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Estimation of Working Error of Electricity Meter Using Artificial Neural Network (ANN)

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Abstract: Together with the rapidly growing world population and increasing usage of electrical equipment, the demand for electrical energy has continuously increased the demand for electrical energy. For this reason, especially considering the increasing inflation rates around the world, using an electricity energy meter, which works with the least operating error, has great economic importance. In this study, an artificial neural network (ANN)-based prediction methodology is presented to estimate an active electricity meter's combined maximum error rate by using variable factors such as current, voltage, temperature, and power factor that affect the maximum permissible error. The estimation results obtained with the developed ANN model are evaluated statistically, and then the suitability and accuracy of the presented approach are tested. At the end of this research, it is understood that the obtained results can be used by high accuracy rate to estimate the combined maximum working error of an active electricity energy meter with the help of a suitable ANN model based on the internal variable factors.

Keywords: artificial neural network; combined maximum working error; electricity meter; metrology

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1. Introduction

In recent years, rapid advancements in technological and scientific developments have enabled the production of smart products and systems based on effective digital communication and machine learning features due to relationality. Therefore, these developments have accelerated the birth of the Fourth Industrial Revolution around the world. However, some significant negatives have come with the COVID-19 pandemic and climate change in the last 5 years. As is known, they are increasingly affecting the whole world. For this reason, in order to ensure a cleaner, livable, sustainable, and economic world, the European Green Deal was accepted by the European Union in 2019 [1]. Within the scope of this agreement, there is a focus on using renewable energy sources more efficiently rather than relying on limited resources such as fossil fuels. Based on green and digital transformation strategies, new methods in different sectors are preferred over classical production methods. Therefore, using limited resources effectively and efficiently, and preferring renewable energy sources is important.

Today, attention is drawn to the increasing demand for electric vehicles and fast electric vehicle charging units. Also, there are approximately 50 million electricity meter subscribers in Türkiye [2]. In addition, it is known that the working error of an electric energy meter may be either have either positive or negative consequences for the subscribers, affecting

their bills significantly. Therefore, it is thought that electricity energy meters will always play a greater and more effective role in technological developments. In this context, using smart meters, designed and used to work with the least error, will be more important.

An electricity energy meter is defined as a device that continuously measures electrical energy by integrating power over time and records the result correctly [3]. There are different types of electricity energy meter in the literature, depending on the current passing through the circuit or design features, connection structure, type of energy measured, manufacturing technique, or consumption method [4]. The electricity energy meter can be classified as active, reactive, or combi, according to the energy measured [5]. An active electrical energy meter is a device used to measure the active energy part of electrical energy used in the system. A reactive electrical energy meter is designed to measure reactive energy, in which current and voltage behave on semiconductor elements in a way that produces an output proportional to the energy to be measured [5]. On the other hand, the combi-type electrical energy meter is a meter that has the ability to measure reactive and active energy together [4].

When the research results regarding the working method of electricity meters are examined, it is seen that the electricity energy meter is designed to measure in energy circuits where the current, voltage, and frequency waveforms are known beforehand. So, the working error rate of the electricity meter's active and reactive energy measurements may be slightly higher than the expected values in systems with current and voltage with harmonic components [6]. Thus, measuring electrical energy with minimum calculation error and optimum uncertainty is very important. Because of that, in most studies, the measurement error and power quality of the electricity energy meter in harmonic component waveform systems are always research subjects [7].

Measurement errors in energy meters used in the measurement of electrical energy can exceed 2%, which is defined as the acceptable limit value according to the line current, grid voltage and frequency, and the characteristics of the load [8]. It is measured that these errors can exceed 10% for high dimmer firing angles in Light Emitting Diode (LED) and Compact Fluorescent Lamp (CFL) fixtures used in modern lighting systems [9]. Although the use of smart meters compatible with smart grid systems has become widespread in recent years to reduce these errors [10], there are disadvantages, such as the presence of effects that cause measurement errors, especially EMI, in variable-load industrial applications, security problems caused by being open to remote access, and infrastructure costs [8,10]. It is evaluated that the Hamming code will be used to reduce these measurement errors under different loading conditions, and algorithms such as Reed–Muller (RM) codes, Golay code, binary BCH codes, and artificial intelligence applications will be used [11].

Energy losses and the costs of these losses due to measurement errors of electricity meters vary regionally and seasonally because measurement errors are affected by many variables such as environmental factors, design of the measuring device, load characteristics, and line parameters [12,13]. A research report by Snyder and Myers [14] in the USA found that the cost of measurement error for 100,000 consumers at 1% measurement error is USD 120,000 each year. This cost shows that serious costs can arise for consumers in conditions where measurement errors are higher.

The operating errors specified in the test reports of type approvals of electricity meters that will be put into the market must remain within the permissible error margins within the scope of legal regulations. Therefore, it cannot be said that the operating errors specified here are directly wrong for users. The main issue here is to determine electricity meters that consistently have values that are very close to the maximum permissible error limits and operating errors that are generally against users. So, in this context, it is important to ensure that the manufacturer, the distribution company, and the public authorities take

the necessary corrective and quality-enhancing actions. However, this study, unlike this situation, aims to estimate the combined operating error of an electricity meter with less test data and to ensure that the manufacturer increases production quality with less labor and cost. Similarly, it is aimed at ensuring that the distribution company may choose the appropriate meter with fewer operating errors for different environmentally conditioned regions. In addition, it is focused on ensuring that public authorities responsible for inspection duties may conduct more effective and efficient inspections by focusing on meters considered riskier due to the high number of operating errors.

This study examines whether the prediction of the combined working error of an electrical energy meter can be successfully made using the ANN model. In this context, it is made using the real test values of the active electricity meter, which is part of the combi-type electricity meter, based on artificial neural network-based methodology. Therefore, the variable factors affecting the measurement error during the electricity energy meter operation are considered. A suitable ANN model is created on the Matlab platform to carry out this study, and then, a combined working error is estimated. For this purpose, real data from the records of national-type approvals from the Ministry of Industry and Technology are used in Türkiye. The results are evaluated using statistical performance evaluation methods regarding minimum error and maximum significance criteria.

2. Materials and Methods

This article aims to predict a combined working error rate by using the multilayer structure based on a feedforward backpropagation algorithm on the artificial neural network model. Therefore, this section of this study consists of three main topics. In the first part, the definition of some important terms and then the calculation methods of comprehensive maximum error (CME) of an electrical energy meter are investigated. The second part presents the structure of an artificial neural network model. In the last part, the data are trained by a suitable artificial neural network model. Afterward, at the different temperature, voltage, current, and power factor (PF) stations, the comprehensive maximum errors are estimated by ANN for test data of different electrical energy meters.

2.1. Comprehensive Maximum Error (CME)

As is known, in accordance with the relevant technical regulation, before the electricity energy meter is placed on the market, it must meet the requirements of type approval tests, such as durability, electromagnetic distortion, current, voltage, frequency, and power factor distortion, phase shift, and harmonic distortion. In this context, apart from other requirements, the maximum permissible error (MPE) value is determined to ensure metrological measurement accuracy. With national legislation, in the Organization Internationale de Metrologie Legale (OIML) R46 recommendation guide, the extreme values of the permitted working error of an electricity energy meter are defined at reference conditions [3]. On the other hand, the combined error is known as the comprehensive permissible error (CME). In regulations, it is seen that the error values for current and voltage circuit tests are determined in the range of 0.7–9%. Also, this error value varies with the temperature [15].

According to research findings in the literature, the measurement error of an electrical energy meter is affected critically due to the harmonic distortion rates in the electrical distribution system after the installation and factors such as temperature, pressure, humidity, and wind arising from external environments. In this context, a prediction model with artificial intelligence is used based on the effect of environmental factors on real data. In this research, it is determined that the effect of environmental temperature values on the measurement error of the smart electricity energy meter during the working period is positive, while humidity is found to have a significant negative effect [16]. So, it is thought

that the working error of an electrical energy meter can approach more critical levels that violate measurement accuracy because of these factors. Therefore, it is evaluated that these errors may have a significant technical and economic impact on consumers, distribution companies, and manufacturers when using electricity meters.

In the OIML R46 recommendation document, there are two methods to calculate the combined comprehensive maximum error of an electricity energy meter at a certain load. The first method is based on the Gauss distribution assumption, and it follows the formula shown below:

$$e_{c(p,i)} = \sqrt{e^2(PF_p, I_i) + \delta e_{p,i}^2(U) + \delta e_{p,i}^2(f) + \delta e_{p,i}^2(T)} \quad (1)$$

In this formula, for each current I and each power factor PF, I denotes each current, and PF_p denotes each power factor, $e(PF_p, I_i)$ is the inherent error measured at current I_i and power factor PF_p in the process of testing. $\delta e_{p,i}(U)$, $\delta e_{p,i}(f)$, and $\delta e_{p,i}(T)$ are the maximum additional error. It is measured in the test when the voltage, the frequency, and the temperature work, respectively, under the rated operating conditions. This error varies in the whole range, at current I_i and power factor PF_p [17,18].

In the second method, instead of Gaussian distribution, a rectangular distribution is kept for the effects of influence factors, and this formula is shown below:

$$e_c = 2\sqrt{\frac{e_{base}^2}{3} + \frac{e_{voltage}^2}{3} + \frac{e_{frequency}^2}{3} + \frac{e_{unbalance}^2}{3} + \frac{e_{harmonic}^2}{3} + \frac{e_{temperature}^2}{3}} \quad (2)$$

In the second formula e_{base}^2, $e_{voltage}^2$, $e_{frequency}^2$, $e_{unbalance}^2$, $e_{harmonic}^2$ and, $e_{temperature}^2$ terms indicate the maximum error shift obtained in the test for base, voltage, frequency, unbalance, and harmonic and temperature variation, respectively, by taking into account the measurement uncertainty of the type test [3]. As seen clearly from both methods, besides the base error shift, the combined comprehensive maximum error is affected by variable factors: current, voltage, temperature, power factor, and unbalance. Also, it is seen from the type approval test reports that manufacturers of electricity energy meters generally prefer to use the first method in calculating the combined maximum error before placing it on the market.

On the other hand, research showed that the internal factors affecting the CME while working the active electricity meter are current, voltage, frequency, power factor, temperature, tilt, instability, and harmonic distortions [4,5]. Also, it is stated that some factors, such as tilt and temperature, have little influence on CME [19]. Furthermore, in a different study, it was evaluated that the most basic issues affecting the measurement error of the electricity meter are small power factor amounts, harmonic distortion rates, low rates of measured parameters, the calculation methods to determine the power of the electronic electricity meter, and changes in design [6].

Moreover, in a result from another study, apart from the effect of current, voltage, frequency, temperature, and power factors on the CME of an electricity energy meter, the meter constant, harmonic error, short-term overcurrent error, and active and reactive power consumption rates also have a significant effect on the measurement error. Also, it is concluded that there is no statistically linear relationship between the CME and these independent variables [4].

2.2. Artificial Neural Network

Artificial neural network (ANN) is a model inspired by nerve cells' structure and working logic, which play an important role in the nervous system of living beings [20]. ANN is a method that produces successful results in many fields, from transportation to health and education to commerce. The ANN model is an integrated structure that consists

of input, output, and hidden layers. In an ANN model, the data transmitted to the output layer is processed within the scope of certain requirements in the input layer. To obtain a successful response, the connection strength and weight are adjusted according to the input results [21]. In the ANN structure, each layer has independent neurons belonging to its own layer. Also, these neurons are connected to all neurons in the next layer. Different weight values make the connections between these neurons. They are called synaptic weights in the literature [22,23]. Generally, the results obtained by multiplying each of the inputs by the weight are simply summed with the threshold value. Then, they are processed with the activation function to create a suitable result, and the output data are obtained. Therefore, the learning ability of an artificial neuron cell depends on the appropriate adjustment of weights within the chosen learning algorithm [24].

The artificial neuron cells do not have a linear structure when the properties of the cells that make up artificial neural networks are examined. For this reason, non-linear nerve cells that perform their functions spread throughout the network, allowing the artificial neural network to gain a non-linear feature. So, ANN can provide more successful solutions to complex non-linear problems due to its flexible ability in image processing, mapping, classification, and pattern recognition studies [21]. In the literature, artificial neural networks can be categorized as radial basis ANN, single ANN, or multilayer neural networks ANN. In addition, there are different learning algorithm types, such as quick propagation algorithm (QP), flexible propagation algorithm (RP), and backpropagation algorithm (BP) in ANN models [25].

The backpropagation algorithm was discovered by Seppo Linnainmaa in 1970. It is generally the most frequent and widely preferred learning algorithm in the studies because it can be easily proven mathematically and easily understood. Also, it received its name because it progresses backward from the output layer to the input layer during operation [26]. The flexible (resilient) propagation algorithm (RPROP) was discovered by Riedmiller and Barun in 1993. In this algorithm, generally, sigmoid transfer functions are preferred in the intermediate layers. This function is also known as the compressive function in the literature. Because the input data, which has an unlimited width, is stuck in a limited part [27]. So, the main goal here is to keep the negative effects of the partial derivative result away from the learning stages in the ANN model [28]. Falhmann determines the quick propagation algorithm, and it is based on the Newton method. So, it is preferred for training multilayer processes [29]. It has rules focused on educated guesswork and experience. This method determines other approximate solutions that can be considered successful rather than the most appropriate [30]. Therefore, the successful results of this algorithm are better than those of other methods. Moreover, it produces more successful results for data with low noise values [31].

In a different study on whether the error amount of electricity meters can be predicted by using ANN methodology, the effectiveness of the model is developed by focusing on the SISO (singular input singular output) system in order to measure the error that mathematical models in energy measurement for dynamic and non-linear systems cannot explain. This study used experimental data and simulation results to conduct a non-linear autoregressive exogenous neural network model (NARX). It is stated that this model can be applied successfully to electrical energy meters [32].

In this study, the ANN method is used to analyze energy meter data and perform error estimation. However, methods such as extreme gradient boosting (XGBoost) and support vector machines (SVMs) can also be preferred as estimation algorithms in the literature. Although XGBoost and SVM algorithms can make more successful estimations by increasing the number of input parameters and data, the ANN method is preferred in applications where the number of data is more limited [33,34]. Although ANN and

XGBoost methods can be used interchangeably, the ANN method, which has the ability to capture complex patterns with interconnected node (neuron) layers [35], offers a more suitable solution for the current data set.

Other innovative estimation models in power systems include machine learning-based federated model-agnostic meta-learning and multi-task learning estimation algorithms [36,37]. While the federated model-agnostic meta-learning estimation algorithm is effectively used in applications with distributed data sources where confidentiality is essential, ANN can converge to the result faster in cases where a centralized data set is available. The multi-task learning algorithm is more suitable for problems where multiple tasks are defined. At the same time, ANN can be preferred in analyses where the effects of variables on a single parameter are examined.

2.3. Using the ANN Model to Estimate CME

In this research, it is preferred to develop an ANN model to estimate the combined maximum working error of active electrical energy meters. In the literature studies, it has been seen that there is no linear relationship between the parameters affecting the combined operating error of the electricity meter. Therefore, this work aims to use the artificial neural network model to perform successful error estimation results. To carry out this study, the variables "model", "class", "minimum current", "transient current", "reference current", "maximum current", "THD harmonic", "Single harmonic", "Power consumption (W)", "Power consumption (VA)", "Temperature", "Operating current", "Power factor (cos f)", and "MİH" are determined as input parameters and the amount of "composite maximum error" is determined as output parameter for ANN model. At this stage, the "THD harmonic" variable is set as the resultant magnitude of all harmonic components in the test report, and the "Power consumption (W)" variable is set as the resultant magnitude of active power consumption in current and voltage circuits. Also, these input measures are obtained from the real test reports of type approval certificates. In this context, considering the assumption that there may be a heteroscedasticity problem between these variables and the existence of a non-linear relationship between the variables, the analysis study should be normalized and linearized. For this purpose, square root transformation, arcsin transformation, logarithmic transformation, square transformation, and hyperbolic transformation methods are examined to transform the determined variables. In this context, the data set is expanded by adding 5 different meter data to only 3 different meter data. Then, all the obtained data are normalized using the logarithmic transformation transfer function. To develop a suitable model with ANN, type test reports of 9 different combi-type electricity energy meters were used as a base. While 5 reports belong to the C class, the rest belong to the B class active electricity energy meter. All test reports were obtained from the Ministry of Industry and Technology database in Türkiye. Afterwards, ANN study is carried out using the data of such test results. Then, the prediction of the combined maximum working error study is made in Matlab. This work used the Matlab R2023b version to create the ANN model.

First, in the literature's initial stage of this ANN modeling study, the related variable factors and their effectiveness rate in calculating the combined maximum error of active electricity energy meters at a certain load are examined. Therefore, two methods specified in OIML R46 [3] recommendation document and TS EN 50470-3:2022 standard [17] are investigated. After this examination work, the model, class, minimum current, transient current, reference current, operating current, maximum current, total harmonic distortion amount, odd harmonic distortion amount, active and reactive power consumption amount, ambient temperature, power factor, and MPE variables are determined as input parameters; the combined maximum error rate is defined as the output parameter for this ANN model.

Then, the data of relevant variable values of 9 different active electricity energy meters is broken down according to temperature, power factor, current, and MPE values. At the end of this work, an 864*14-sized data set is created for all electricity energy meters. A total of 768*14-sized data of the 8 different model electricity energy meters are used for training purposes in order to develop a suitable ANN model, and 96*14-sized data of the other unshown electricity energy meters are used to test the success of the created ANN model.

To obtain a more successful rate in ANN, the model data values are defined as "1", "2", and "3" in the data set for the A, B, and C class electricity energy meter, relatively. Subsequently, to learn the non-linear relationship between all variables more accurately in the ANN model, this data set is converted to the "0–1" range data set by using the logarithmic sigmoid function [38]. After that, the data are normalized between 0 and 1 values and transferred to the Matlab.

It is known that the ANN structure developed based on the Feed Forward Back-propagation Multilayer Perceptron model is widely preferred in prediction applications, especially in fields of study such as engineering [39]. In other words, ANN is used quite frequently in prediction studies because this model has a very high prediction success rate, especially in non-linear models [40]. For this reason, the ANN model is considered appropriate for predicting the CME of the electricity energy meter in this study. Furthermore, this model is easier to use and can achieve more successful results in performance tests.

Many training and learning functions can be used to develop the ANN model on the Matlab platform. In this scope, the backpropagation algorithm (BP) and Levenberg–Marquardt (LM) algorithm can be given as an example. Generally, the backpropagation algorithm is widely used in ANN studies. However, this algorithm is not recommended for daily applications that are easy to implement because it does not have a good convergence speed level, and its efficiency is at lower values. Moreover, this algorithm requires first-order derivative information. Therefore, this situation slows down the learning speed [41].

On the other hand, the second-order derivative information is used in the Newton and Levenberg–Marquardt (LM) learning algorithm, and this property increases the speed of the LM algorithm efficiently. For this reason, the LM algorithm is frequently preferred in the training studies of artificial neural networks, too. This algorithm successfully combines the stability feature of the steep descent method and the effective speed feature of the Newton algorithm in its structure [42]. In other words, the LM algorithm is widely used in training studies of artificial neural networks, considering the effective stability and speed features it provides. Also, it is a standard technique for non-linear least-square issues, extensively adopted in different disciplines for dealing with data-fitting applications. Therefore, the feed-forward network type Levenberg–Marquardt (LM) algorithm is preferred to optimize the work as the learning model in this ANN study [43,44]. To develop a successful ANN learning model, after adjusting the variables, the algorithm of learning, activation of a function, number of layers, number of neurons in the layers, and the performance function to be used must be determined properly. Therefore, it is assumed that this ANN study has 14 independent input variables and one dependent output variable. All calculations are made by considering some assumptions used in the literature to find the most effective number of layers and the number of neurons. In this regard, within the framework of the method in the study conducted by Heaton [45], tests are performed on up to 28 neurons in the hidden layer. The performance measurement results of these tests are shown in Table 1 below.

Table 1. The performance results are according to the number of neurons in the hidden layer of ANN.

Number of Neurons	R^2	RMSE	cov	MAPE
1	0.7953	0.1341	28.2884	0.2313
2	−0.0077	0.2976	62.7696	0.3562
3	0.3333	0.2420	51.0577	0.2826
4	−0.0077	0.2976	62.7696	0.3562
5	0.3500	0.2390	50.4123	0.2647
6	−0.0077	0.2976	62.7696	0.3562
7	0.3422	0.2404	50.7157	0.2797
8	0.3636	0.2365	49.8825	0.2599
9	0.3469	0.2396	50.5325	0.2698
10	0.3551	0.2381	50.2168	0.2606
11	0.3587	0.2374	50.0738	0.2607
12	0.3509	0.2388	50.3801	0.2692
13	0.3607	0.2370	49.9980	0.2606
14	0.3572	0.2377	50.1343	0.2624
15	0.3498	0.2390	50.4225	0.2715
16	0.1347	0.2758	58.1667	0.3895
17	0.3566	0.2378	50.1592	0.2642
18	−0.0077	0.2976	62.7696	0.3562
19	−0.0077	0.2976	62.7696	0.3562
20	0.3602	0.2371	50.0150	0.2628
21	0.3451	0.2399	50.6032	0.2666
22	0.3619	0.2368	49.9485	0.2563
23	0.3473	0.2395	50.5192	0.2740
24	0.3590	0.2373	50.0621	0.2630
25	0.3694	0.2354	49.6540	0.2564
26	0.3571	0.2377	50.1361	0.2628
27	0.3583	0.2375	50.0928	0.2623
28	0.3590	0.2373	50.0656	0.2611

Some statistical criteria compare the results of studies conducted with artificial neural networks. Estimating the quality of performance success between networks is possible by looking at the minimum error rate. For this purpose, the Root Mean Square Error (RMSE) method is recommended as a criterion [46]. The MAPE value eliminates the negative effects of comparing models of different unit values. It is known that the use of the MAPE method is more popular among performance measurements in these types of models. This is because this model expresses the estimated error values in percentage form. So, it eliminates the possible deficits for comparisons of models with varied unit rates because it states the prediction errors comparatively and the number of data or minority of the observation values are not generally important in this method because the produced results are relative [47]. A high linear relationship between the real value and the estimated value is manifested by high R^2 and low RMSE and "cov" measurements. While smaller values of RMSE and covariance (cov) indicate higher accuracy of predictions, the larger R^2 value indicates a higher linear relationship between predicted and measured values [48].

In this context, when Table 1 is examined, it is seen that the largest R^2 value and the lowest values of RMSE, cov, and MAPE occurred in the 1st and 22nd neuron structures. So, in the training work, the tests are performed with the 1st and 22nd neurons in the hidden layer on the ANN model. Then, it is seen that the model, which has 22 neurons in the hidden layer and 1 neuron in the output layer, carried out more effective results. So, after determining and specifying which neurons should be used, the suitability of other parameters is chosen by testing them in terms of performance.

It is known that the ANN structure developed based on the feed-forward back-propagation multilayer perceptron model is widely preferred in estimation applications, especially in fields such as engineering [49]. Since this model has a very high estimation success in non-linear models, it is frequently used in estimation studies [50]. For this reason, it was evaluated that it would be appropriate to use this model in the study to make its usability easier and to achieve more successful results in terms of performance.

In the prediction work with the ANN, the "logsig" function is preferred as the transfer function in the hidden layer because it is understood that it gave the best results in this study. Similarly, the "trainlm" function is preferred as the training function, since the feed forwards are widely used in the backpropagation model. Also, the "LearnGDM" function is preferred as the adaptation learning function to obtain more successful results. In the output layer, the "tansig" function is preferred as the transfer function, the "trainlm" function is preferred as the training function, and the "LearnGDM" function is preferred as the adaptation learning function. So, after determining the input parameters and selecting the appropriate network, the suitability of many learning functions was determined by investigating them one by one using the trial and error method. At the end, it is understood that it gave the best results in the studies. In order to evaluate the performance of the network, the "MSE (Mean Square Error)" function is used as a basis. The structure of this developed ANN model is shown in Figure 1.

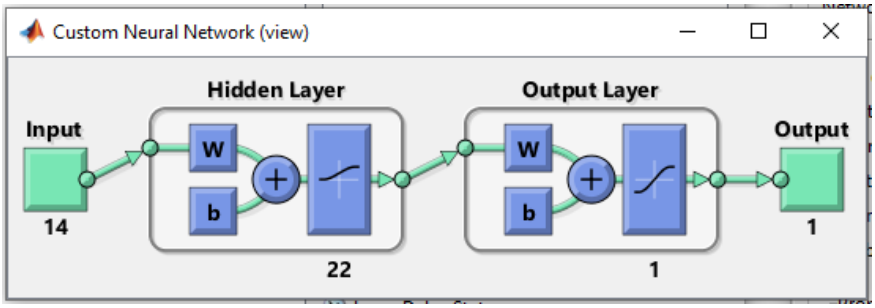


Figure 1. The structure of ANN model used in the study.

On the other hand, the number of iterations is determined to show each sample network 50 times, and the error rate coefficient needed to stop the training is accepted as 0.001. Also, this study conducted experiments to choose the learning coefficient in the range of 0.5–0.9, since there is no specific method to determine the learning coefficient.

Consequently, an ANN model is created within the framework of the determined features, and this ANN model is trained and then optimized for the situation in which the most successful performance is achieved. Following the completion of the ANN training phase, tests are carried out to assess the learning performance of the network. It is important that, at this stage, data that has never been seen before are used for ANN.

3. Results and Discussion

As known to be used, the data are prepared, and the appropriate structure, learning functions, the number of iterations, and learning coefficients are determined for the ANN model in Section 2 of this article. Then, the ANN model is developed and trained successfully. The results of the estimation of combined maximum working errors are obtained with ANN, and they are evaluated statistically. The images of these works are shown in Figures 2 and 3, respectively.

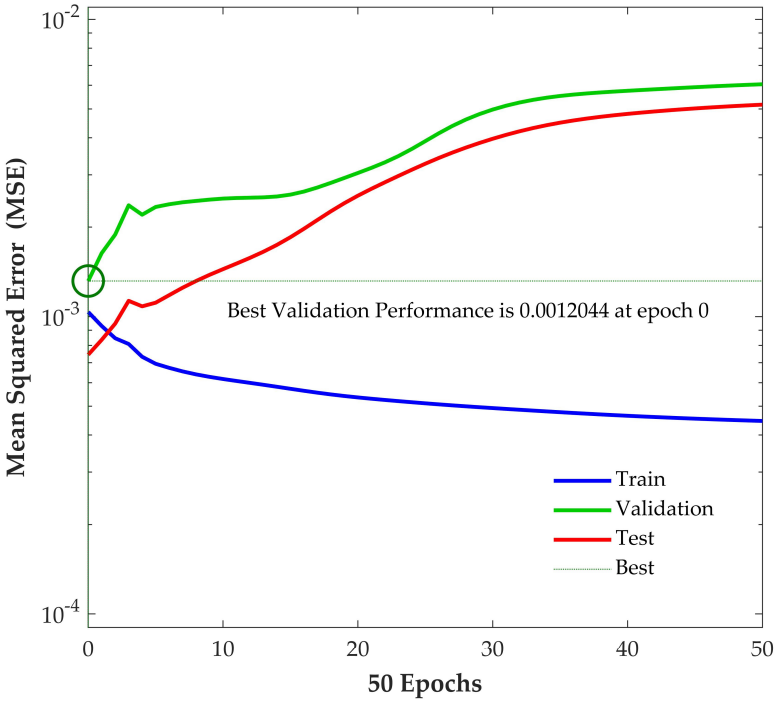


Figure 2. Best validation performance of ANN.

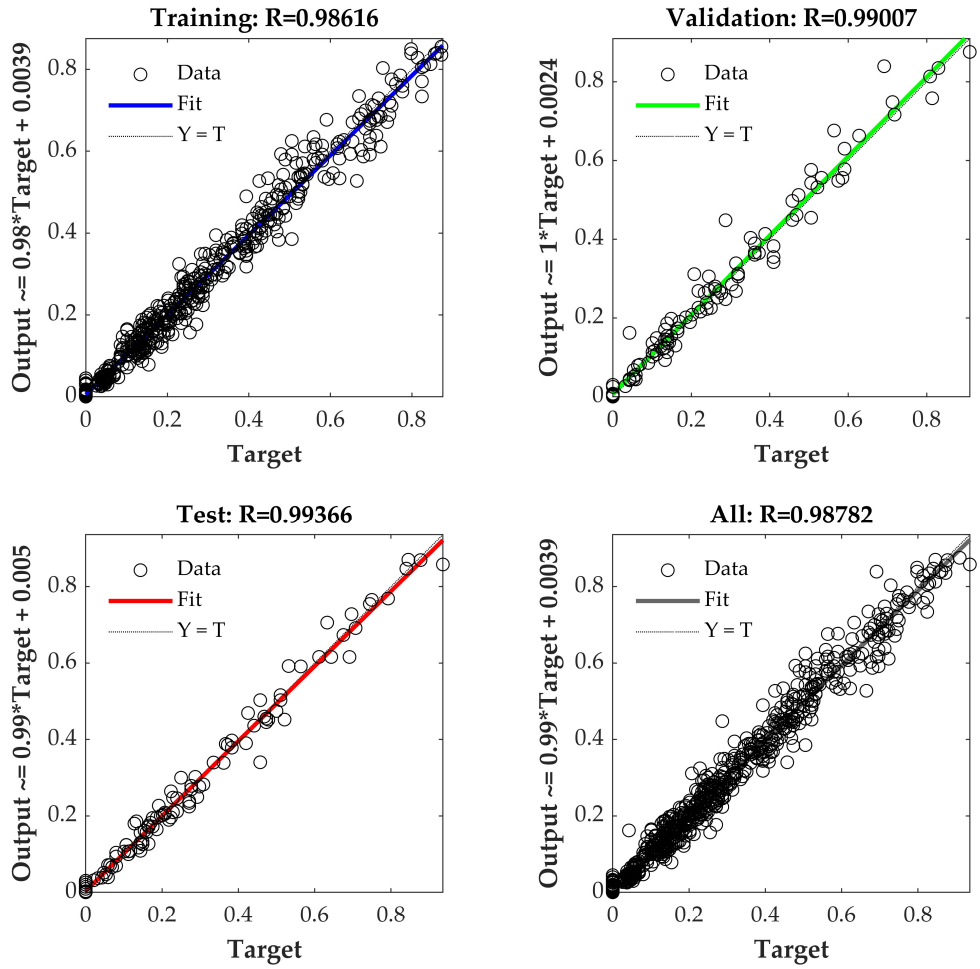


Figure 3. The results of training regression of ANN.

In this study, 1000 iterations are used in the training of ANN. The network training process is completed in 50 iterations. The lowest mean square error (MSE) value is reached in the third iteration. According to Figure 2, the MSE value is 0.0012044 in the work. Figure 3 shows the average error values of the training, validation, and test data used in the ANN model over 50 iterations. According to these results, it is understood that the training studies of ANN achieved a success level, which is very close to the best situation. Moreover, higher success rates are achieved in testing and validation studies, too. As a result of this study, within the framework of the existing data and the based method, functions, structure, and all parameters, the model has achieved a success rate of 0.98616% in training studies and a success rate of 0.99366% in test studies. Furthermore, the ANN has approached a success level of 0.98782% in all studies and 0.99007% in validation.

After obtaining these results, the actual test data and the results produced by the ANN model are compared favorably. In order to examine these data on a graph, the harmony of actual and predicted values is shown in Figure 4. When this graph is examined, it can be seen that although the general success rate of the error of prediction work is good, the consistency of the predictions that are obtained for some cases is weaker. In this comparison, it is examined whether the amount of estimated error remains within the permissible limits. In the study created in this direction, the data that shows the actual test values, prediction results, and error differences between actual and estimation data are presented in Table 2.

Table 2. The estimation results and comparison of the ANN model.

Actual Value	Estimation Value	Error Value	Error Value (%)	Actual Value	Estimation Value	Error Value	Error Value (%)	Actual Value	Estimation Value	Error Value	Error Value (%)
0.7606	0.8309	−0.0703	−9.24	0.5798	0.5886	−0.0088	−1.52	0.4787	0.4355	0.0432	9.03
0.0000	0.0063	−0.0063	0.00	0.5426	0.5340	0.0086	1.58	0.2766	0.3056	−0.0290	−10.49
0.0000	0.0004	−0.0004	0.00	0.4894	0.4826	0.0068	1.38	0.3191	0.3716	−0.0525	−16.43
0.8245	0.833	−0.0085	−1.03	0.5798	0.5501	0.0297	5.12	0.3670	0.4659	−0.0989	−26.94
0.9574	0.9503	0.0071	0.75	0.3883	0.3897	−0.0014	−0.36	0.2766	0.2918	−0.0152	−5.50
0.9149	0.8902	0.0247	2.70	0.0000	0.0001	−0.0001	0.00	0.2819	0.2959	−0.0140	−4.96
0.9415	0.8665	0.0750	7.96	0.0000	0.0000	0.0000	0.00	0.2500	0.2523	−0.0023	−0.92
1.0000	0.9618	0.0382	3.82	0.3936	0.3918	0.0018	0.46	0.2394	0.1948	0.0446	18.62
0.9043	0.9132	−0.0089	−0.99	0.5638	0.5773	−0.0135	−2.39	0.7500	0.5859	0.1641	21.88
0.9202	0.9203	−0.0001	−0.01	0.4574	0.4718	−0.0144	−3.14	0.0000	0.0000	0.0000	0.00
0.9894	0.9836	0.0058	0.58	0.3883	0.4233	−0.0350	−9.01	0.0000	0.0000	0.0000	0.00
0.9202	0.9451	−0.0249	−2.70	0.5798	0.5981	−0.0183	−3.16	0.4628	0.5788	−0.1160	−25.07
0.5745	0.6310	−0.0565	−9.84	0.4947	0.5047	−0.0100	−2.03	0.6064	0.5762	0.0302	4.98
0.0000	0.0031	−0.0031	0.00	0.4894	0.5095	−0.0201	−4.12	0.4521	0.4789	−0.0268	−5.92
0.0000	0.0001	−0.0001	0.00	0.5851	0.5160	0.0691	11.81	0.4096	0.4306	−0.0210	−5.13
0.7021	0.6346	0.0675	9.62	0.4894	0.5183	−0.0289	−5.91	0.5319	0.5055	0.0264	4.97
0.6649	0.7360	−0.0711	−10.69	0.3723	0.2076	0.1647	44.24	0.4362	0.3656	0.0706	16.18
0.7394	0.7339	0.0055	0.74	0.0000	0.0000	0.0000	0.00	0.4574	0.5408	−0.0834	−18.22
0.7021	0.6937	0.0084	1.20	0.0000	0.0000	0.0000	0.00	0.4681	0.4358	0.0323	6.90
0.7766	0.7827	−0.0061	−0.79	0.1330	0.2095	−0.0765	−57.54	0.4362	0.4738	−0.0376	−8.63
0.7606	0.7812	−0.0206	−2.70	0.2287	0.3918	−0.1631	−71.30	0.9894	0.8923	0.0971	9.81
0.7713	0.7503	0.0210	2.72	0.1330	0.1612	−0.0282	−21.22	0.0000	0.0000	0.0000	0.00
0.8457	0.8489	−0.0032	−0.37	0.1596	0.2279	−0.0683	−42.82	0.0000	0.0000	0.0000	0.00
0.7713	0.7879	−0.0166	−2.16	0.6596	0.4656	0.1940	29.41	0.8298	0.8895	−0.0597	−7.20
0.5000	0.4684	0.0316	6.32	0.4628	0.1922	0.2706	58.47	0.9149	0.8412	0.0737	8.05
0.0000	0.0008	−0.0008	0.00	0.2128	0.2174	−0.0046	−2.18	0.7128	0.7995	−0.0867	−12.17
0.0000	0.0000	0.0000	0.00	0.3191	0.3698	−0.0507	−15.87	0.6702	0.8196	−0.1494	−22.29
0.4362	0.4700	−0.0338	−7.76	0.1755	0.1789	−0.0034	−1.92	0.7766	0.811	−0.0344	−4.43
0.4947	0.4444	0.0503	10.16	0.5798	0.4225	0.1573	27.13	0.8085	0.7244	0.0841	10.40
0.5904	0.5657	0.0247	4.19	0.0000	0.0000	0.0000	0.00	0.7021	0.7913	−0.0892	−12.70
0.5266	0.4958	0.0308	5.85	0.0000	0.0000	0.0000	0.00	0.6862	0.6637	0.0225	3.27
0.4574	0.4646	−0.0072	−1.56	0.3085	0.4212	−0.1127	−36.53	0.7074	0.7109	−0.0035	−0.49

It is considered that some situations are due to the scarcity of data to train the ANN model, since in the training study, the actual data of only eight electricity energy meters could be used because of insufficient inventory. Also, the diversity of all types of electricity energy meters could not be provided, so the actual data of only the B and C classes of electricity energy meters are used in the study. Unfortunately, the A and D class electricity meter data could not be accessed as desired due to some restrictions in the Ministry's database.

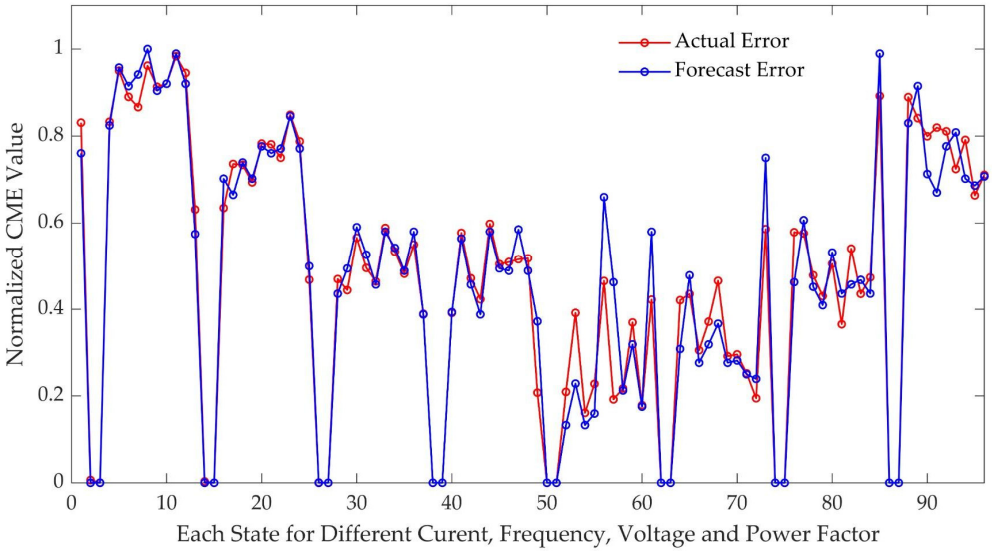


Figure 4. The comparison of real test data and prediction results of ANN.

Consequently, the results of the tests, which are performed according to different learning functions and different neuron numbers, are presented in Table 3. In this scope, the most successful test results have been examined statistically according to MAPE, R^2, RMSE, and cov performance measurement methods. In this study, the ANN model with a hidden layer, 22 neurons, and used logsig function for the first layer and tansig function for the second layer is selected. According to this model, the MAPE value is 0.090484174, the RMSE value is 0.064483104, the cov value is 13.60204609, and the R^2 value is 0.9526827 are obtained at the validation condition.

Table 3. The performance results of ANN.

Statistical Performance Measurement Method	Model Results with 12 Hidden Neurons, Used Logsig and Tansig Functions	Model Results with 22 Hidden Neurons, Used Logsig and Purelin Functions	Model Results with 22 Hidden Neurons, Used Logsig and Tansig Functions	Model Results with 25 Hidden Neurons, Used Logsig and Purelin Functions
R^2	0.926119272	0.921556157	0.952682700	0.915302136
RMSE	0.080575228	0.083026244	0.064483104	0.086272461
cov	16.99651368	17.51353019	13.60204609	18.19828632
MAPE	0.125829036	0.136487062	0.090484174	0.139312023

The ANN algorithm used in this study has strong learning capabilities, but it has some disadvantages such as potential over-learning, sensitivity to small data sets and the need for a relatively large data set, lack of transparency, and hyper parameter tuning difficulties [51,52]. Therefore, its use should be used with caution and different artificial intelligence or machine learning methods should also be evaluated depending on the data set. The results obtained in this study show that these disadvantages of the ANN model are not observed in electricity meter data, and a successful prediction model can be established.

4. Conclusions

Even though the legally allowed amount of measurement error of electricity energy meters may seem low, when millions of electricity meters are considered, these error values have a great impact and importance on transactions for subscribers, distribution companies, and electrical energy producers. In this study, ANN methodology is used as a different approach to determine the combined maximum working error of an active electricity energy meter intended to be put on the market. Therefore, some variable domestic factors that affect CME, such as voltage, current, temperature, frequency, and harmonic distortion rates, are determined. The ANN model used the actual test values of class B and C of active

electricity meters of eight different models. Then, the CMEs are estimated for a different class C active electricity energy meter that has never been shown to ANN before. According to the prediction values, the model is optimized based on minimum error and maximum significance methods. MAPE, R^2, RMSE, and cov performance measurement methods are used in this evaluation. In the optimization study, the largest R^2 value is 0.9526827, the smallest RMSE is 0.064483104, cov is 13.60204609, and MAPE is 0.090484174. Values are achieved by using the determined parameters. At the end of the study, successful results are obtained at a rate of 0.98616% in training and 0.98782% in all studies.

Afterward, the comparative graph of the actual operating error values, which are obtained from the test reports, and the estimated CME values, which are predicted by ANN, are presented. So, it has been seen that the ANN model can be used successfully to estimate the CME of an active electricity meter intended to be put on the market. It is thought that with this study, the CME of a reactive and active electricity energy meter can be estimated successfully. It is considered that such estimations will be useful in the transactions of electricity distribution companies, which have millions of electricity meter users, as well as public authorities.

In future studies, more successful results can be achieved by using different ANN models and learning algorithms using this data set. In addition, the effectiveness of this ANN study can be increased by taking into account the Pareto principle by obtaining more test reports. In the literature, there is an idea that was first put forward for economic applications and that defends the hypothesis that 80% of the outcome of any situation consists of 20% of the causes. It is stated that it has found successful application in many areas other than economics [53]. So, by including the test values of class A and D active electricity energy meters in this data set, this ANN model's success and efficiency rate may be increased.

On the other hand, as a continuation of this study, future studies can be advanced by using richer software libraries such as FANN of different programs. Also, the results to be obtained can be compared with different methods and examined. In addition, various artificial intelligence methods such as genetic algorithm [54] and fuzzy logic [55] can be tried, and the findings to be obtained can be compared in detail with these ANN results. Furthermore, it can also be investigated whether the successful ANN results obtained in this study are effective in measuring the error of the reactive electricity meter. Afterward, the total measurement error from the active and reactive electricity meter of the combi-type electricity meter can be analyzed and examined. In addition, the effects of the operating error that occur during the manufacturing phase of the meter and other external factors such as pressure, humidity, and temperature in the environment where the meter is used on the measurement error can be examined together, and evaluations can be made.

Lastly, it is known that millions of subscribers use electricity meters worldwide. During the operation of the electricity meter, operating errors that may occur in favor of or against the subscribers can directly affect bills [56]. Therefore, knowing the importance of the parameters affecting the operating error will play an important role in selecting the most suitable meter to be used by the distribution companies according to the region where the electricity meter is used. In addition, it will allow the electricity meter manufacturer to develop its measurement method, production quality, and design by taking this situation into account. On the other hand, more effective and efficient controls can be provided by considering the operating error rates of electricity meters in the inspections to be carried out by the public institutions using the developed artificial neural network model. In this way, the quality of the service and the quality of infrastructure provided by metrology can be increased.

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References

1. The Ministry of Trade of Republic of Türkiye. European Green Deal. Available online: https://trade.gov.tr/exports/green-action-plan (accessed on 28 January 2025).
2. Republic of Turkey Energy Market Regulatory Authority. *Electricity Market Sector Report 2023*; Republic of Türkiye Energy Market Regulatory Authority, Strategy Development Department: Ankara, Türkiye, 2024. Available online: https://www.epdk.gov.tr/Detay/Icerik/1-1271/electricityreports (accessed on 28 January 2025).
3. *OIML R46-1/-2*; Edition 2012(E) Active Electrical Energy Meters. Organisation Internationale de Metrologie Legale (OIML): Bucharest, Romania, 2012.
4. Tasci, M.; Duzkaya, H. Investigation of the effect of variable parameters on comprehensive maximum error of active electricity meters by test results. In Proceedings of the 2023 12th International Conference on Renewable Energy Research and Applications (ICRERA), Oshawa, ON, Canada, 29 August–1 September 2023; pp. 73–78.
5. *TS-EN 50470-1*; 2007-Electricity Metering Equipment (a.c.)—Part 1: General Requirements, Tests and Test Conditions—Metering Equipment (Class Indexes A, B, and C). Turkish Standard Institution: Ankara, Türkiye, 2007.
6. Diahovchenko, I.; Volokhin, V.; Kurochkina, V.; Špes, M.; Kosterec, M. Effect of harmonic distortion on electric energy meters of different metrological principles. *Front. Energy* **2019**, *13*, 377–385. [CrossRef]
7. Carstens, H.; Xia, X.; Yadavalli, S. Measurement uncertainty in energy monitoring: Present state of the art. *Renew. Sustain. Energy Rev.* **2018**, *82*, 2791–2805. [CrossRef]
8. Apse-Apsitis, P.; Vitols, K.; Grinfogels, E.; Senfelds, A.; Avotins, A. Electricity meter sensitivity and precision measurements and research on influencing factors for the meter measurements. *IEEE Electromagn. Compat. Mag.* **2018**, *7*, 48–52. [CrossRef]
9. Masnicki, R. Some remarks on the accuracy of energy meters. In Proceedings of the 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Palermo, Italy, 12–15 June 2018.
10. Avancini, D.B.; Rodrigues, J.J.P.C.; Martins, S.G.B.; Rabelo, R.A.L.; Al-Muthadi, J.; Solic, P. Energy meters evolution in smart grids: A review. *J. Clean. Prod.* **2019**, *217*, 702–715. [CrossRef]
11. Shah, A.L.; Mesbah, W.; Al-Awami, A.T. An algorithm for accurate detection and correction of technical and nontechnical losses using smart metering. *IEEE Trans. Instrum. Meas.* **2020**, *69*, 8809–8820. [CrossRef]
12. Kampik, M.; Skórkowski, A.; Pecyna, M.; Sowula, K. The influence of subsequent harmonics of the load current on errors of electronic energy meters. *Energies* **2024**, *17*, 1003. [CrossRef]
13. Xiong, S.; Zhang, J.; Zhang, B.; Sun, G.; Chen, Z.; Qi, J.; Sun, Y. Effects of environmental and electrical factors on metering error and consistency of smart electricity meters. *Appl. Sci.* **2021**, *11*, 11457. [CrossRef]
14. Synder, A.F.; Myers, G. *Modern Electricity Meter Safety, Accuracy and Performance Testing*; EnerNex LLC: Knoxville, TN, USA, 2016; pp. 6–7.
15. Directive 2014/32/EU of the European Parliament and of the Council of 26 February 2014 on the Harmonisation of the Laws of the Member States Relating to the Making Available on the Market of Measuring Instruments (Recast). *Off. J. Eur. Union* **2014**, *L96*, 149–250.
16. Ma, J.; Teng, Z.; Tang, Q.; Qiu, W.; Yang, Y. Measurement error assessment for smart electricity meters under extreme natural environmental stresses. *IEEE Trans. Ind. Inform.* **2022**, *18*, 3905–3914. [CrossRef]
17. *TS-EN 50470-3*; 2022-Electricity Metering Equipment—Part 3: Particular Requirements—Static Meters for AC Active Energy (Class Indexes A, B and C). Turkish Standard Institution: Ankara, Türkiye, 2022.
18. Zhang, J.; Luo, D.; Zhang, Q.; Zhang, B.; Zhu, L.; Wen, H. Evaluation of comprehensive maximum error of power energy meter based on OIML recommendation R46. In Proceedings of the 13th World Congress on Intelligent Control and Automation (WCICA), Changsha, China, 4–8 July 2018; pp. 1031–1036.

19. Zhang, W.; Ma, J.; Duan, J.; Li, N.; Yi, K.; Teng, Z. Performance evaluation for smart electricity meters using machine learning. In Proceedings of the 2nd International Conference on Electronics, Communications and Information Technology (CECIT), Sanya, China, 27–29 December 2021; pp. 830–834.
20. Kurban, A.O. Analysis of shafts surface pressures using neural network. *Ind. Lubr. Tribol.* **2004**, *56*, 217–225. [CrossRef]
21. Dongare, A.D.; Kharde, R.R.; Kachare, A.D. Introduction to artificial neural network. *Int. J. Eng. Innov. Technol. (IJEIT)* **2012**, *2*, 189–194.
22. Hagan, M.T.; Demuth, H.B.; Beale, M.H. *Neural Network Design*, 2nd ed.; Martin Hagan: Stillwater, OK, USA, 2014; pp. 12/1–50.
23. Heaton, J. *Artificial Intelligence for Humans, Volume 3: Deep Learning and Neural Networks*; Heaton Research Inc.: Chesterfield, MO, USA, 2015; pp. 113–132, ISBN 978-1505714340.
24. Cho, V.A. Comparison of three different approaches to tourist arrival forecasting. *Tour. Manag.* **2003**, *24*, 323–330. [CrossRef]
25. Karayiannis, N.; Venetsanopoulos, A.N. *Artificial Neural Networks: Learning Algorithms, Performance Evaluation, and Applications*, 1st ed.; Springer Science & Business Media: New York, NY, USA, 2013; pp. 219–257, ISBN 978-0-7923-9297-2.
26. Gomolka, Z. Backpropagation algorithm with fractional derivatives. *ITM Web Conf.* **2018**, *21*, 1–10. [CrossRef]
27. Riedmiller, M.; Braun, H. A direct adaptive method for faster backpropagation learning: The RPROP algorithm. In Proceedings of the IEEE International Conference on Neural Networks, San Francisco, CA, USA, 28 March–1 April 1993; Volume 1, pp. 586–591.
28. Santra, A.K.; Chakraborty, N.; Sen, S. Prediction of heat transfer due to presence of copper–water nanofluid using resilient-propagation neural network. *Int. J. Therm. Sci.* **2009**, *48*, 1311–1318. [CrossRef]
29. Falhmann, S.E. *An Empirical Study of Learning Speed in Backpropagation Networks*; CMU: Pittsburgh, PA, USA, 1989; pp. 1–17.
30. Aquino, I.; Perez, C.; Chavez, J.K.; Oporto, S. Daily load forecasting using quick propagation neural network with a special holiday encoding. In Proceedings of the 2007 International Joint Conference on Neural Networks, Orlando, FL, USA, 12–17 August 2007; pp. 1935–1940.
31. Kurani, A.; Doshi, P.; Vakharia, A.; Shah, M. A Comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. *Ann. Data Sci.* **2023**, *10*, 183–208. [CrossRef]
32. Jaiswal, S.; Wath, M.G.; Ballal, M.S. Modeling the measurement error of energy meter using NARX model. In Proceedings of the IEEE International Instrumentation and Measurement Technology Conference, Taipei, Taiwan, 23–26 May 2016; pp. 1–6.
33. Stevanović, S.; Dashti, H.; Milosević, M.; Al-Yakoob, S.; Stevanović, D. Comparison of ANN and XGBoost surrogate models trained on small numbers of building energy simulations. *PLoS ONE* **2024**, *19*, e0312573. [CrossRef]
34. Akhtar, S.; Shahzad, S.; Zaheer, A.; Ullah, H.S.; Kilic, H.; Gono, R.; Jasinski, M.; Leonowicz, Z. Short-term load forecasting models: A review of challenges, progress, and the road ahead. *Energies* **2023**, *16*, 4060. [CrossRef]
35. Chanal, A.; Gulia, P.; Gill, N.S.; Chatterjee, J.M. Performance analysis of an optimized ANN model to predict the stability of smart grid. *Complexity* **2022**, *2022*, 7319010.
36. Tan, M.; Hu, C.; Cheni, J.; Wang, L.; Li, Z. Multi-node load forecasting based on multi-task learning with modal feature extraction. *Eng. Appl. Artif. Intell.* **2022**, *112*, 104856. [CrossRef]
37. Feng, C.; Shao, L.; Wang, J.; Zhang, Y.; Wen, F. Short-term load forecasting of distribution transformer supply zones based on federated model-agnostic meta learning. *IEEE Trans. Power Syst.* **2025**, *40*, 31–45. [CrossRef]
38. Tahani, M.; Vakili, M.; Khosrojerdi, S. Experimental evaluation and ANN modeling of thermal conductivity of graphene oxide nanoplatelets/deionized water nanofluid. *Int. Commun. Heat Mass Transf.* **2016**, *76*, 358–365. [CrossRef]
39. Mouloodi, S.; Rahmanpanah, H.; Gohery, S.; Burvill, C.; Dives, H.M.S. Feedforward backpropagation artificial neural networks for predicting mechanical responses in complex nonlinear structures: A study on a long bone. *J. Mech. Behav. Biomed. Mater.* **2022**, *128*, 105079. [CrossRef] [PubMed]
40. Liu, C.; Zhu, L.; Belkin, M. Loss landscapes and optimization in over-parameterized non-linear systems and neural networks. *Appl. Comput. Harmon. Anal.* **2022**, *59*, 85–116. [CrossRef]
41. Wilamowski, B.M.; Yu, H. Improved computation for Levenberg–Marquardt training. *IEEE Trans. Neural Netw.* **2010**, *21*, 930–937. [CrossRef]
42. Yan, Z.; Zhong, S.; Lin, L.; Cui, Z. Adaptive Levenberg–Marquardt algorithm: A New Optimization Strategy for Levenberg–Marquardt neural networks. *Mathematics* **2021**, *9*, 2176. [CrossRef]
43. Revanesh, M.; Gundal, S.S.; Arunkumar, J.R.; Josephson, P.J.; Suhasini, S.; Devi, T.K. Artificial neural networks-based improved Levenberg–Marquardt neural network for energy efficiency and anomaly detection in WSN. *Wirel. Netw.* **2024**, *30*, 5613–5628. [CrossRef]
44. Rokonuzzaman, M.; Rahman, S.; Hannan, M.; Mishu, M.K.; Tan, W.-S.; Rahman, K.S.; Pasupuleti, J.; Amin, N. Levenberg-Marquardt algorithm-based solar PV energy integrated internet of home energy management system. *Appl. Energy* **2025**, *378*, 124407. [CrossRef]
45. Heaton, J. *Introduction to Neural Networks with Java*, 2nd ed.; Heaton Research Inc.: Chesterfield, MO, USA, 2007; pp. 77–106.
46. Xu, Y.; Fenerci, A.; Øiseth, O.; Moan, T. Efficient prediction of wind and wave induced long-term extreme load effects of floating suspension bridges using artificial neural networks and support vector machines. *Ocean Eng.* **2020**, *217*, 107888. [CrossRef]

47. Cuhadar, M.A. Comparative study on modelling and forecasting tourism revenues: The case of Turkey. *Adv. Hosp. Tour. Res. (AHTR)* **2020**, *8*, 235–255. [CrossRef]
48. Mohammadi, K.; Shamshirband, S.; Motamedi, S.; Petković, D.; Hashim, R.; Gocic, M. Extreme learning machine based prediction of daily dew point temperature. *Comput. Electron. Agric.* **2015**, *117*, 214–225. [CrossRef]
49. Afzal, S.; Ziapour, B.M.; Shakri, A.; Shakibi, H.; Sobhani, B. Building energy consumption prediction using multilayer perceptron neural network-assisted models; comparison of different optimization algorithms. *Energy* **2023**, *282*, 128446. [CrossRef]
50. Dellosa, J.T.; Palconit, E.C. Artificial Intelligence (AI) in renewable energy systems: A condensed review of its applications and techniques. In Proceedings of the 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Bari, Italy, 7–10 September 2021.
51. Yaghoubi, E.; Yaghoubi, E.; Khamees, A.; Vakili, A.H. A systematic review and meta-analysis of artificial neural network, machine learning, deep learning, and ensemble learning approaches in field of geotechnical engineering. *Neural Comput. Appl.* **2024**, *36*, 12655–12699. [CrossRef]
52. Patil, V.J.; Khadake, S.B.; Tamboli, D.A.; Mallad, H.M.; Takpere, S.M.; Sawant, V.A. A comprehensive analysis of artificial intelligence integration in electrical engineering. In Proceedings of the 2024 5th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI), Lalitpur, Nepal, 18–19 January 2024.
53. Dunford, R.; Su, Q.; Tamang, E. The Pareto principle. *Plymouth Stud. Sci.* **2014**, *7*, 140–148.
54. Chen, L.; Huang, Y.; Lu, T.; Dang, S.; Kong, Z. Metering equipment running error estimation model based on genetic optimized LM algorithm. *J. Comput. Methods Sci. Eng.* **2022**, *22*, 197–205. [CrossRef]
55. Sumarmad, K.A.A.; Sulaiman, N.; Wahab, N.I.A.; Hizam, H. Microgrid energy management system based on fuzzy logic and monitoring platform for data analysis. *Energies* **2022**, *15*, 4125. [CrossRef]
56. Savacool, B.K.; Hook, A.; Sareen, S.; Geels, F.W. Global sustainability, innovation and governance dynamics of national smart electricity meter transitions. *Glob. Environ. Change* **2021**, *68*, 102272. [CrossRef]

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