09	69.70
7.87	212.51	76.77	16.47	198.18	68.46
15.88	202.93	73.50	18.07	213.68	66.39
12.59	221.75	67.63	10.79	213.46	68.19
11.21	174.17	67.26	15.77	213.56	69.35
9.86	185.12	67.04	13.66	179.83	68.49
12.85	225.65	67.08	11.31	198.08	67.83
10.47	214.80	66.53	11.72	245.65	68.53
9.32	197.95	65.85	12.32	205.27	67.67
8.48	209.51	66.65	14.46	244.42	67.86
7.32	195.37	68.72	14.86	246.98	67.78
11.92	193.40	66.89	10.49	210.46	66.12
9.13	185.30	69.15	9.85	202.91	69.45
12.24	192.74	68.90	15.66	224.19	74.78
16.83	174.63	68.16	11.52	205.45	73.88
12.71	208.57	74.01	15.69	210.98	72.66
13.69	227.85	72.02	7.54	210.19	74.96
16.54	203.54	73.96	16.81	193.31	73.60
10.23	186.75	74.62	15.69	179.02	71.32
8.98	208.26	75.15	12.38	184.22	73.30
10.45	198.27	71.51	11.25	205.47	75.71
11.29	189.08	71.47	11.28	187.8	70.60
14.63	202.71	74.09			

The application of this method by exploiting the data in figure 2 gives accurate results, but the problem resides in finding the right structure of the network, which requires a lot of time to determine hidden layers number as well as the neurons number that must be integrated in each layer, as well as the choice of activation function is quite important to obtain an accurate prediction.

To remedy this problem, an algorithm of k-Nearest Neighbors (k-NN) [11]a machine learning algorithm that belongs to the class of simple and easy to implement supervised learning algorithms that can be used to solve classification and regression problems [12]. Secondly, the RMS statistical method will be used to optimize the response (boiler efficiency) [13].

The steam flow M_f and the outlet temperature T_c were considered as independent variables (inputs). The dependent variable is chosen as the efficiency of the boiler (output) noted R.

For computation, we used Python [14] as a programming language that can be used in many contexts and can be adapted to any type of use thanks to specialized libraries. The Python language has a large number of libraries: for data analysis, scientific computing, visualization and machine learning. We also used Minitab, a data analysis and statistical software that allows predicting, visualizing and analyzing data.

In this case we have a training database made up of N "input-output" pairs. The estimate of the output associated with a new input x, the approach of the k nearest neighbors must be taken into account (in an identical way) the k training samples whose entry is closest to the new one input x [15], according to a distance to be defined. Since this algorithm is based on distance, normalization can improve its accuracy [16].

We can say for this k-NN classification, the result obtained is a membership class. Likewise, an input object can be classified according to the obtained majority result of the membership class statistics of its k nearest neighbors [17].

As shown in Figure 3, our proposed approach is to divide the input and output data into three categories: learning, validating, and testing. For the creation of a model we will use the training data. Validation data is used to verify the quality and accuracy of the training step. Test data is not used in the training phase and is only used to evaluate performance and review the modeling [18].

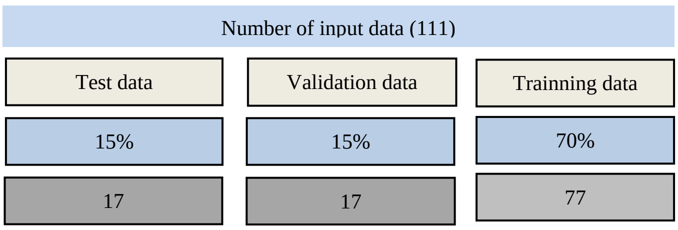

Figure 2. Data repartition

3. RESULTS OBTAINED AND INTERPRETATIONS

3.1. Results Obtained

For this part, the results that we obtained by this calculation we compared them with the real results. The total number of data used in the modelling is 111.

Among these, for training we used 70% of those intended for training, validation 15% and the rest for testing the network.

The graphical error of the calculation results is shown in Figure 2. This graphical error is the difference between the actual output and the predicted output.

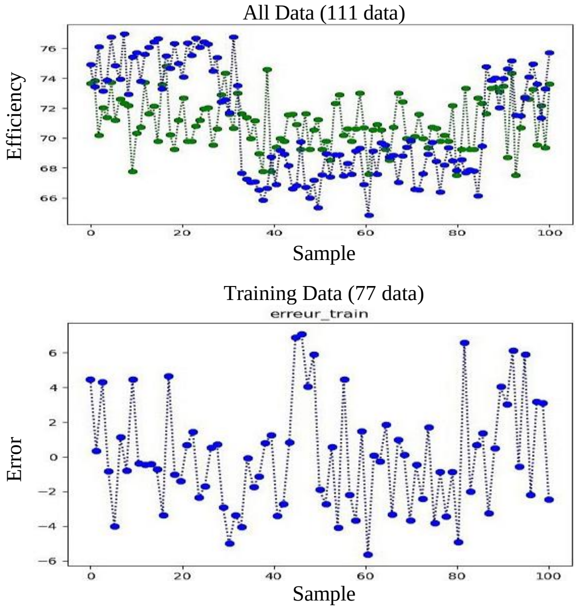

Figure 3. Comparison of experimental and modeling data for the training stage (77 data)

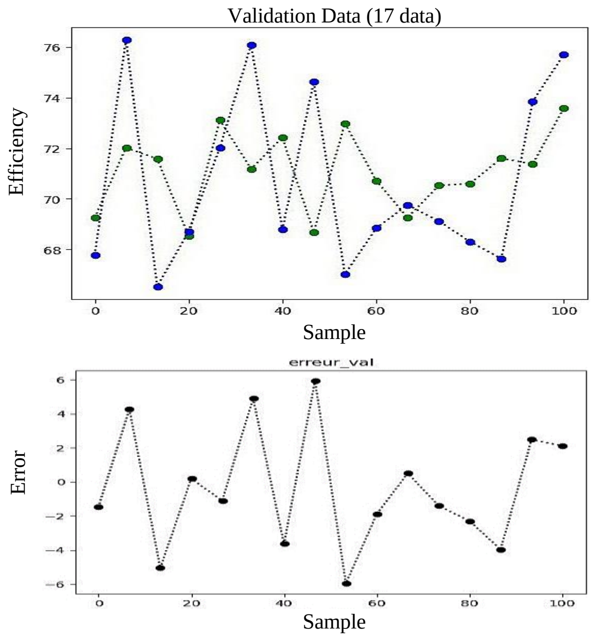

Figure 4. Experimental data and modeling comparison: validation step (17 data)

3.2. Interpretation

For the three categories of training, validation and testing the error in the modelling data is presented is in Figures 3 to 5 respectively. Based on these results, the error data for the learning, validation and test phases are obtained by 6, 5 and 6, respectively.

In training Test data is not involved. As a result, the error of test data is larger than that of validation and training.

As a conclusion, we have obtained efficient modeling results (efficiency prediction) with a low error margin. Then, using the RSM method, we will optimize the output response according to the inputs (flow and temperature) to be efficient.

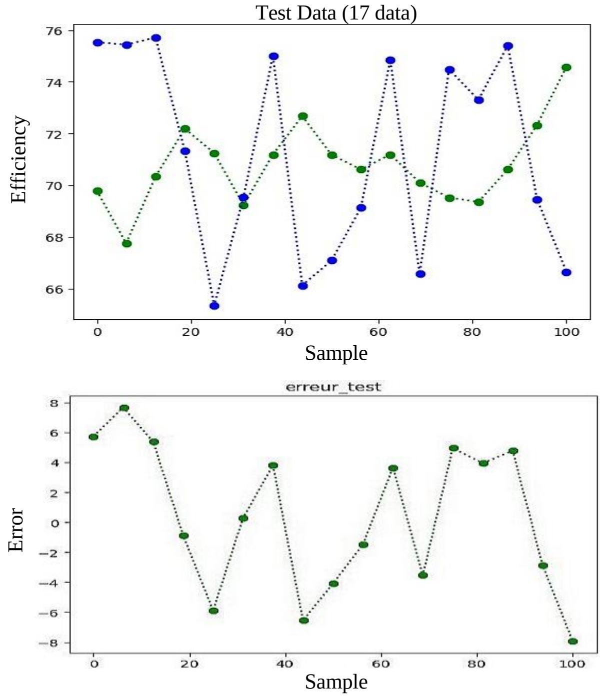

Figure 5. Comparison of experimental data and modeling: test step (17 data)

In statistics, the response surfaces method (RSM) consists in establishing the relationships between the dependent and independent variables involved in an experiment. For this method the main idea is the use of a series of experiments. Box and Wilson propose the use of a second-degree polynomial model, admitting that this model is only an approximation. This developed model has the advantage of being easy to apply and estimate, even if little information is available on the processes.

Response surface design or RSM is defined as the set of applied mathematical techniques and statistics that allow us to create empirical models. The purpose of the response surface is to optimize the response (output variable) influenced by several independent variables (input variables). In our case, the flow rate and the outlet temperature of the boiler, and the efficiency of the dependent variable, are the two independent variables discussed in our study.

This RMS method can be represented by a second degree polynomial ($\dot{M}_s$ denotes the flow rate and T the temperature):

$$R\left(\dot{M}_s\right) = k_0 + k_1\dot{M}_s + k_2 T + k_{12}\dot{M}_s T + k_{11}\dot{M}_s^2 + k_{22}T^2 \quad (2)$$

In Figure 6, the RSM optimization for equation (2) are presented.

This RMS method allows us to determine the optimal values of the constants, k_0, k_1, k_2, k_{11}, k_{22} and k_{12}, which are obtained by the RSM optimization. In this case expression 3 becomes a regression equation in uncoded units:

$$\begin{aligned} R &= 74.2 - 1.22D + 0.081T + 0.0325D \times D \\ &- 0.000349T \times T + 0.00193D \times T \end{aligned} \quad (3)$$

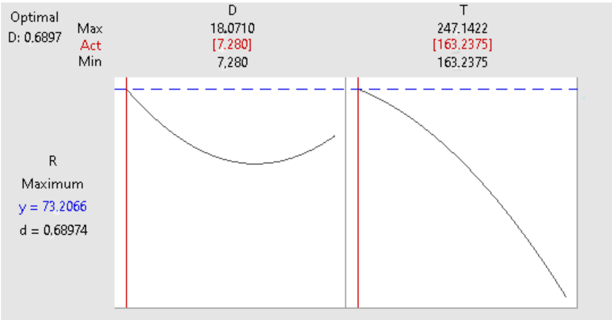

Figure 6. Response surface method (RSM) (inputs: flow and temperature)

Table 2. Optimal values of the constants calculated by the RSM method

Constant	k_0	k_1	k_2	k_{11}	k_{22}	k_{12}
Optimal value	74.2	1.22	0.081	0.0325	- 0.000349	0.00193

The response surface obtained by the RMS method and the experimental data are presented in a 3D graph in Figure 7. Note that R is the efficiency, $\dot{M}_s$ the mass flow and T the temperature.

Surface diagram of R, $\dot{M}_s$ and T

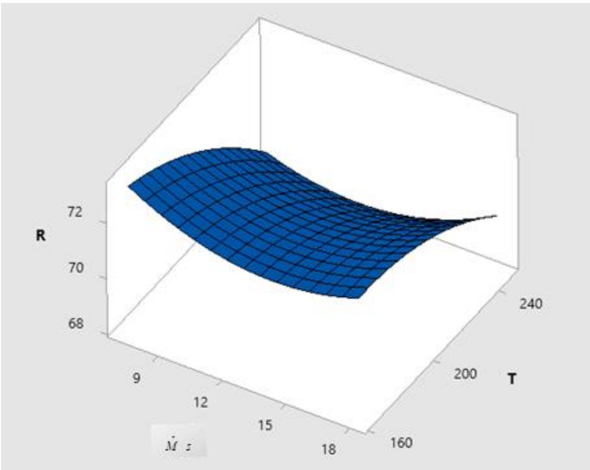

Figure 7. 3D presentation of the response surface and experimental data: Efficiency, temperature and flow rate

Table 3. The optimal efficiency of the boiler (obtained from the rsm)

Variable	Efficiency of the boiler (%)	Mass flow rate (kg/s)	Temperature (°C)
The optimum according to RSM	73.20	7.28	163.2375

We obtained the optimum flow rate is 7.28 kg/s and for the temperature is 163.23 °C.

4. CONCLUSIONS

In this study, we used, in the modeling process, a total number of data of 111, which has been divided into 15% for validation and 70% for training and the rest is reserved for testing. Modeling using the K-NN method produces a prediction error of approximately 5. The error associated with the learning step, the validation step and the test step was less than 6%, 5% and 6%, respectively. By definition, the response surface method (RSM) is a series of statistical and mathematical techniques that can be applied with the aim of building classical models. The objective of RSM is therefore the optimization of the response (output variable), which is influenced by several independent variables (inputs). Thereby, as results of our study, we obtained the optimum for the flow is 7.28 kg/s and for temperature is 163.23 °C, for an efficiency of 73.20%.

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