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ARTIFICIAL NEURAL NETWORK BASED FAULT DETECTION AND CLASSIFICATION METHOD FOR AIR CONDITIONERS

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Abstract

Air Conditioners (AC)s are devices that balance the air exchange and humidity rate as well as provide heating/cooling functions in order to keep the temperature of the environment within the desired conditions and needs. In this study, a new fault detection and classification method for AC is proposed. The method is based on the fact that power consumptions of appliances imply significant information about the appliances' health. Hence, according to the proposed method, power profiles of considered AC are created during its operations. Artificial Neural Network (ANN) configuration of AC is specifically designed and trained by created power profiles. Trained ANN is used to detect and classify faults in the present power profile before major malfunctions occur. Taking action against detected faults helps prevent increased power consumption and serious security issues. Performance and efficiency of the Method designed for classification and detection of errors is between 95.1% - 97.01%.

Keywords

Air Conditioner,
Fault detection,
Fault classification,
Power profile,
Artificial Neural Network

Time Scale of Article

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1. INTRODUCTION

In recent years, devices have started to gain the ability to update status information by communicating with people owing to the development of the Internet of Things (IoT) technology. Hence, people gain opportunity to observe and control appliances from anywhere, anytime.

IoT concept improved many technologies that facilitate human life and provide significant improvements in appliance features. Companies offer their products to the markets with these features [1-2-3-4-5]. One of the emerging technologies in this context is early fault detection in appliances.

During utilization of appliances, aging effect or user errors may result in some malfunctions that decrease durability, increase power consumption, and also create serious safety problems, such as electric shock, fire, etc. [5,6]. Consequently, early detection of faults in appliances avoids these undesired situations. Therefore, studies on fault detection of appliances have increased considerably in recent years: At [7], the vibration data of an asynchronous motor of oven extractor hood is analyzed and fault estimation is made. Some of fault detection studies are generally based on monitoring the operation of appliances with multiple sensors: For example, in [8], a model is proposed to identify and predict faults in boilers of heating and ventilation systems. In the proposed approach, each boiler has sensors to observe

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temperature, number of starts and heating requests and the duration of each cycle. Boiler faults are tried to be predicted by training sensor data with a machine learning method. In [9], fault detection by sound sensor data is studied for air conditioner, while the authors of [6] considered a washing machine. In that work, fault classification is performed by training the data obtained from accelerometer, force, gas, sound, and temperature sensors with an attribute learning model. A fault prediction system based on IoT is proposed for some mechanical equipment groups in [10]. Table 1 summarizes remarkable fault detection studies in the literature by means of their methods, considered appliances and sensor types.

Table 1. Synthesis of Remarkable Appliance Fault Detection Studies in the Literature

Study	Method Used	Application Area	Sensors
(Prist et al. 2020)	Machine learning	Commercial kitchen	Vibration
(Fernandes et al. 2020)	Machine learning	HVAC systems	Temperature
(Yang et al, 2019)	Principal component analysis	Air-conditioner	Sound
(Gupta et al. 2021)	Semantic information	Washing machine	Accelerometer, force, gas, sound, temperature
(Hosseini et al. 2020)	Time deviation	Refrigerator	Power meter

Although above mentioned studies have contributed to the literature significantly, they have some limitations, such as, the necessity of multiple sensors and mounting these sensors on the products properly.

An alternative study to these multi-sensor-based works is given in [11]. In that work, continuously monitored power consumption of a refrigerator -instead of multi-sensors data- is considered for detecting faults. However, the proposed method is based on durations of on-off cycles of refrigerator operation and is not applicable to all appliances.

In this study, a new fault prediction method for Air Conditioner (AC) is proposed. Outdoor temperature, indoor temperature and the user's setting for indoor temperature are important factors in the operation of an air conditioner. Both outdoor and indoor temperature values and user’s setting determine the cooling or heating operation modes. Any fault in any component affects the power consumption of that component during its operation. The proposed method consists of measuring AC power consumption, which provides important information about the health of the component. The method uses ANN since it provides accurate, reliable, and fast solutions. In the proposed method, power consumption measurements are held for a number of ACs during their operations and the corresponding power profiles are created. Specifically designed ANN, namely AC-ANN, is trained by created power profiles and the temperature values (outdoor temperature, indoor temperature, and the user's setting for indoor temperature). AC-ANN is used to detect the anomalies in the power profiles of the AC for detecting faults and fault classes. Feedforward ANN configuration with a single hidden layer trained by Bayesian regularization-based backpropagation is used for AC-ANN. Input layer of AC-ANN has equal number of nodes consisting of features extracted from power profiles, while the output layer presents the fault-free situation and defined faulty situation(s). Hidden layer is designed experimentally due to the training performance of AC-ANN. The efficiency and performance of the method is validated by simulations, where the ability to detect the presence of considered situations is found to be in 95.1%–97.01%. Unlike other studies in the literature, the proposed method not only detects whether there is a fault or not in a home appliance (such as an air-conditioner), but also enables the cause of the fault to be found in detail.

1.1 Air Conditioner

Air Conditioners (AC)s are devices that balance the air exchange and humidity rate as well as provide heating/cooling functions in order to keep the temperature of the environment within the desired conditions and needs.

AC is composed of the indoor and outdoor units. Outdoor unit is composed of passive components such as condenser and expansion valve that provide heat conversion, and active components such as a compressor and outdoor unit fan. Indoor unit, on the other hand, consists of a passive component such as an evaporator, which provides heat conversion, and an active component, i.e., blower fan. During the operation of AC, active components are activated in certain sequences and consume electricity. Passive components do not consume electricity directly, but any anomaly in the passive components will affect the electricity consumption of the active components. Active components have different electricity consumption rates and operating times. For example, the compressor is the highest power consuming component, while the blower fan is the least power consuming component. AC operations are affected by the temperature of the indoor and outdoor environments. For example, if the outdoor environment is very hot, the indoor environment is cooled in a longer time, otherwise the indoor environment can be cooled in a shorter time. Therefore, the operating time of the components and the corresponding electricity consumption of AC vary according to indoor and outdoor temperatures. For example, power consumption graphs of an AC's cooling operation under similar conditions for different temperature settings (T_1set and T_2set) such that $T_1set < T_2set$ are represented in Figure 1. During cooling operation, decreasing room temperature to a lower degree ($T_1set < T_2set$) should consume more electricity because the duration for activating compressor + outer fan + blower fan is longer.

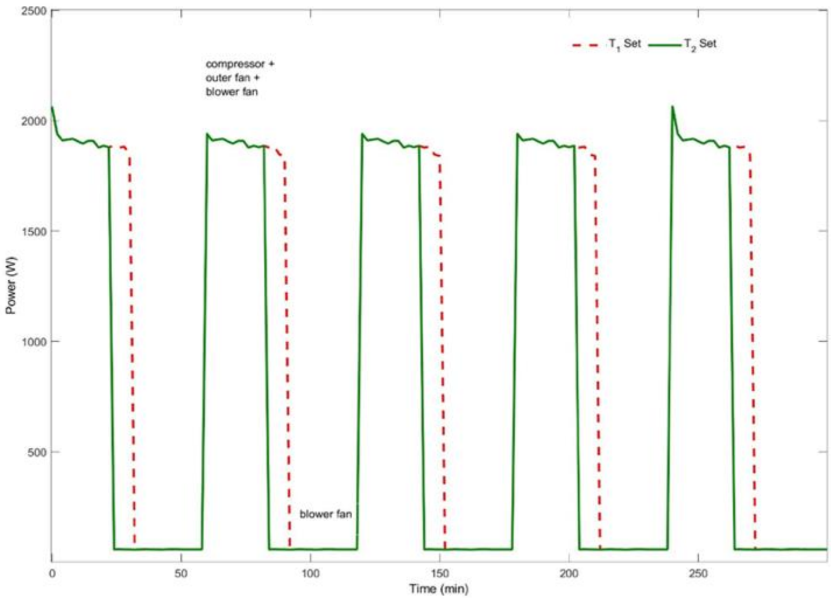

Figure 1. Power consumption of AC for different temperature set values

2. ARTIFICIAL NEURAL NETWORK

An Artificial Neuron Network (ANN) is developed with inspiration from biological nervous system.

An ANN model consists of layers such as, an input layer which receives outer data, an output layer which produces the definitive result, and a number of hidden layer(s) between them. Layers are made up of a number of interconnected nodes, namely neurons [12]. Each neuron has weighted inputs, a transfer function, and an output. The number of hidden layers and neurons in the layers depends on the problem studied [13]. Each neuron of a layer connects only to the neurons of the previous and next layers.

The feedforward architecture, which is one of the most commonly used architectures among ANN architectures, is the type of architecture that does not have a direct connection from the output neurons to the input neurons and therefore does not keep track of the previous output data. In Figure 2, a typical feed-forward ANN consisting of the input layer with n input nodes, the hidden layer with m hidden nodes and the output layer with k output nodes.

Back Propagation Algorithm (BPA) is the most commonly used training algorithm through many different learning rules for feed-forward multilayered ANNs.

According to BPA, information from input neurons is transmitted by ANN to optimize weights between neurons. Optimization of the weights is made by propagating the error backwards during the training phase. The input and output values in the training data set are read by the ANN so that the weight values of the connections are adjusted to reduce the difference between the predicted values and target values. By ANN, the error in the predicted output value is minimized with many training cycles (epochs) until it reaches a certain level of accuracy.

In the BPA procedure, a random number with a value less than 1.0 is initially assigned to the weight of each connection. Then, inputs received by input layer propagate in forward direction through the hidden and output layers for producing their outputs. With each training data, error related to the output response is calculated and a backpropagation algorithm is used for updating weights and biases of the ANN. The details about the update procedure are summarized as follows:

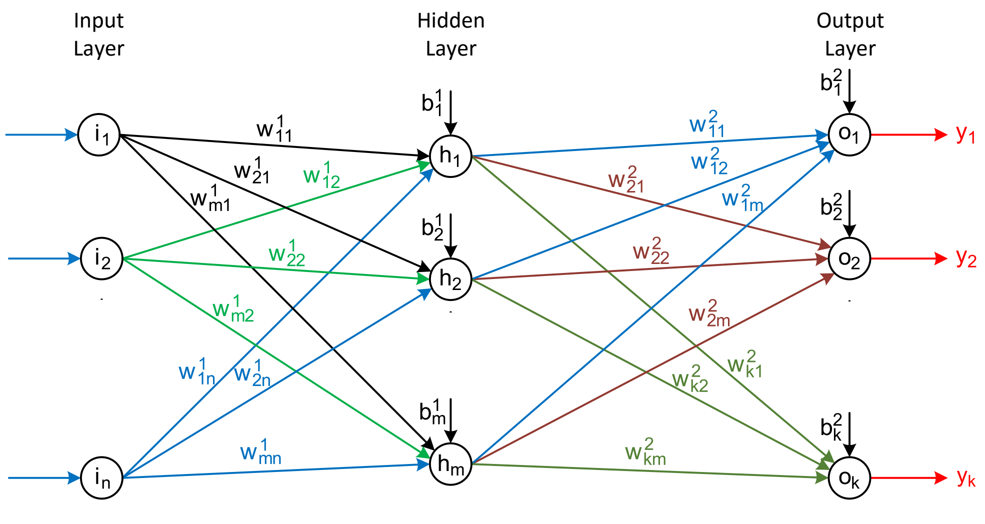

Figure 2. General View of ANN

Each neuron in hidden layer(s) and output layer forms its activation quantity as the sum of weighted average of inputs and corresponding bias which is added to shift the sum relative to origin. Thus, the activation quantity of ith neuron of mth layer is calculated as follows [14]:

$$z_i^m = \sum_{j=1}^{p_{m-1}} w_{ij}^m x_j^{m-1} + b_i^m \tag{1}$$

where, p_{m-1} stands for the number of neurons in $(m-1)$th layer; w_{ij}^m represents the weight of the connection which is between the jth neuron of the $(m-1)$th layer and the ith neuron of the mth layer;

x_j^{m-1} represents the input from jth neuron of the $(m-1)$th layer to the mth layer while b_i^m is the bias of the ith neuron in the mth layer.

Then, in order to obtain the neuron's own scalar output, the activation quantity of each neuron passes through a nonlinear activation function (i.e., step, sign, sigmoid, linear functions and etc.) which express the relationship between the input data and output data. For sigmoid activation function, the output of the ith neuron in the mth layer is calculated as follows [14,15]:

$$y_i^m = f(z_i^m) = \frac{1}{1+e^{-z_i^m}} \tag{2}$$

Here, y_i^m represents the mth output neurons in the ith layer. Error related to the output response is calculated as the sum of the squared error [14,15].

$$\epsilon(t) = \frac{1}{2}\sum_{i=1}^{n_o}(yd_i(t) - y_i(t))^2 \tag{3}$$

where n_o is the number of output layer neurons (for example, n_o is k for the output layer in Figure 2) yd_i is the desired output of the ith output neuron and y_i is the actual output of the ith output neurons. Obtained error is backpropagated to the preceding layers for minimizing the error via adjusting weights and biases of the ANN as follows [14,15]:

$$\Delta w_{ij}^m(t) = \eta_w \delta_i^m(t) x_j^{m-1}(t) \tag{4}$$

$$\Delta b_i^m(t) = \eta_b \delta_i^m(t) \tag{5}$$

where $\delta_i^m(t) = g'(z_i^m(t))(\sum_{j=1}^{n_m}\delta_j^{m+1}(t)w_{ij}^{m+1}\ (t-1))$ in the hidden layer and $\delta_i^m(t) = (yd_i(t) - y_i(t))$ in the output layer. Here, $g'(z_i) = \partial g(z_i)/z_i$ and $g(z_i)$ represents the activation of neuron i. The constants η_w(0< η_w<1) and η_b(0< η_b<1) express the learning rates for the weights and biases. After calculating the adjustment factors of the weights and biases, each weight and bias is updated [14,15].

$$w_{ij}^m(t) = w_{ij}^m(t-1) + \Delta w_{ij}^m(t) \tag{6}$$

$$b_i^m(t) = b_i^m(t-1) + \Delta b_i^m(t) \tag{7}$$

The process described above is repeated for each training data, updating the input forwards and the output error backwards until a predefined termination condition is met. In order to eliminate underfitting and overfitting problems and to improve the success of the standard BPA applications many regulation methods such as Levenberg-Marquardt, Quasi-Newton, Scaled Conjugate Gradient, Gradient Descent, Resilient Backpropagation, Bayesian Regularization [16] have been developed over the past few years.

In this work, the training data set consists of data to be collected during the durability test that the manufacturer performs at the end of the production process. Therefore, limited number of data is available. Hence, Bayesian Regularization which is more useful [16,17] than other regulation methods in solving problems with scarce of data, is used in this work. Also, adding a penalty term consisting of the squares of all mesh weights and adjusting the objective function accordingly makes the network more responsive [17].

$$\epsilon(t) = \alpha\sum_{\mathrm{i=1}}^{n_o}(yd_i(t) - y_i(t))^2 + \beta\sum_{i,j}^{n_o,p_o}(w_{ij})^2 \tag{8}$$

Here, α and β are regularization parameters and their taking the most appropriate value allows the model to be generalized. The complexity of the ANN model is governed by regularization parameters

α and β, which need to be estimated from the data [17]. Where, p_o is the number of nodes of jth layer connected to the weights w_{ij} based on ith layer.

ANNs are trained by training algorithms (which is BPA in this work) using training data set until predefined terminating error condition is met. Then the performance and accuracy of the trained ANN is estimated by testing data set.

3. FAULT DETECTION AND CLASSIFICATION METHOD FOR ACs

In this study, a fault prediction and classification method for AC by using the developed ANN, i.e., AC-ANN, is proposed.

The proposed method takes into account the fact that any fault occurring in the components of an air conditioner has an impact on the power consumption of this component during its operation. For example, in case of a fault in high power consuming components, the maximum power consumption in the power profile is affected when this faulty component starts operating. Additionally, failure of any component affects the average of the overall power profile. Hence, power profiles are decisive for detecting probable faults at any component. In devices such as air conditioners, components do not work continuously; thus, they work on and off for certain periods of time according to the operating program of the device. Frequency decomposition of power profiles is also decisive for detecting the faults that may occur in device components. Because activation of faulty components reveals unexpected amplitudes at some frequency points. In this work, the frequency decomposition of power profiles has been carried out with Fast-Fourier-Transform (FFT), which is an efficient method to compute the Discrete-Fourier-Transform.

In this work, power consumption values of ACs are monitored during their operations. During the operation of AC, connected smart plug to the appliance continuously sends measurement results of instantaneous power consumption to Main Controller (MC) which creates the corresponding power profile P^{AC}. Power profile is a chronologically ordered array of power consumption values, sampled every 1 min. In order to discard unnecessary information and reduce the size of the network, not directly the power profile but some features extracted from P^{AC} and FFT of P^{AC}, i.e., P_{FFT}^{AC}, are interpreted by appliance specific designed ANNs to predict the faults. Developed AC-ANN configuration for detection and classification of AC faults is given in Figure 3.

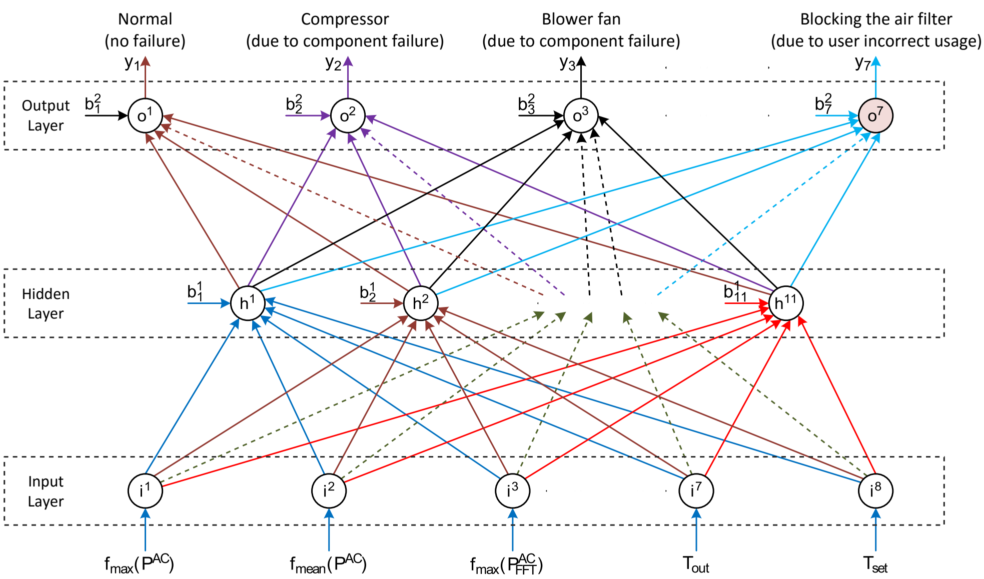

Figure 3. AC-ANN configuration

Input layer of AC-ANN has eight nodes which welcome the considered features of power profiles as inputs. The features are as follows: maximum amplitude in P^{AC}, i.e., $f_{max}(P^{AC})$, mean amplitude of in P^{AC}, i.e., $f_{mean}(P^{AC})$, maximum amplitude in P_{FFT}^{AC}, i.e., $f_{max}(P_{FFT}^{AC})$, sum of all amplitudes in P_{FFT}^{AC}, i.e., $f_{sum}(P_{FFT}^{AC})$, sum of the top n amplitudes in P^{AC}, i.e., $f_{sum_n}(P_{FFT}^{AC})$, indoor temperature (T_{in}), outdoor temperature (T_{out}) and user's set temperature for indoor (T_{set}).

Output layer of AC-ANN presents fault states of the appliance by 1 and 0 which represent the corresponding fault has occurred or not, respectively. AC-ANN has 7 output nodes, for 6 failure situations and the fault-free situation, such as y_1 represents the fault-free (Normal) situation, y_2 represents the compressor failure, y_3 represents the blower fan failure, y_4 represents the outer unit fan failure, y_5 represents the expansion valve failure, y_6 represents the open door/window failure and y_7 represents the blocking the air filter failure.

Training data set of ANNs consists of vectors of input data and the associated output data. Each input data is formed with 5 features extracted from the power profiles and FFT of power profiles, while the corresponding faulty situation or fault-free situation is the associated output data. Note that, in this work power profiles for training data sets are supposed to be created by appliance manufacturers during appliance durability tests. In this work, 6 independent faults are defined for an AC; such as component failures (compressor failure, blower fan failure, outer unit fan failure, expansion valve failure), user-related failures (open door/window failure and blocking the air filter failure). In order to obtain the corresponding power profiles, temporary failures were created by interfering with the mechanics of the components or by creating the misuse of the air-conditioner. For example, deflecting the shaft eccentricity of outer unit fan causes the outer fan failure, similarly deflecting the shaft eccentricity of blower fan causes the blower fan failure. Expansion valve failure is created by shifting the bulb position of the expansion valve. Opening the door or window of the room where the indoor unit is located for a long time provokes the open door/window failure. Blocking the air filter with an object is another user-related failure.

Figure 4 shows the Mean Square Error (MSE) vs. number of epochs graphs for various AC-ANN structures with different number of hidden layer neurons.

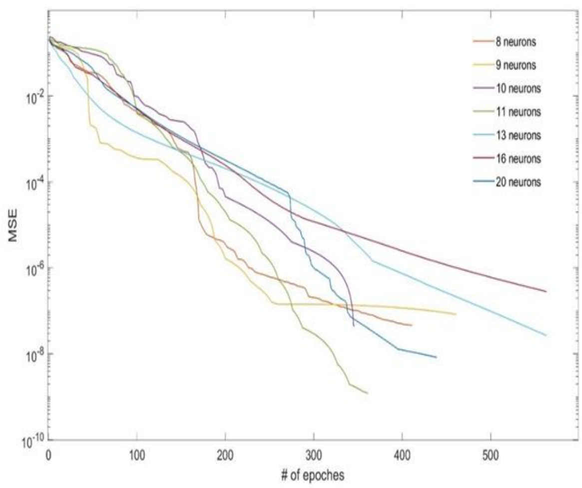

Figure 4. Training performance of AC-ANN

For analysis of the reliability and performance of AC-ANN, several experiments and simulations have been done by using Keysight VEE program and MATLAB Neural Network Toolbox.

In these experiments, an AC which performs both cooling and heating functions with a cooling capacity of 24000 BTU/h and a heating capacity of 25590 Btu/h is used. For the experiments, 180 power profiles are created and the corresponding input-output patterns are obtained for six faulty situations and the fault-free situation under different outdoor and indoor temperature conditions. Some examples of input-output patterns from the training data set are given in Table 2.

Table 2. Training Data Samples for AC-ANN

Input								Output						
$f_{max}(P^{AC})$	$f_{mean}(P^{AC})$	$f_{max}(P^{AC}_{FFT})$	$f_{sum}(P^{AC}_{FFT})$	$f_{sum_n}(P^{AC}_{FFT})$	T_{in}	T_{out}	T_{set}	y_1	y_2	y_3	y_4	y_5	y_6	y_7
(Watts)	(Watts)	(Watts)	(Watts)	(Watts)	(°C)	(°C)	(°C)							
2013.8	520.14	634.45	5781.6	3089.35	25	35	25	1	0	0	0	0	0	0
2013.8	520.14	634.45	5781.6	3088.57	25	35	25	1	0	0	0	0	0	0
--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
2042.1	545.39	652.65	5799.4	3145.34	26	36	25	0	1	0	0	0	0	0
2043.0	545.89	653.89	5798.8	3151.87	25	35	25	0	1	0	0	0	0	0
--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
2024.2	531.04	642.38	5788.9	3100.90	25	35	25	0	0	0	0	0	0	1
2024.8	530.88	642.96	5789.1	3102.85	24	35	25	0	0	0	0	0	0	1

After training by using 140 input-output patterns, the accuracy and performance of AC-ANN was tested with testing data set which consists of 40 input-output patterns. Due to the limited size of the dataset, Bayesian Regularization is chosen for training. Bayesian regularization does not require the validation data set to be separate from the training data set; it uses all the data [16]. The overall mean square error of this validation is 1.66E-09 and the computational time is 0.262 seconds. The confusion matrix in Table 3 represents the performance and efficiency of the trained AC-ANN. By using that confusion matrix, accuracy, precision, recall and F1-score values are obtained for each anomaly class. As a result, for considered anomaly classes AC-ANN provides accuracy in 95.1% - 97.01%, precision in 95.2% - 97.11%, recall in 96.2% - 97.01% and F1-score in 96.67% - 96.93%.

Table 3. Confusion matrix of AC-ANN testing

		Predicted						
		y_1	y_2	y_3	y_4	y_5	y_6	y_7
Actual	y_1	7						
	y_2		8					
	y_3			6				
	y_4				5			
	y_5		1			6		
	y_6						4	
	y_7		1					2

4. RESULTS

Early detection of faults in appliances avoids undesirable situations, such as increasing power consumption and safety problems. The works on early detection of appliances have increased in recent years due to the advancement of IoT technologies.

AC-ANN is designed as a feedforward ANN configuration with 1 hidden layer trained by BPA. Input layer of AC-ANN has input nodes assigned to decisive features obtained from power profiles and the output layer presents the fault-free and defined faulty situations, while the hidden layer is designed experimentally by considering the training performance of the configuration.

In this work, in order to provide a valuable contribution to the fault detection and classification works, a new fault prediction method for AC is proposed. The method is based on measuring power consumptions of AC at different operating temperatures (outdoor, indoor and user's set) and uses extracted features of power profiles to train the AC-ANN. There are a few similar studies in the literature; however, this study strongly distinguishes itself from the others. This is because, in this study, not only the presence of a fault is detected, but also whether the fault originates from a specific component or is due to a usage error is determined. For example, [9], which is the most similar study in the literature, claims only to detect the presence of faults in AC.

The efficiency and performance of the proposed method is justified by simulations, where the ability to detect the presence of considered situations is found to be in 95.1%–97.01%. Due to this promising result, direction of feature work will be to extend this method to other electrical appliances.

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CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Cengizhan Abay: Writing – Review & Editing, Visualization. **Hanife Apaydın Özkan:** Methodology, Investigation, Formal analysis, Visualization, Supervision, Project administration, Funding acquisition, Writing – Original Draft.

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