Case Studies in Thermal Engineering 28 (2021) 101561

Contents lists available at ScienceDirect

Case Studies in Thermal Engineering

journal homepage: www.elsevier.com/locate/csite

Classification of flame extinction based on acoustic oscillations using artificial intelligence methods

Yavuz Selim Taspinar [a,*], Murat Koklu [b], Mustafa Altin [c]

[a] Doganhisar Vocational School, Selcuk University, Konya, Turkey
[b] Department of Computer Engineering, Selcuk University, Konya, Turkey
[c] Technical Sciences Vocational School, Konya Technical University, Konya, Turkey

ARTICLE INFO

Keywords:
Fire extinguishing
Sound wave
Acoustic
Rule based classification
Low frequency sound

ABSTRACT

Fire, one of the most serious disasters threatening human life, is a chemical event that can destroy forests, buildings, and machinery within minutes. For this reason, there have been numerous methods developed to extinguish the fire. Within the scope of this study, a sound wave flame extinction system was developed in order to extinguish the flames at an early stage of the fire. The data used in the study were obtained as a result of experiments conducted with the developed system. The created dataset consists of data obtained from 17,442 experiments. It is aimed to classify the fuel type, flame size, decibel, frequency, airflow and distance features, and the extinction-non-extinction status of the flame through rule-based machine learning methods. In the study, rule-based machine learning methods, ANFIS (Adaptive-Network Based Fuzzy Inference Systems), CN2 Rule and DT (Decision Tree) were used. The methods of Box Plot, Scatter Plot and Correlation Analysis were utilized for statistical analysis of the data. As a result of the classifications, respectively, 94.5%, 99.91%, and 97.28% success were achieved with the ANFIS, CN2 Rule, and DT methods. As a result of the evaluations made by using Box Plot, Scatter Plot and Correlation Analysis.

1. Introduction

Fire is an enormous danger to nature. Forest and building fires can result in loss of life, serious injuries, and material damage to a great extent. There are only minutes between the start of the fire and that it reaches a very large scale. Therefore, detecting and extinguishing fires at an early stage has great importance [1]. Conventional fire extinction systems cannot be used at the initial stage of the fire because expertise is needed and the panic situation exist. Water, CO_2, and various gases can be used in fire extinction, depending on the type of combustible material [2,3]. It is not possible to extinguish all types of fires by using only one type of extinguisher. For this reason, studies on the discovery of alternative fire extinction have been continued [4].

Fires can be extinguished via sound wave fire extinguishers that do not harm nature and can be used repeatedly [5,6]. The basic principle of this type of extinguishers is that the flame is chocked by leaving it without oxygen, through the airflow resulting from the compression and expansion movements of sound waves in the air [7]. It was found that the flame is affected by low-frequency sounds [8,9] and the pressure created by the low-frequency sound wave causes a decrease in fuel mass via extinguishing the flame. It was also determined that the frequency range required for the flame to be extinguished with sound wave is 30 Hz–50 Hz [10]. Studies have also

* Corresponding author.
E-mail addresses: ytaspinar@selcuk.edu.tr (Y.S. Taspinar), mkoklu@selcuk.edu.tr (M. Koklu), maltin@ktun.edu.tr (M. Altin).

https://doi.org/10.1016/j.csite.2021.101561
Received 6 September 2021; Received in revised form 10 October 2021; Accepted 14 October 2021
Available online 15 October 2021
2214-157X/© 2021 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

been carried out on the extinguishing ability of sound waves within different gravitational environments. It has been observed that in a low-gravity environment, flames can be extinguished more easily with sound waves than in a normal gravity environment. Moreover, it was determined that low-frequency sound waves are more effective in flame extinction [11]. Since conventional fire extinguishers can damage devices in environments with a lot of electronic devices, the usability of sound-wave fire extinction systems in spacecraft has been simulated. In experiments, it was observed that flames in the range of 60 Hz–90 Hz could be extinguished [12]. In addition, liquid fuel droplets' and flames' status of being affected by sound waves with different frequencies were also examined in the studies [13]. It was determined that as the drip rate of the fuel droplets increases, the extinction decreases, while the fuel droplet flames are extinguished via the sound waves at early stages [14]. It was observed that the acoustic effect reduces the flame size and decreases the interaction between the fuel and the flame, besides it can extinguish the flame by chocking it with moving back and forth [15,16].

In another study, sound waves, which cause the evaporation of the fuel and the removal of oxygen from the environment by affecting the air and fuel mixture, were tested in extinguishing rubber-based fuel flames. As a result of these experiments, it was determined that the flames can be extinguished in the frequency range of 50–70 Hz [17]. In addition to that, studies have been carried out on detecting fire via image processing methods and extinction with sound waves [18]. There are also studies in which the sound wave flame extinguisher is directed according to the fire area with the data obtained from the sensors [19]. In the studies on sound wave fire extinction, generally, flames of the same size have been worked on.

In this study, different from the studies in the literature, different fuel, frequency, distance, and flame sizes in the sound wave flame extinction system were used. 17,442 experiments were conducted and the data were collected. The major contributions in this study are as follows:

(i) The distribution of the data in the dataset which is created with the data obtained from the experiments was analyzed in detail with box plot and scatter plot.
(ii) The relationships between 7 features in the dataset were analyzed. Accuracy, sensitivity, specificity, and F-1 score metrics were used for performance analysis of classification models.
(iii) Unlike current studies in the literature, 3 different liquid fuels (gasoline, thinner, kerosene), and Liquid petroleum gas (LPG) fuel were used in the flame extinction experiments.
(iv) ANFIS, CN2 Rule, and DT, from rule-based classification methods, were used in the study. As a result of the classifications, 94.5%, 99.91%, and 97.28% success were obtained with ANFIS, CN2 Rule, and DT methods, respectively.
(v) By the obtained results, the required value ranges for extinguishing the flames with the sound wave flame extinction system were determined.

Considering the contributions given above, studies can be carried out on the usability of the sound wave fire extinguishing system in large fires. As a result of the data obtained, it is revealed that it is possible to extinguish fire with sound waves. The sound wave fire extinguishing system and the experimental setup created in the study were produced exclusively for this study. This system can be made in larger sizes so that large fires can be extinguished.

The study is designed as follows: In the Materials and Methods chapter, background information on data acquisition, dataset, classification methods, box plot, scatter plot, correlation analysis, and performance analysis is given. Experimental Results chapter includes the distribution of data in the dataset, classification results and performance analysis. Lastly, in the Conclusion chapter, the discussion of the results, the limitations of the current study, and future studies are given.

2. Material and methods

In this chapter, information about the experimental setup, data acquisition and dataset will be given. Besides, the rule-based classification algorithms used in the study, the confusion matrix and performance metrics required to analyze the performances of these algorithms will be explained. With the purpose of analyzing the data in the dataset in detail, the concepts of box plot, scatter plot, and correlation analysis will be explained.

2.1. Experimental setup and data acquisition

An experimental setup was created in order to examine the quenching of flames with sound waves. A sound wave flame extinction system is placed in a fire chamber made of fire-rated A1 non-combustible material. There is a collimator with 4 subwoofers in the sound wave flame extinguisher, and the total power of the subwoofers is 1000W. The subwoofers are 250W each. There are 2 amplifiers in the system to amplify the audio signals coming from the signal generator. Each amplifier is connected to 2 subwoofers. When the system is started, it draws high current instantly. For this reason, the power of the system is provided by a specially designed power supply. The collimator is created so that the airflow created by the sound waves can be focused on a single point. The sound frequencies created by the frequency generator on a control panel come to the subwoofers after being amplified in the amplifiers.

The sound waves, created as a result of vibrations that occurred on subwoofers, are sent over the flame through the 13 cm diameter hole on the collimator. Collimator is a design that allows sound waves to propagate from source to target without scattering them. While the sound waves emanating from the subwoofers travel through the air without a collimator, the sound waves scatter and cause the airflow created in the air to decrease [17]. For this reason, the use of a collimator is inevitable in such acoustic studies. It is not only used in acoustic studies. It is not only used in acoustic studies. It enables beams [20] and airflow [21] to be directed and sent to the target without scattering.

Sound waves propagate through compression and expansion in the air. As a result of these movements, an air flow is created and the flame is extinguished with this air flow. Compression and expansion movements in the air lead the flame to choke by removing the oxygen around the flame. In Fig. 1, the fire room where the experiments were carried out and the sound wave flame extinction experimental environment is illustrated. Fig. 2 shows the sound wave flame extinguishing system specially produced for this study.

Experiments were carried out with 4 different fuel types in 5 different fuel containers. These 5 fuel containers enabled us to obtain 5 different sizes of flames. Fuel containers are made of metal material. Liquid fuels were burned by filling in the fuel container in each trial. Since the fuel in the fuel containers is depleted each time, it was refilled at each trial. The fuel containers used in the study are shown in Fig. 3.

Experiments were repeated at different sound frequencies and distances, and a total of 17,442 experiments were carried out. Decibel meter, anemometer, infrared thermometer and camera were utilized to collect data during the experiments. The brands and features of these devices are shown in Table 1.

2.2. Dataset

A dataset was created with the data obtained as a result of the experiments. This dataset has a total of 7 features, as 6 input features and 1 output feature. The description and value ranges of these features are shown in Table 2.

2.3. ANFIS (Adaptive-Network Based Fuzzy Inference Systems)

ANFIS is a hybrid machine learning method that uses the inference feature of fuzzy logic and the learning ability of ANN (Artificial Neural Network) [22]. Learning is performed by optimizing the fuzzy rule base and membership function values with ANN in classification processes which will be performed by using datasets containing input and output values. In fuzzy logic, instead of the learning ability, membership functions and fuzzy rules are utilized to create input-output pairs [23]. The ANFIS structure used in the study is shown in Fig. 4.

The ANFIS structure consists of 5 layers. Here, x and y are input nodes, and Layer 1 is fuzzification layer. The membership degrees calculated based on the output, input value and membership function of each node in this layer are calculated. Layer 2 is the rule layer. Each node in this layer shows the rules and their numbers extracted from the fuzzy logic rule inference system. Layer 3, the normalization layer, accepts all nodes from the rule layer as input value and the normalized firing level of each rule is calculated. Layer 4 is de-fuzzification layer. Each node in this layer is associated with the input values and the output values of each node of the normalization layer. The weighted result values of the rule at each node in the defuzzification layer are calculated. Layer 5 is the summation layer. The value of each node coming from Layer 4 is summed up and the actual value of the ANFIS system is calculated [24].

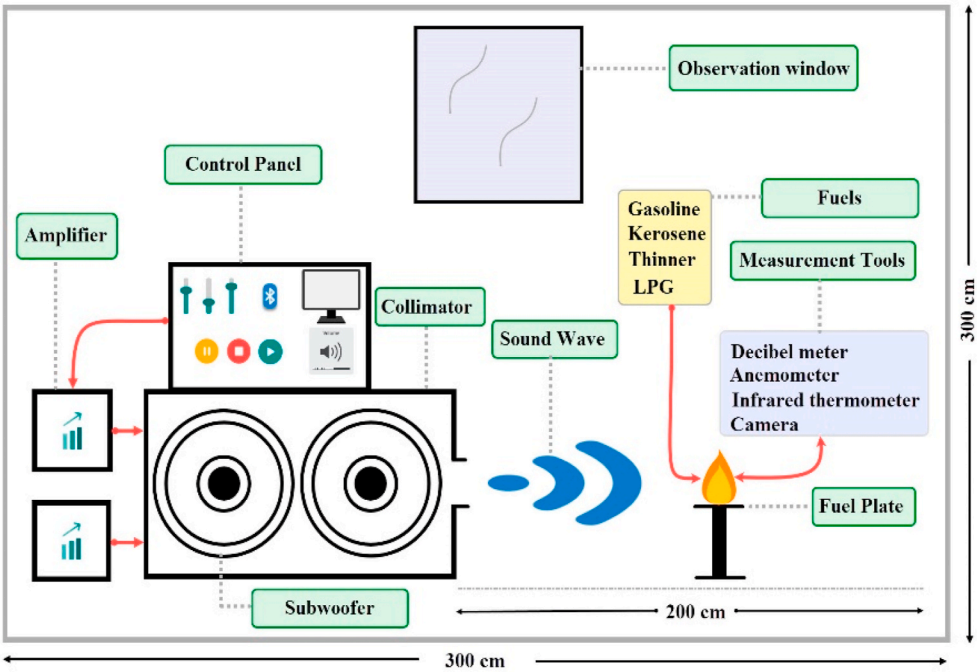

Fig. 1. Sound wave flame extinction experiment environment: Room dimensions, observation window and experimental setup.

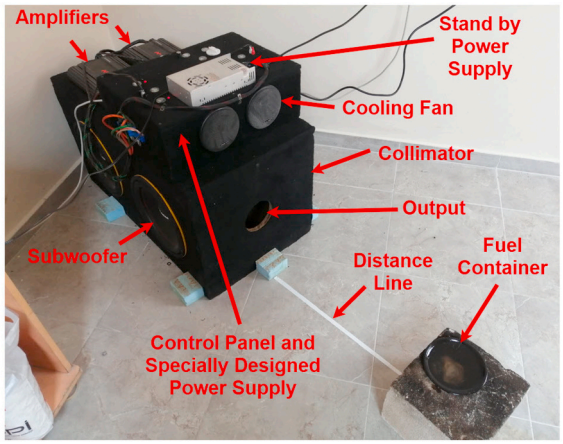

Fig. 2. Sound wave flame extinguishing system.

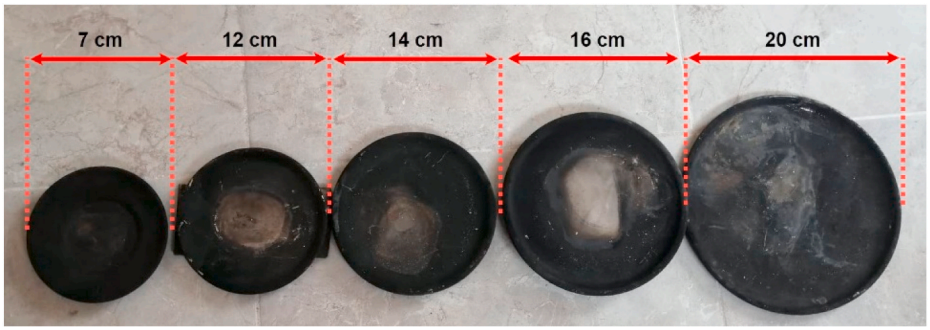

Fig. 3. Liquid fuel containers and dimensions used in the.

2.4. CN2 rule

The CN2 algorithm is a rule-based algorithm based on finding the best rule set. This algorithm, which uses the statistical difference ratio in the rule base, tries to find the best rule set by removing the rules that cannot exceed a certain threshold. While it is trained, the algorithm runs in a loop, where the best rules are found by using classification examples and then the rules covered by those rules are removed. The loop ends when the dataset is exhausted or no important rule is found. At the end of the training, a sequential rule list, free from unimportant rules, creates the structure of the model. The if-then system is used in the creation of the CN2 rule algorithm [25].

In CN2, classification processes are performed by using the created rules. While creating the rule, the desired number of checks is performed in the IF process. Equations and inequalities can be used. On the other hand, the THEN process includes the class variable. The rules created through this algorithm can be used when creating decision support systems. In the model used in the study, classification processes were carried out with a total of 736 rules.

2.5. Decision tree

They are rule-based systems widely used in classification processes [26]. The learning process is carried out by making assumptions about the target classes divided into categories. Image processing is frequently used in machine learning fields. Numerical features are distributed to the nodes according to the threshold values which are created by using the data. It follows a top-down strategy. The aim is to divide the data into small clusters by applying a set of decision rules. A decision tree consists of nodes and branches. Each node represents a feature in the category to be classified. The division of a node into sub-nodes is performed by the algorithm and the optimum number of nodes is determined to estimate the class variable. The size of the created decision tree can be determined beforehand [27].

Decision nodes and leaf nodes are determined according to the learning status of the model during the training phase of the algorithm. The depth of the tree is predetermined. This depth should be determined at the optimum level for the model to perform learning in the best way. The depth of the decision tree used in the study was determined as 5.

Table 1
Measuring devices used to obtain data from experiments with a sound wave flame extinguisher.

PRODUCT IMAGES	DEVICE	BRAND	VERSION	FEATURES
	Decibel meter	UNI-T	Ut-353BT	Measurement range: 30–130 dB Operation temperature: 0 … +40C Operation moisture: <%80 Connection: Bluetooth
	Anemometer	UNI-T	Ut-363BT	Airflow velocity measurement range: 0–30 m/s Operation temperature: 10 … +50C Operation moisture: <%80 Connection: Bluetooth
	Infrared Thermometer	Bosch	GIS 1000C	Measurement range: 40 … +1000C Resolution: 0.1C Laser class: 2.635 nm Connection: micro USB, Bluetooth Internal camera Internal relative moisture meter
	Camera	Prosilica	GT2000C	Megapixel: 2.2 Resolution: 2048x1088 Sensor type: CMOS FPS: 53.7 Operation temperature: 20 … +65C Connection: USB

Table 2
Information about the features in the dataset.

FEATURES	MIN/MAX VALUES	UNIT	DESCRIPTION
SIZE	7, 12, 14, 16, 20	cm	In order to adjust the flame size, 5 different sizes of fuel containers were used. It was recorded for ease of procedure in classification problems as follows. 7 cm=1, 12 cm=2, 14 cm=3, 16 cm=4, 20 cm=5
FUEL	Gasoline, Kerosene, Thinner, LPG		Fuel type
DISTANCE	10–190	cm	Indicates the distance of the fuel container to the collimator.
DECIBEL	72–113	dB	Indicates the decibel value in the area where the flame exist.
AIRFLOW	0–17	m/s	Indicates the airflow created by sound waves.
FREQUENCY	1–75	Hz	Indicates the frequency of the sound wave.
STATUS	0, 1		0 indicates the non-extinction state, 1 indicates the extinction state

2.6. Confusion matrix and performance evaluation

Confusion matrix, where the results of the classification model can be seen, are the tables utilized to evaluate the model by looking at the correlations between the actual and predicted values [28]. In Table 3, the confusion matrix used in the study is shown.

The TP and TN values shown in Table 3 give the correct prediction number of the classes. FP and FN values give the number of wrong predictions. On the matrix, TP (True positive) value indicates the number of correctly classified positive data, FP (False positive) value indicates the number of false classified positive data, TN (True negative) value indicates the number of correctly classified negative data and FN (False negative) value indicates the number of misclassified negative. There are performance metrics that measure the success of the model with results from the confusion matrix [29]. Accuracy, F1 score, precision, sensitivity and specificity metrics were used in the study. Table 4 gives the calculation of these metrics and their features.

2.7. Box plot

Frequently used in data analysis, Box Plot is a type of chart that shows the distribution and trend of numerical data by demonstrating data percentages (quartiles) and averages. It shows 5 different features of the dataset. The minimum value, mean, first quartile (25%), median (median), third quartile (75%) and maximum value are shown on the graph [30].

The amount of data in each quartile is equal. By using the Q1, Q2, and Q3 values, it can be understood in which intervals the data are stacked. By looking at the closeness of the median value to Q1, and Q3, it is seen in which quarters the data are stacked more [31].

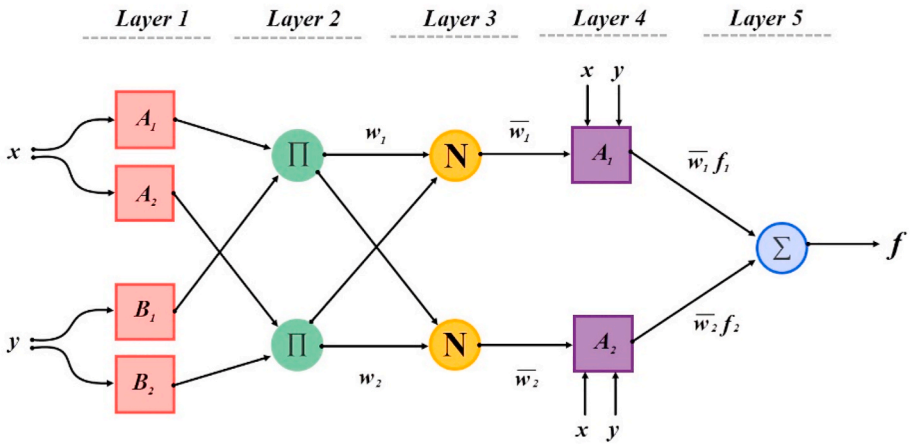

Fig. 4. ANFIS structure.

Table 3
Confusion matrix.

		Actual Class	
		0	1
Predicted Class	0	TN	FP
	1	FN	TP

Table 4
Calculation and features of performance metrics used in the study.

ABBREVIATION	*DESCRIPTION*	*FORMULA*
ACC	Accuracy: Indicates the overall classification success of the classifier.	$ACC = \frac{TP+TN}{TP+TN+FP+FN}$
FSC	F-1 Score: It is a metric that includes all error costs, not just FP and FN.	$FSC = 2*\frac{PRE*RCL}{PRE+RCL}$
PRE	Precision=Positive predictive value= It is a metric that shows the proportion of positive samples classified as true.	$PRE = \frac{TP}{TP+FP}$
SNS	Sensitivity=True positive rate: Indicates how many of the samples that should have been predicted positively were predicted positively.	$SNS = \frac{TP}{TP+FN}$
SPC	Specificity=True negative rate: Indicates how many of the samples that should have been predicted as negative were predicted as negative.	$SPC = \frac{TN}{TN+FP}$

In this study, by looking at the Q1, Q2, and Q3 values, it has been examined in which intervals the data obtained from the experiments with the sound wave flame extinguishing system show stacks. In this way, it is aimed to interpret the value ranges required to extinguish the flame.

2.8. Scatter plot

Scatter plot is a graph that makes it possible to detect and interpret the relationship between two variables. These graphs are utilized to determine the corresponding value of the other variable for each variable value and see to which variable the result is more dependent on and which variable the result is more affected by Ref. [32].

2.9. Correlation analysis

This is a method specifying the strength of the relationship between two or more variables. It takes a value between −1 and +1 to show how much the variables are affected by each other. A positive value means that there is a positive relationship between variables and a negative value means that there is a negative relationship between variables.

As the values approach 0, the correlation between the variables decreases. The correlation coefficient indicates a low correlation between ±0.01–0.29, moderate correlation between ±0.30–0.70, and a high correlation between ±0.71–0.99. A value of 0 indicates no relationship between the variables, and a value of ±1 indicates a perfect relationship [33].

3. Experimental results

3.1. Data analysis

It is necessary to obtain appropriate models to accurately determine the sound values required for extinguishing the fire flame. In order for the models to be trained properly, the datasets designed in accordance with the solution of the classification problem are needed. The data in the dataset must be accurately measured and in sufficient numbers. The distribution of class variables to be predicted is also an effective factor in terms of training a model with high success of prediction. Considering this information, there are 6 input variables and 1 output variable in the dataset created as a result of 17,442 experiments. The graphical representation of the processes performed during the study is given in Fig. 5. Accordingly, sound wave flame extinction experiments were carried out to obtain the data. The data obtained through measuring instruments during the experiments were recorded. Then, these data were analyzed. The data in the dataset is divided into two parts as 80% train and 20% test. After the models were trained, the tests were carried out with the test data. The classification performances of the models were analyzed.

Input variables are given as input to machine learning algorithms and the output variable is expected to be estimated. The distribution of input data according to the output data can be used to estimate the output. Rule-based systems work on this principle. In the study, rule-based classification was performed. However, the rule-based decision support system to be created as a result of this study should be carefully analyzed to ensure reliability. For this purpose, the box plot graph, which shows the distribution of the data and the areas of stack, was utilized. The distribution and trends of the input data according to the output data are shown in Fig. 6 with the box plots.

In Fig. 6 (a) for the non-extinction state (0), there are 4 differences between Q1 and Q2, while there are 7 differences between Q2 and Q3. Since the Q2 (median) value is closer to Q1, it can be observed that non-extinction (0) data are stacked in the 91–95 dB range. Since Q2 value is closer to Q1, for the extinction state (1), it can be stated that the extinction state (1) values are stacked in the 90–96 dB range.

In Fig. 6 (b), it is seen that the median value is equidistant from Q1 and Q3 for the non-extinction state (0). The median value for the extinction state (1) is equidistant from Q1 and Q3. For both cases, the data are equally distributed.

In Fig. 6 (c), the median value is almost equidistant from Q1 and Q3 for the non-extinction state (0). The non-extinction data are evenly distributed in the 13–60 Hz range. For the extinction state (1), the median value is closer to Q1. This indicates that the extinction (1) data are stacked in the range of 14–23 Hz.

In Fig. 6 (d), for the non-extinction state (0), median value is closer to Q3. This indicates that non-extinction data are stacked in the range of 4–5. For the extinction state (1), median value is closer to Q1. This indicates that the extinction (1) data are stacked in the range of 2–3.

In Fig. 6 (e), for the non-extinction state (0), the median value is almost equidistant from Q1 and Q3. This indicated that the non-

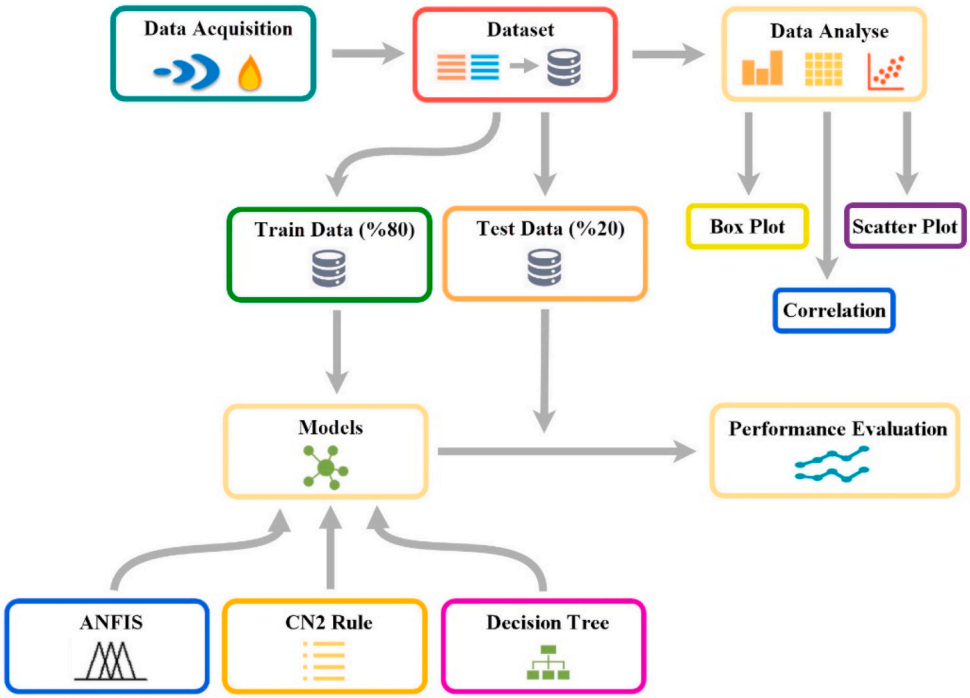

Fig. 5. Classification and analysis of the data obtained from the sound wave flame extinction system.

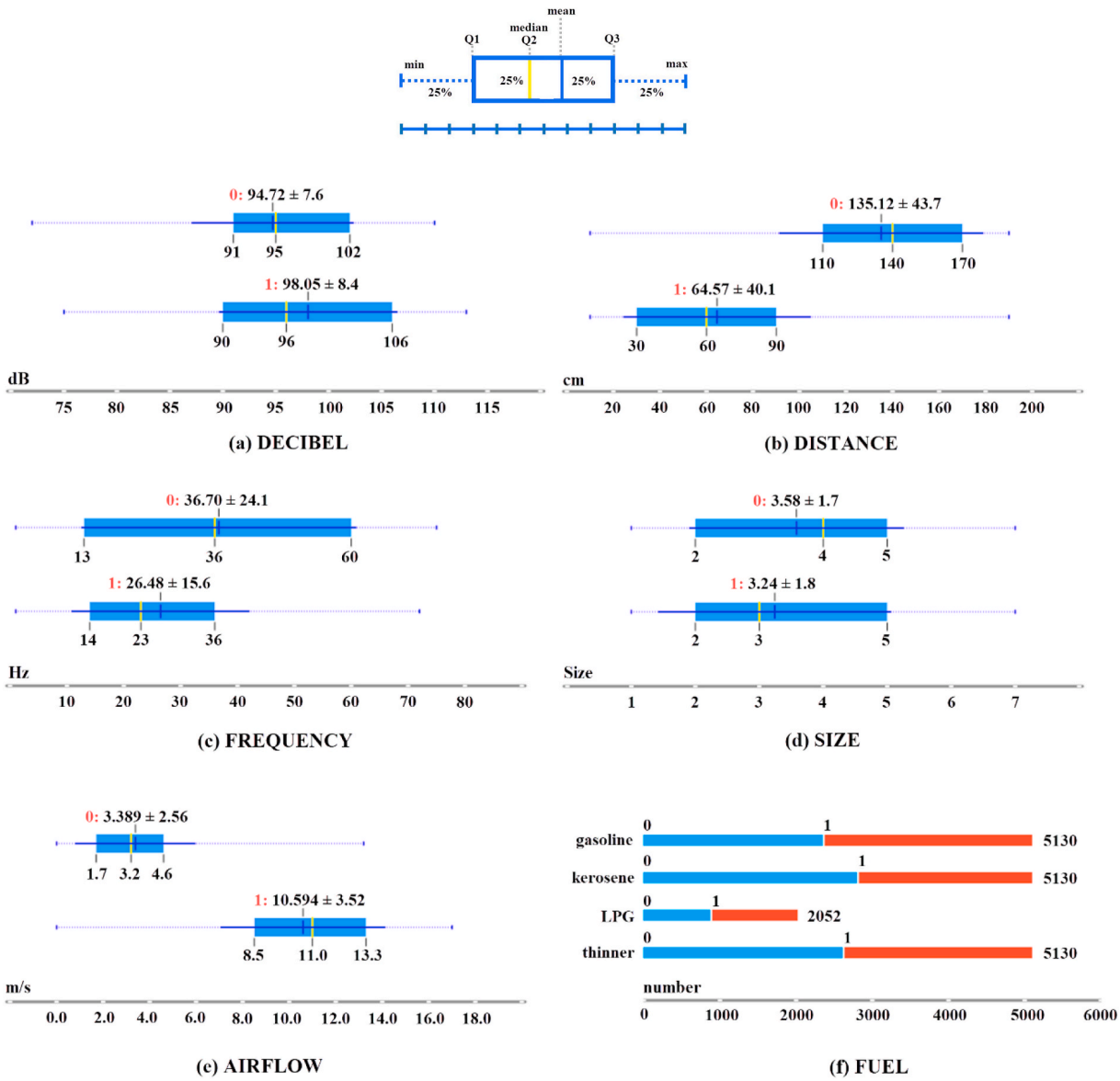

Fig. 6. Distribution of decibel (a), distance (b), frequency (c), size (d), airflow (e) and fuel (f) data according to non-extinction and extinction state.

extinction data is evenly distributed. For the extinction state (1), it is seen that the Q1 value is 8.5, the Q2 (median) value is 11 and the Q3 value is 13.3. Median value is closer to Q3. This indicated that the extinction (1) data are stacked in the range of 11–13.3.

Fig. 6 (f) gives the distribution of non-extinction state (0) and extinction state (0) data according to the fuel type. For the gasoline fuel, there are 2381 non-extinction state (0) values and 2749 extinction state (1) values. For the kerosene fuel, there are 2831 non-extinction state (0) values and 2299 extinction state (1) values. For the thinner fuel, there are 2642 non-extinction state (0) values and 2488 extinction state (1) values. For LPG fuel, there are 905 non-extinction state (0) values and 1147 extinction state (1) values.

The scatter plot graph has been utilized to analyze the extinction status of the flame in more detail according to each input value. Thanks to the scatter plot and box plot graphics, the input values required to extinguish the flame can also be observed in more detail. Fig. 7 gives the scatter plots showing the extinction status of the flame for each input value.

According to Fig. 7 (a), the decibel value decreases as the distance to the sound wave flame extinguishing system increases. In general, it has been observed that the flame can be extinguished in the value ranges of 85–98 dB and 100–110 dB.

Fig. 7 (b) demonstrates that the flame can be extinguished within the decibel ranges of 85–98 dB and 100–110 dB, within the 2.5–17 m/s airflow range. According to Fig. 7 (c), the airflow value decreases as the distance increases. It can be stated that the flame can be extinguished with high airflow at close distances and low airflow at long distances. It was observed that flames can be extinguished within the range of 2.5–17 m/s airflow value.

According to Fig. 7 (d), the range of values required to extinguish the flame at frequencies between 10 and 50 Hz is 85–113 dB.

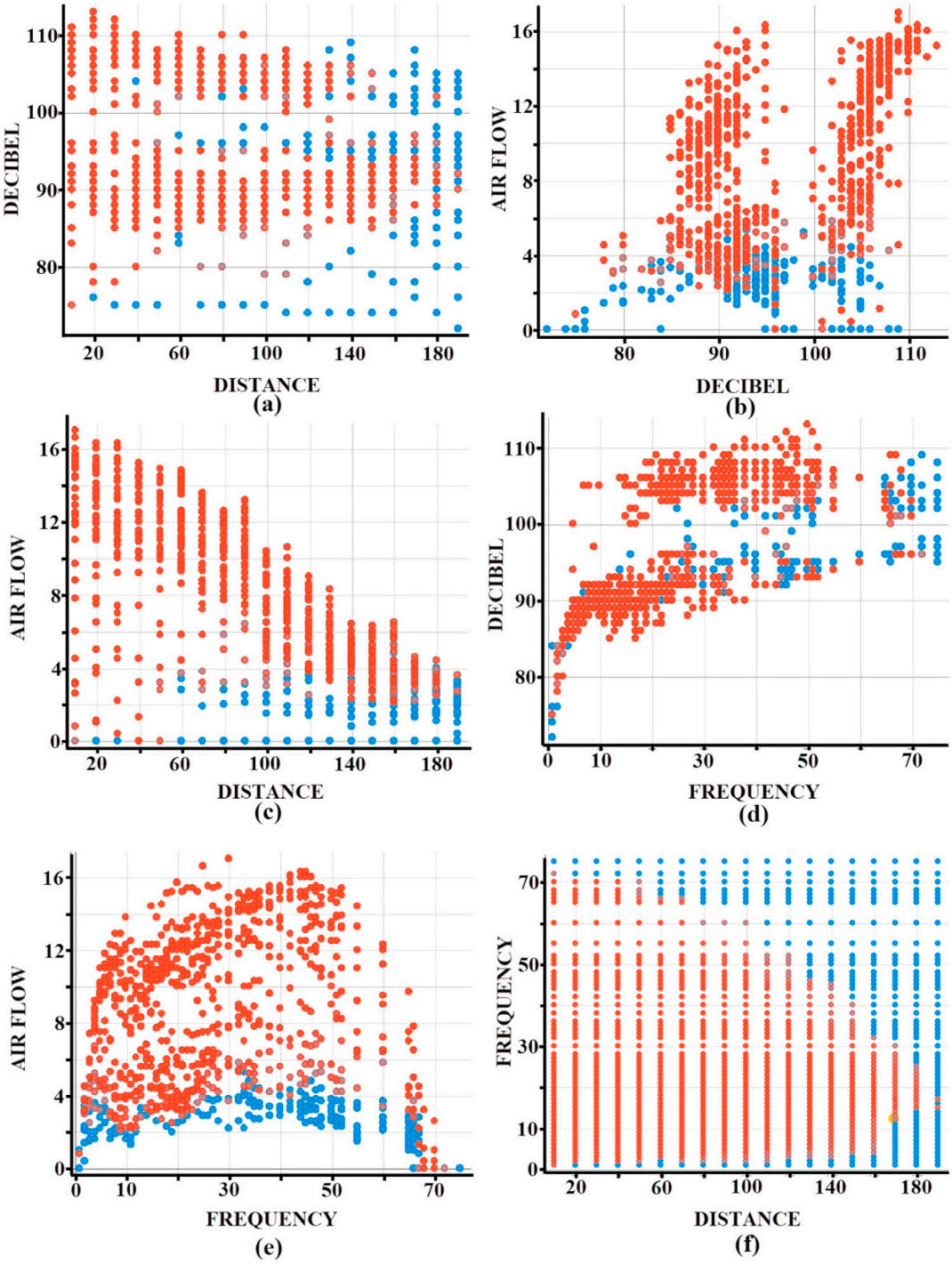

Fig. 7. Distribution graphs of extinction state according to input data (Red: Extinction State (1), Blue: Non-extinction state(0)). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Fig. 7 (e) shows the variation of the airflow created by the sound pressure according to the frequency change. The flame could be extinguished in the 2–70 Hz frequency range. However, this range is not an effective extinguishing range for every fuel type, flame size and distance. For the frequency range of 10–50 Hz, it was observed that the airflow is obtained effectively and the flames can be extinguished. When Fig. 7 (f) is examined, it is seen that flames with 10–55 Hz frequency ranges can be effectively extinguished at distances of 10–100 cm and flames with 12–30 Hz frequency ranges at distances between 100 and 170 cm for all fuel types.

By looking at the box plot in Fig. 6 and scatter plot in Fig. 7, sufficient information can be obtained about the values required to extinguish the flame. However, the correlation between the 6 different variables required to extinguish the flame is extremely important for rule extraction. In Table 5, correlation coefficients are given in order to reveal the relationship between the variables.

According to Table 5, there is a moderate positive relationship between frequency and decibel. There is a strong negative relationship between the airflow created by distance and sound pressure. Accordingly, it can be estimated that the airflow decreases as the distance increases. It is seen that all variables are effective in flame extinction.

By utilizing the graphs and correlation coefficients, the values required for extinguishing the flame can be estimated. However, it is necessary to classify the extinction and non-extinction status of the flame with machine learning methods by using the data in the created dataset and to analyze the extent to which the existing data can be predicted.

3.2. Forecasting for flame extinction

Within the scope of this study, rule-based ANFIS, CN2 rule, and DT methods were used to estimate the extinction status of the flame. Firstly, the ANFIS model was created to estimate the extinction state of the flame with the aim of creating a robust model by using the uncertainty in fuzzy theory. In order to determine the classification success of the model, the dataset is divided into two parts as 80% for training and 20% for testing. In the creation of the model, 0.001 as the learning coefficient, 100 as the epoch number, and triangular membership function (trimf) as the membership function were used.

As a result of the training of the ANFIS model using 13,993 rows of data, a total of 729 rules were created. The model created by using these rules was tested with the part of the dataset, which contains 3489 rows of data, reserved for testing. The model estimated the extinction (1) and non-extinguishing (0) status of the flame. In Table 6, the confusion matrix obtained as a result of the classification made with the ANFIS model is given.

According to Table 6, the number of correctly classified cases is 3297, and the number of incorrectly classified cases is 192. As a result of the calculations made by using the data in Table 6, FSC, PRE, SNS, SPC, and ACC metrics were calculated. The performance metrics belong to the ANFIS model are given in Table 9.

The second method used in the study is the CN2 Rule method. The CN2 model is trained with the part of the dataset reserved for training. The trained model includes 739 rules. The model was tested through test data and as a result, confusion matrix in Table 7 was obtained.

According to the confusion matrix data in Table 7, the number of correctly classified cases is 3486 while the number of incorrectly classified cases is 3. By using the data in Table 7, the FSC, PRE, SNS, SPC and ACC performance metrics of the CN2 Rule model were calculated and shown in Table 9.

The third method used in the study is DT, which is also a rule-based method. The created DT model was tested with the part of the dataset reserved for testing. In Table 8, the confusion matrix obtained from the model is given.

In Table 8, it is seen that 3394 case data are classified correctly and 95 case data are incorrectly classified. Using the data in Table 8, the FSC, PRE, SNS, SPC and ACC performance metrics of the DT model were calculated and shown in Table 9.

According to Table 9, the highest classification success was obtained from the CN2 model. FSC, PRE, SNS and SPC values were also obtained from the CN2 model in parallel with the classification success. The second highest classification success belongs to the DT model. The ANFIS model has the lowest classification success among these three classification models. In Table 10, the classification successes of the models are given in percent.

In the tests of the machine learning models used in the study, the highest classification success was obtained from the CN2 Rule model with 99.91%. The DT model has the second highest classification success with 97.28%. The lowest classification success belongs to the ANFIS model with 94.50%. ROC curves are graphs that provide information about the models' performance of classification. In Fig. 8, the ROC curves obtained from the classification models are given.

According to Fig. 8, the CN2 Rule method has the highest classification performance. The DT Model has a higher performance than the ANFIS method, while the lowest classification performance belongs to the ANFIS method.

4. Conclusions

In this study, a detailed analysis of the dataset with 6 input features and 1 output feature obtained as a result of 17,442 experiments performed with the sound wave flame extinction system was carried out. Based on the results of this analysis, the input value ranges required to extract a rule base have been determined. Fuel type, flame size, distance, decibel, frequency, and airflow values were analyzed by considering the extinction and non-extinction status of the flame, which is the output value. As a result of these analyzes, it has been found that the flames in the frequency range of 10–55 Hz can be extinguished effectively between 10 and 100 cm distance range, and the flames in the frequency range of 12–30 Hz can be extinguished effectively between 100 and 170 cm distance range. It has been determined that the required decibel ranges to extinguish the flame are 85–98 dB and 100–110 dB, and the airflow created by the sound pressure should be in the range of 2.5–17 m/s. The found values are valid for every fuel type and every flame size.

When the correlation analysis of the features was examined, it has been seen that all the features are related to each other and between the extinction and non-extinction status of the flame. By analyzing these correlations, more important features can be selected in order to extinguish the flame in the rule-base inference.

Three different rule-based machine learning models were used in order to analyze the accurate estimation of the extinction and non-extinction status of the flame with the data in the data set created by using the data obtained from the experiments. CN2 Rule Model, DT Model, and the ANFIS Model, which is created by combining Fuzzy and Neural Network methods, were used in the study. It

Table 5
Correlations between the variables required to extinguish the flame.

FEATURES	DECIBEL	DISTANCE	FREQUENCY	SIZE	AIRFLOW	STATUS
DECIBEL	1	−0.239	0.562	−0	0.377	−0.204
DISTANCE	−0.239	1	0	0	−0.707	0.644
FREQUENCY	0.562	0	1	−0	−0.212	0.244
SIZE	−0	0	−0	1	0	0.097
AIRFLOW	0.377	−0.707	−0.212	0	1	−0.761
STATUS	−0.204	0.644	0.244	0.097	−0.761	1

Table 6
Confusion matrix of ANFIS model.

		TRUE CLASS	
		0	1
PREDICTED CLASS	0	1694 (48.5%)	93 (0.02%)
	1	99 (0.03%)	1603 (45.9%)

Table 7
Confusion matrix of CN2 Rule model.

		TRUE CLASS	
		0	1
PREDICTED CLASS	0	1711 (49%)	3 (0.08%)
	1	0 (0%)	1775 (50.8%)

Table 8
Confusion matrix of DT model.

		TRUE CLASS	
		0	1
PREDICTED CLASS	0	1682 (48.2%)	32 (0.92%)
	1	63 (1.8%)	1712 (49%)

Table 9
Performance metrics of all machine learning models.

	ACC	FSC	PRE	SNS	SPC
ANFIS	0.9450	0.9464	0.9480	0.9448	0.9452
CN2 Rule	**0.9991**	**0.9991**	**0.9982**	**1**	**0.9983**
DT	0.9728	0.9725	0.9813	0.9639	0.9817

Table 10
Models accuracy (%).

	CN2 Rule	DT	ANFIS
Accuracy	99.91	97.28	94.50

was especially preferred that all 3 models are rule-based. The dataset was divided into two parts as 80% training set and 20% test set for use in training and testing the models. The training set contains 13,994 rows of data and the test set contains 3488 rows of data. The success of the models obtained as a result of the training was measured through ACC, FSC, PRE, SNS, and SPC performance metrics by using confusion matrix data. The CN2 Rule has the highest classification success with 99.91%, while it is followed by the DT Model with 97.28% and the ANFIS Model with 94.50%. The number of cases that the CN2 Rule model misclassifies is only 3. Considering the number of data in the dataset, it is clear that the success of all 3 models is quite high. It has been observed that the extinction and non-extinction status of the flame can be predicted with a rule-base to be created according to the data obtained from the models.

As a result of the performed analyzes and classifications, a rule base detection was made to be used in the sound wave flame system. Based on the obtained data, a decision support system was developed by using the rule base. In future studies, the sound wave flame

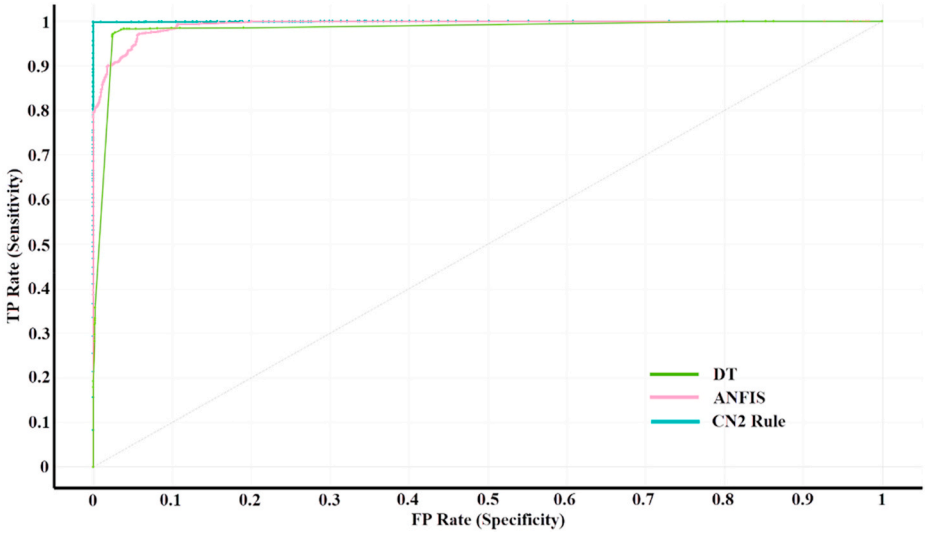

Fig. 8. ROC curves of rule-based classification models.

extinction system will work automatically with the expert system to be created by detecting the flame at an early stage through the image processing methods.

The sound wave fire extinguishing system, which has been designed and tested, can be developed to extinguish larger fires. In this way, it is foreseen that forest fires, house fires, workplace fires can be extinguished. The types of fires that can be extinguished by materials such as water, gas and foam used to extinguish the fire differ. For example, water is insufficient to extinguish the liquid fuels used in this study. Because water is lighter than fossil fuels and loses its ability to suffocate by collapsing during extinguishing. In addition, values such as water data center can cause more damage to the environment during the extinguishing of fires that occur in places where electronic equipment is located. It is thought that with the sound wave fire extinguishing system, it will be possible to extinguish the fire without damaging the electronic devices by interfering with the fire in the early stages of the fire. In addition, the sound wave fire extinguishing system can also provide the opportunity to intervene in the fire without harming people and nature in any way.

CRediT authorship contribution statement

Yavuz Selim Taspinar: Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Murat Koklu:** Conceptualization, Data curation, Formal analysis, Supervision, Writing – original draft, Writing – review & editing. **Mustafa Altin:** Investigation, Methodology, Project administration, Resources, Software, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This project was supported by the Scientific Research Coordinator of Selcuk University with the project number 20111008. This study is Yavuz Selim TASPINAR's doctoral thesis.

References

[1] A.B. Morgan, J.W. Gilman, An overview of flame retardancy of polymeric materials: application, technology, and future directions, Fire Mater. 37 (4) (2013) 259–279.
[2] M. Rohilla, et al., Condensed Aerosol Based Fire Extinguishing System Covering Versatile Applications: A Review, Fire Technology, 2021, pp. 1–25.
[3] Q. Wang, et al., Fire extinguishing performance and mechanism for several typical dry water extinguishing agents, RSC Adv. 11 (17) (2021) 9827–9836.
[4] R. Kaushik, et al., Optimization of halon 1301 discharge through fire extinguisher cylinder for IFSS, in: Advances in Electromechanical Technologies, Springer, 2021, pp. 809–820.
[5] P. Niegodajew, et al., Application of acoustic oscillations in flame extinction in a presence of obstacle, in: Journal of Physics: Conference Series, IOP Publishing, 2018.
[6] M.R. Angeles, et al., Development of variable acoustic soundwave for fire prevention, in: Computational Science and Technology, Springer, 2020, pp. 331–339.
[7] V. Sharifi, A. Kempf, C. Beck, Large-eddy simulation of acoustic flame response to high-frequency transverse excitations, AIAA J. 57 (1) (2019) 327–340.

[8] F. Baillot, F. Lespinasse, Response of a laminar premixed V-flame to a high-frequency transverse acoustic field, Combust. Flame 161 (5) (2014) 1247–1267.
[9] C. Xiong, et al., Acoustical extinction of flame on moving firebrand for the fire protection in wildland–urban interface, Fire Technol. 57 (3) (2021) 1365–1380.
[10] A.N. Friedman, S.I. Stoliarov, Acoustic extinction of laminar line-flames, Fire Saf. J. 93 (2017) 102–113.
[11] E. Beisner, et al., Acoustic flame suppression mechanics in a microgravity environment, Microgravity Sci. Technol. 27 (3) (2015) 141–144.
[12] R. Zong, et al., Analysis of flame extinguishment and height in low frequency acoustically excited methane jet diffusion flame, Microgravity Sci. Technol. 30 (3) (2018) 237–242.
[13] J. O'Connor, V. Acharya, T. Lieuwen, Transverse combustion instabilities: acoustic, fluid mechanic, and flame processes, Prog. Energy Combust. Sci. 49 (2015) 1–39.
[14] C. Xiong, et al., Extinguishing the dripping flame by acoustic wave, Fire Saf. J. 120 (2021), 103109.
[15] S.-S. Hou, D.-H. Chung, T.-H. Lin, Experimental and numerical investigation of jet flow and flames with acoustic modulation, Int. J. Heat Mass Tran. 83 (2015) 562–574.
[16] L. Hu, et al., Flame height and lift-off of turbulent buoyant jet diffusion flames in a reduced pressure atmosphere, Fuel 109 (2013) 234–240.
[17] S. Jain, A. Ranjan, M. Fatima, Performance evaluation of sonic fire fighting system, in: 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), IEEE, 2021.
[18] S. Ivanov, et al., The using of Deep Neural Networks and acoustic waves modulated by triangular waveform for extinguishing fires, in: New Approaches for Multidimensional Signal Processing: Proceedings of International Workshop, NAMSP, 2020, p. 2021. Springer.
[19] Chaki, S., D. Nandi, and J. Das. Fire extinguishing robot using arduino and DTMF controller. in *Advances In Smart Communication Technology And Information Processing: OPTRONIX 2020*. 2021. Springer.
[20] S. An, et al., Full-field X-ray fluorescence imaging with a straight polycapillary X-ray collimator, J. Instrum. 15 (12) (2020), P12033.
[21] N. Shetye, et al., Sonic wave fire fighter robot using master slave concept, VIVA-Tech Int. J. Res.Innovat. 1 (4) (2021) 1–6.
[22] G. Iannace, A. Trematerra, G. Ciaburro, Case study: automated recognition of wind farm sound using artificial neural networks, Noise Control Eng. J. 68 (2) (2020) 157–167.
[23] I.A. Ozkan, A novel basketball result prediction model using a concurrent neuro-fuzzy system, Appl. Artif. Intell. 34 (13) (2020) 1038–1054.
[24] D.J. Armaghani, P.G. Asteris, A comparative study of ANN and ANFIS models for the prediction of cement-based mortar materials compressive strength, Neural Comput. Appl. 33 (9) (2021) 4501–4532.
[25] M. Zahid, et al., Adopting machine learning and spatial analysis techniques for driver risk assessment: insights from a case study, Int. J. Environ. Res. Publ. Health 17 (14) (2020) 5193.
[26] G. Iannace, G. Ciaburro, A. Trematerra, Wind turbine noise prediction using random forest regression, Machines 7 (4) (2019) 69.
[27] M. Koklu, I.A. Ozkan, Multiclass classification of dry beans using computer vision and machine learning techniques, Comput. Electron. Agric. 174 (2020), 105507.
[28] I. Cinar, M. Koklu, Classification of rice varieties using artificial intelligence methods, Int. J. Intel. Syst. Appl. Eng. 7 (3) (2019) 188–194.
[29] A. Yasar, I. Saritas, H. Korkmaz, Computer-aided diagnosis system for detection of stomach cancer with image processing techniques, J. Med. Syst. 43 (4) (2019) 1–11.
[30] J.A. Ndako, et al., Evaluation of diagnostic assay of patients with enteric fever by the box-plot distribution method, New Microb. New Infect. 38 (2020), 100795.
[31] P.D. Asanka, A.S. Perera, Defining fuzzy membership function using box plot, Int. J. Res. Comput. Appl. Robot. 5 (11) (2017) 1–10.
[32] J. Jo, Y.O. Lee, J. Hwang, Multi-layer nested scatter plot a data wrangling method for correlated multi-channel time series signals, in: 2018 First International Conference on Artificial Intelligence for Industries (AI4I), IEEE, 2018.
[33] W.S. Du, Correlation and correlation coefficient of generalized orthopair fuzzy sets, Int. J. Intell. Syst. 34 (4) (2019) 564–583.