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Research Article

Estimation of Current and Voltage Values Generated from a Thermoelectric Generator Mounted on Automobile Exhaust System by Machine Learning Algorithms: A Comparative Study

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Abstract Electricity is one of the most important sources of energy. Many devices need electrical energy to operate. In addition to the production of electrical energy from renewable sources, the fact that it can be produced from waste heat sources will increase efficiency. As in many systems, it is possible to generate electricity by using thermoelectric generators (TEGs) on the waste heat systems of vehicles using internal combustion engines. Thanks to the electricity obtained from waste heat systems, the load on the alternators and batteries in the vehicles is reduced, thus increasing their service life. In addition, since the charging time of the vehicle battery is reduced, fuel savings can be achieved. Therefore, making electricity generation predictions using machine learning algorithms in internal combustion engines will make a great contribution to the initial project planning phase of the design of automobile systems. Nowadays, research on waste heat energy recovery from automobile exhaust with TEGs using machine learning is a new topic. In this study, a data set containing the attributes of 2692 current and voltage values obtained from a thermoelectric generator on an automobile exhaust system was used. AdaBoost and Random Forest machine learning algorithms were used in the estimation process of the designed model. The most successful result was achieved when estimating the current with the AdaBoost algorithm. In this study, it has been shown that with the proposed model, electrical energy production estimation can be made over the waste heat sources of different systems.

Keywords: Thermoelectric generator, waste heat source, machine learning, estimation, performance, measurement

1. INTRODUCTION

It has been established that internal combustion engines have two important sources of heat dissipation, representing about 70%. Exhaust gas (~35-40%) and radiator (~30%) systems are sources of heat dissipation of internal combustion engines. In such engines, recovering some or all of this wasted heat will increase energy efficiency and reduce fuel consumption. Electricity can be produced from wasted waste heat by using thermoelectric generators for waste heat recovery of an internal combustion engine. Thermoelectric generators are seen to be more advantageous than other thermal energy recovery methods due to their environmental friendliness, low noise level as there are no moving parts, no vibration, no working fluid, low maintenance, scalability, modularity, ability to operate in a wide range of temporary temperature conditions, high reliability level and direct conversion of thermal energy into electrical energy [1].

Thermoelectric generators can be used to generate electricity at many points where heat generation occurs in automobiles. Electricity can be generated with the heat from the brake system and the batteries of electric vehicles; especially the exhaust gas waste heat energy [2, 3]. In vehicles with internal combustion engines, the electrical energy produced by thermoelectric generators reduces the load on the alternator and helps to reduce fuel consumption.

Kunt [4] recovered a waste heat from the exhaust gas of an internal combustion gasoline engine. By comparing the experimental results with the simulation results, it was observed that they were compatible with each other. As a result, it obtained a voltage of 6.75 V and a current of 0.65 A at a load resistance of 10 Ω with a temperature difference of 165 OC between hot and cold surfaces.

Albatati et al. [5] conducted an analytical thermal system design and experimental verification of the TEG system for the recovery of waste heat from the exhaust of truck engines. In the study, they used 100 modules in the TEG system and the total power generated by the system was 1.25 kW. It represents 20% of the alternator power requirement of a truck engine and a power density of 1.4 W/cm2. They found that the experiments and simulation values were compatible.

Li et al. [6] conducted a study on the conversion efficiency of the Automotive Thermoelectric Generator (ATEG). In addition, it improved the maximum electrical power generated by ATEG by optimizing the number of thermoelectric modules (TEMs). According to ATEG's optimization results, the maximum electrical power produced by the system was 139.47 W and the conversion efficiency was 2.51% under stationary motor condition. As a result, the optimized design was tested in different engine conditions. They found that when the exhaust inlet temperature was 805 K and the mass flow rate was 0.5 kg/s, the maximum power and efficiency produced by ATEG increased by 49.8% and 106.5%, respectively, after optimization.

Thermoelectric generators can also be operated using electrical energy in vehicles where they need to be heated or cooled [7]. During their operation, no waste energy or harmful gas emissions are generated.

Electrical energy is of great importance in the economic development of nations [8]. Through electrical power generation estimation studies, it is seen that the amount of energy production for any practical situation can be easily estimated without actually carrying out the design [9]. In addition, the predicted results; it has shown that it is possible to have information about energy production by predicting in advance and that the forecast data can be used in electrically efficient load distribution [10].

In recent years, machine learning, which is a sub-branch of deep learning, has attracted great attention due to its strong generalization ability, unsupervised feature learning ability, and ability to receive training from large data [11]. Using machine learning algorithms, predictions are made by making automatic inferences from patterns, trends, and complex relationships of large amounts of data that human analysts cannot see [10].

Machine learning algorithms are widely applied in pattern recognition, image processing, error detection, classification, and prediction tasks [12]. In recent years, learning-based prediction models have proven to be high-performing in terms of accuracy. Energy estimation applications made by using learning methods have started to be widely used [13].

Chang et al. [14] proposed a novel integration method based on deep learning methods for photovoltaic electrical power output estimation during the day. In the study, they showed that computational efficiency by making prediction accuracy is superior to previous studies. Kadar et al. [15] conducted a spatial electric load estimation study of electric vehicles in Hungary. In the study, it was aimed to determine the electrical power demand of electric vehicles and the distribution of electric charging production centers. MdShahiduzzaman et al. [16] created a renewable energy generation forecast model from solar and wind energy in twelve countries. In the study, the predictive success of Support Vector Machine (SVM), Linear Regression (LR) and Long Short-Term Memory (LSTM) algorithms were compared, and more successful results were obtained with the Linear Regression machine learning algorithm. Kishore et al. [17] performed precise and efficient temperature estimation to protect the charge and operating environment of electric vehicles (EV). In the study, energy efficiency for air conditioning and cabin cooling of electric vehicles was aimed by estimating the temperature. Baran et al. [18] applied digital weather forecasting to predict power losses in electricity transmission lines. In the study, they presented a method for estimating resistive power losses in electrical distribution lines. Ullah et al. [19] proposed to efficiently detect electricity thieves in smart grids by designing a hybrid model with machine learning and deep learning methods. In the study, AdaBoost was used as the machine learning method and AlexNet was used as the deep learning model. Chang et al. [20] designed a suitable model to predict the quality of a semiconductor based on machine learning technologies. In the study, they showed that the improved AdaBoost model not only improved prediction accuracy, but also prediction reliability for semiconductor manufacturing. Khudhair et al. [21] established the feasibility of building a smart system to predict electrical energy consumption, as the market share of electricity is expected to increase in the coming decades. Adhya et al. [22] presented a comparative study between three machine learning algorithms to predict the likely charging demand of electric vehicles. In the study, MSE, MAE, RMSE and R-squared value performance measures were used in the comparison process. Ranganathan and Rajagopalan [23] carried out the model for predicting excess energy and user availability for V2G (Vehicle to Grid) services using machine learning algorithms. They used the Mean Absolute Percentage Error (MAPE) scale for the success of the estimation process. Nti et al. [24] reviewed and analyzed 77 academic studies published in the last nine years (2010-2020), in which electricity demand forecasting research was conducted. In the studies, it has been revealed that the Artificial Neural Networks model is mostly used. In the studies, it was observed that the most used error metric was the Root Mean Square Error (RMSE) (38%), and the second was the Average Absolute Percentage Error MAPE (35%). In addition, the study also found that 50% of the electricity demand forecast depends on weather and economic parameters, 38.33% on past energy consumption, 8.33% on household lifestyle, and 3.33% on stock indices. Parhizkar [25] used the Random Forest algorithm to estimate the energy consumption of selected cities with high success. Wang et al. [26] used the MIFS-AdaBoost machine learning algorithm to predict electric vehicles (EV) ownership. In the literature, studies comparing the prediction success of Random Forest and AdaBoost algorithms together have been conducted [27].

In this study, a current and voltage estimation model was created by using the electric current and voltage values produced from the thermoelectric generator mounted on the exhaust system of a Toyota brand car under real driving conditions. AdaBoost and Random Forest machine learning algorithms were used in the prediction model. By using these algorithms, prediction successes were measured and compared according to MSE, RMSE, MAE, MAPE error metric measures and R-squared correlation coefficient according to different training and test data values.

2. MATERIAL AND METHODS

In this study, the designed system is installed on the exhaust pipe of a car, and the combined images of the TEGs are given in Figure 1. Here, it consists of a thermoelectric generator, cables, data loading system, data set and computer system.

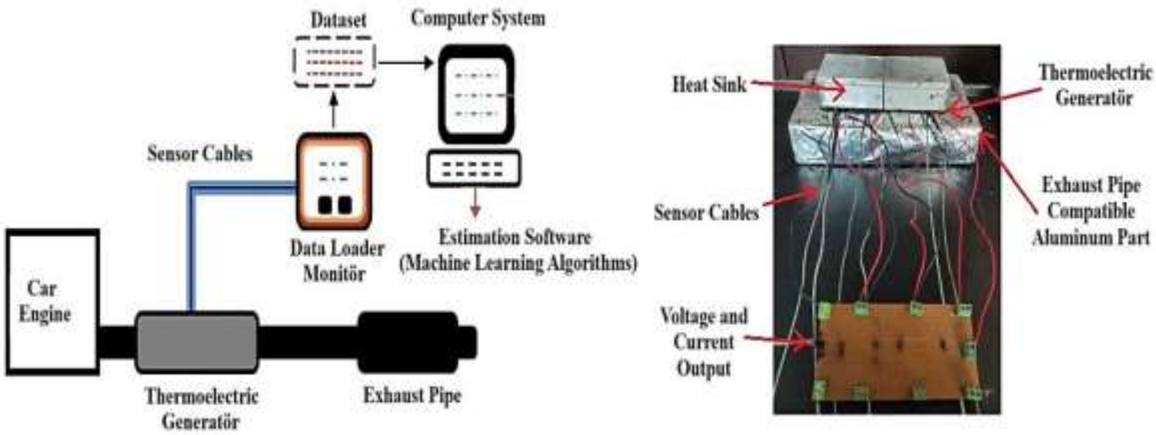


Figure 1: Diagram of the Designed System.

In this system, four TEGs are placed in the vehicle's exhaust pipe. TEGs are cooled with aluminum cooling fins. In addition, temperature sensors are placed to measure the temperatures of the cold and hot areas of the TEGs. While the data from these sensors is recorded with the data loader, the voltage and current information produced by the TEGs is recorded instantly.

Six temperature sensors were connected to the TEG devices. In addition, there is a temperature sensor to measure the temperature of the test environment (outdoors). The temperature data obtained from a total of seven sensors, as well as current and voltage data, were recorded. A data set was created by organizing the recorded data. Machine learning algorithms were trained using randomly selected data (75%, 50% and 25%) from this data set. Current and voltage estimations were made on the trained model using the feature data of randomly selected test data. The estimation values obtained were compared with the actual values and the estimation success was measured.

The vehicle used in the experiments is a 1.6 liter naturally aspirated 2021 model Toyota Corolla. The vehicle has an automatic CVT transmission and can be operated manually if desired. Test drives were carried out in manual mode. The experiments were carried out at the same time and at the same ambient temperature every day. In addition, wind resistance was ignored. Because the thermoelectric generators mounted on the exhaust pipe are inside the shaft tunnel, there is very little chance of exposure to wind. Therefore, wind resistance is ignored. Fans are used to cool the TEGs. Road and driving conditions are given in Table 1.

Table 1: Test conditions for the vehicle and road used for the test.

Test condition definitions	Values
Road length	15.4 km
Ambient temperature	29 ^{o}C
Rolling resistance coefficient	0.0015
Average traffic density	20%
Road surface	Asphalt
Road slope	4 km (landing), 4 km (ascent) and 7.4 km (straight)
Gearbox	6 forward manual
Experiment speeds	40, 60, 80 and 100 km/h
Tyre pressure	221 kPa

2.1. Thermoelectric Generator Structure

Approximately 70% of the heat energy generated in vehicles with internal combustion engines (ICE) is discharged through exhaust, cooling and lubrication systems [28]. This heat energy is called waste heat energy. Waste heat energy discharged through exhaust accounts for approximately 30% of this rate [29]. The heat energy discharged from here, together with the burnt gases, is transferred to the external environment along the exhaust pipe. From the moment they first exit the exhaust manifold, the burnt gases are expelled through the exhaust pipe, losing their temperature. If thermoelectric generators (TEG) are placed in the appropriate sections on the exhaust pipe, electricity is produced from waste heat energy [30-32]. TEGs produce electricity by taking advantage of the temperature difference in their environment [33]. This potential for electricity generation is called the Seebeck effect [34]. TEGs have positive and negative semiconductor pairs connected to each other by copper wires. These pairs are insulated from the external environment with a ceramic plate from the top and bottom (Figure 2).

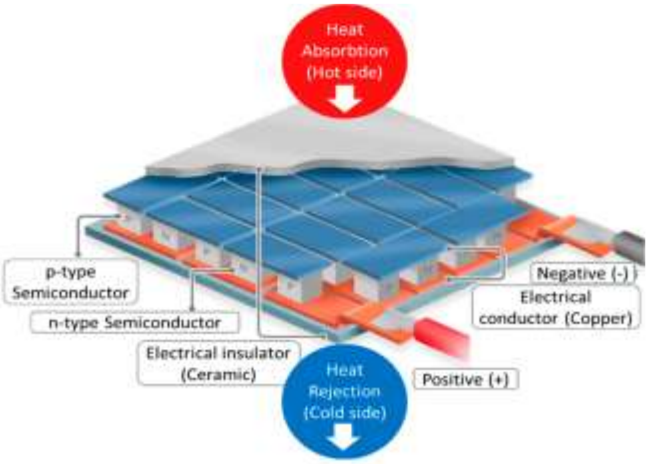


Figure 2: Internal structure of TEG [33].

If the ceramic plates are touched to a cold surface on one side and a hot surface on the other, electricity is produced from the temperature difference in the TEG (Figure 3).

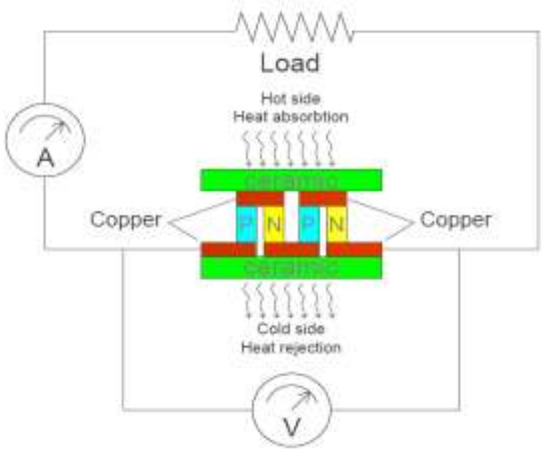


Figure 3: Electricity generation with TEGs [34].

The amount of electricity production in TEGs depends on the magnitude of the temperature difference between hot and cold sources. In internal combustion engines, the temperature of the exhaust gases is around 700 ºC when they first exit the exhaust manifold [35]. This temperature decreases along the exhaust pipe depending on the outdoor temperature. For the best possible electricity generation, it is necessary to place the TEGs close to the exhaust manifold. The cold sides of TEGs face the external environment. This area is cooled by the air flow while the vehicle is moving with the heat exchanger with aluminum cooling fins placed on it. However, when the vehicle stops, it is necessary to place a fan on the heat exchangers for cooling.

2.2. Machine Learning Algorithms

Machine learning algorithms are used for classification and regression forecasting operations in many different areas [36]. It is widely used, healthcare, disease diagnosis prediction [37], depression risk estimation [38], prediction of heating and cooling loads of residential buildings [39], capacity estimation of lithium-ion batteries [40], wind power forecasting [41], Churn prediction in industry [42], charge [43] and carbon emission estimation [44]. In this study, voltage and current estimations that TEG devices can produce were carried out by using AdaBoost and Random Forest algorithms. The machine learning algorithms used can be successfully applied on the data obtained in different roads, vehicles and geographical conditions. However, the attributes of the records in the data set to be processed must be selected correctly.

2.2.1. AdaBoost Machine Learning Algorithm

Freund and Schapire [45] developed AdaBoost.M2 to solve regression problems and named the new method AdaBoost.R in 1997. In this method, regression problems are calculated by reducing classification problems. AdaBoost.R algorithm and introduced the AdaBoostR2 algorithm and obtained successful results [46]. By using this algorithm, it is seen that successful predictions are made to the correct learning structures repeated on the training data [44].

In the AdaBoost algorithm, the data set is reconstructed by adding re-weights for incorrectly estimated samples. In boosting by reweighting all the training examples are used to train the weak learning machine with weights assigned to each example [46]. The flowchart of the AdaBoost algorithm is shown in Figure 4.

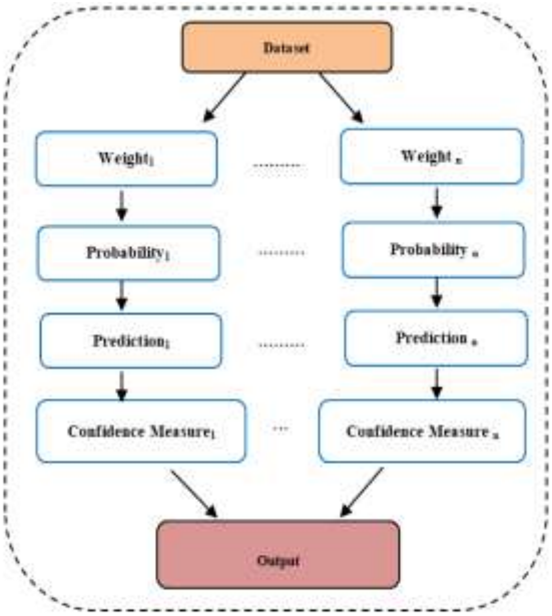


Figure 4: The flowchart of the AdaBoost algorithm

In this algorithm, weight calculations are performed first (with updated results), followed by the generation of probability, prediction function, and reliability coefficient. In the final stage, a new prediction value is produced [39, 46].The weight calculation (recalculation) is presented in equation 1.

$$w_i = w_i \beta^{(1-L_i)} \qquad (1)$$

The probability is computed based on the assigned weight values, as illustrated in equation 2 [46].

$$p_i = \frac{w_i}{\sum w_i} \qquad (2)$$

The prediction process utilizes the computed probability value to identify losses. A linear loss function is adopted in this study, as illustrated in equation 3 [39, 46].

$$L_i = \frac{y_i^p(x_i) - y_i}{D} \qquad (3)$$

The loss function is denoted by L_i and D refers to the distribution. The dataset consists of feature values x_i and y_i. Based on these values, the average loss is computed, as shown in equation 4 [39, 46].

$$\bar{L} = \sum_{i=1}^{n} L_i p_i \qquad (4)$$

Based on the computed loss values, the reliability coefficient is obtained. Its formulation is provided in Equation 5 [46].

$$\beta_i = \frac{\bar{L}}{1-\bar{L}} \qquad (5)$$

The reliability coefficient is represented by β_i. At the final stage, the output prediction value is calculated.

2.2.2. Random Forest Machine Learning Algorithm

The Random Decision Trees (RDT) algorithm, which forms the basis of the Random Forest (RF) algorithm, was first introduced by Ho [47] in 1995. An improved version of this algorithm, the Random Forest algorithm, was developed by Breiman [48]. RF makes classification and regression problems a different model. By using this algorithm, the training phase of training test data is carried out very quickly. Random Forest is made up of a large number of DTs (Decision Trees). In the Random Forest algorithm, there is a difference between decision trees. In this algorithm, records are randomly selected to generate a random forest tree and obtain the result [27]. In the RF algorithm, the most appropriate partitioning is selected from a randomly selected set of features for each intermediate node [49].

The Random Forest algorithm is based on multiple decision trees. In this algorithm, the values of the new data are estimated by averaging the results of the predictions obtained with multiple decision trees. When the correct attributes are selected, they are used in this algorithm to obtain high-success predictions [50]. Many decision trees that act as regression functions are generated using the random forest algorithm. In the final stage, the output of all decision trees is averaged to create the output of the random forest regression [40]. The flowchart of the Random Forest algorithm is shown in Figure 5.

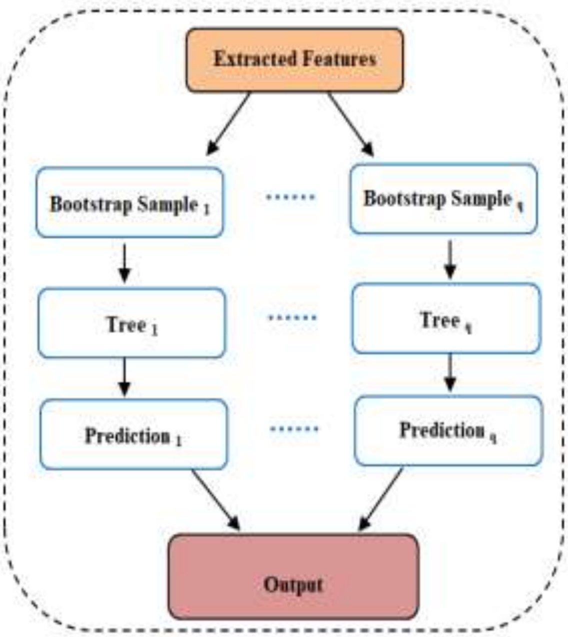


Figure 5: The flowchart of the Random Forest algorithm.

The data set and the attributes of the data in it are shown in the equation 6 [40].

$$S_n = (X_1, Y_1 \ldots . X_n, Y_n) \qquad (6)$$

S_n is data set and X_n, Y_n are features. Prediction function is shown in the equation 7 [40, 48].

$$\hat{Y}q = \hat{h}(X, S_n^{Q_q}) \qquad (7)$$

S_n^{Qq} is bootstrap sample and X is input vector. q prediction trees output numbers. At last output function is shown in equation 8 [40,41]

$$\hat{Y} = \frac{1}{q}\sum_{l=1}^{q} \hat{h}(X, S_n^{Qq}) \qquad (8)$$

L tree-structured based in Random Forest algorithm. $\hat{Y}$ the output of l th tree ($l = 1,2.\dots q$) [40].

2.3. Machine Learning Evaluation Metrics

The MSE, MAE, RMSE, metrics are used in the predictive performance analysis of a model to determine error rates. The R-Squared metric measure is used to evaluate the prediction success performance of a model.

2.3.1. MAE (Mean Absolute Error)

The MAE metric measure is calculated as the average of the absolute error values on a data set. The result represents the difference between the original values and the predicted values. MAE is a popular success measurement metric. Changes in MAE are shown linearly. In this metric, scores increase linearly with increasing errors between the forecast and the original data. The different errors obtained in MAE cannot be weighted more or less. The MAE metric is measured as the average of the absolute error values. Absolute is a mathematical function that used to make numbers for positive. When calculating MAE, it will necessarily be positive. Therefore, the difference can be positive between expected and predicted values. The MAE calculation is shown on equation 3[51].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_1 - y_i| \qquad (3)$$

y_1, represents the actual data, y_i indicates the estimated data, and n indicates the number of test data

2.3.2. MSE (Mean Squared Error)

The MSE metric measure represents the difference between the original and predicted values, which is subtracted by squaring the average difference over the data set. This metric value is measured the mean square error of the mismatch between the predicted results and the test data. A low MSE result value means that the predicted values match the actual values. The MSE calculation is shown on equation 4.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_1 - y_i)^2 \qquad (4)$$

2.3.3. RMSE (Root Mean Squared Error)

The RMSE metric measure is the error rate relative to the square root of the MSE metric measure. The RMSE is calculated in order of magnitude of the observed values. Therefore, it varies significantly from one application to another. The RMSE calculation is shown on equation 5[52].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_1 - y_i)^2} \qquad (5)$$

2.3.4. MAPE (Mean Absolute Percentage Error)

The MAPE metric measure demonstrates the accuracy of a prediction. The size of the error between the estimate and the actual value is calculated. The MAPE calculation is shown on equation 6[51].

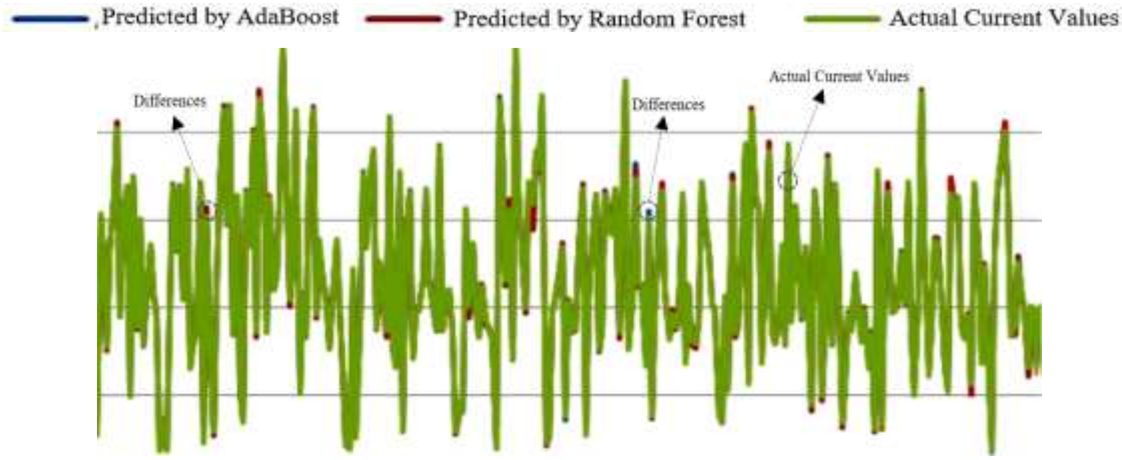
$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_1 - y_i}{y_1}\right| * 100 \qquad (6)$$

2.3.5. R-squared (Coefficient of determination)

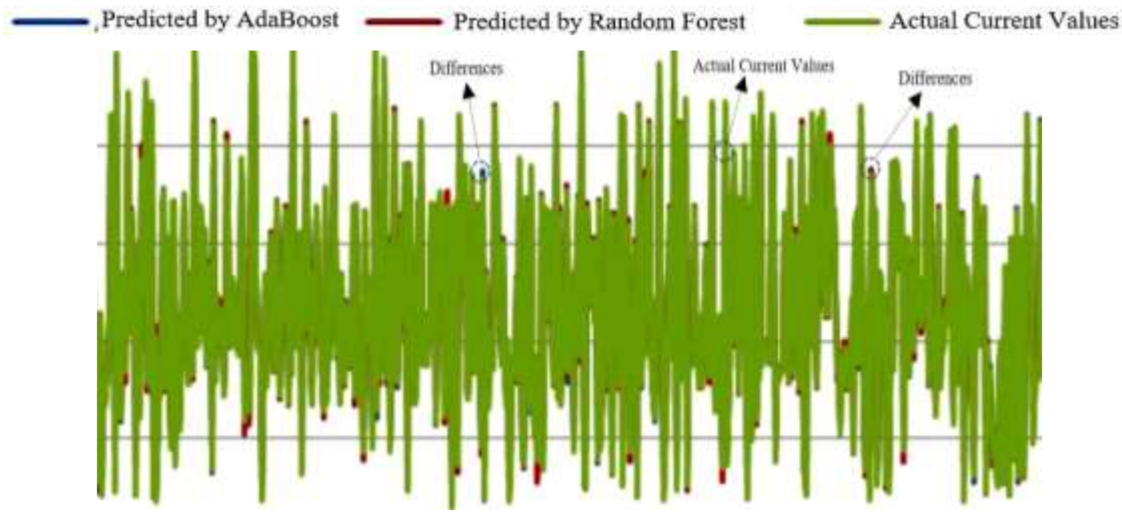
The R-squared (R^2) metric measure represents the coefficient of how well the predicted values fit compared to the original values. The value between 0 and 1 obtained with this metric is interpreted as a percentage. It is used to test how well the model fits the data with linear regression. When the number of terms increases in the designed model, the R-squared value also increases. The value of R-squared data can be positive or negative. If it is negative, a forecast mismatch occurs. The R-squared success calculation is shown on equation 7.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_1 - y_i)^2}{\sum_{i=1}^{n}(y_1 - \overline{y_1})^2} \qquad (7)$$

$\overline{y_1}$ shows the sum of the actual data.



(a)



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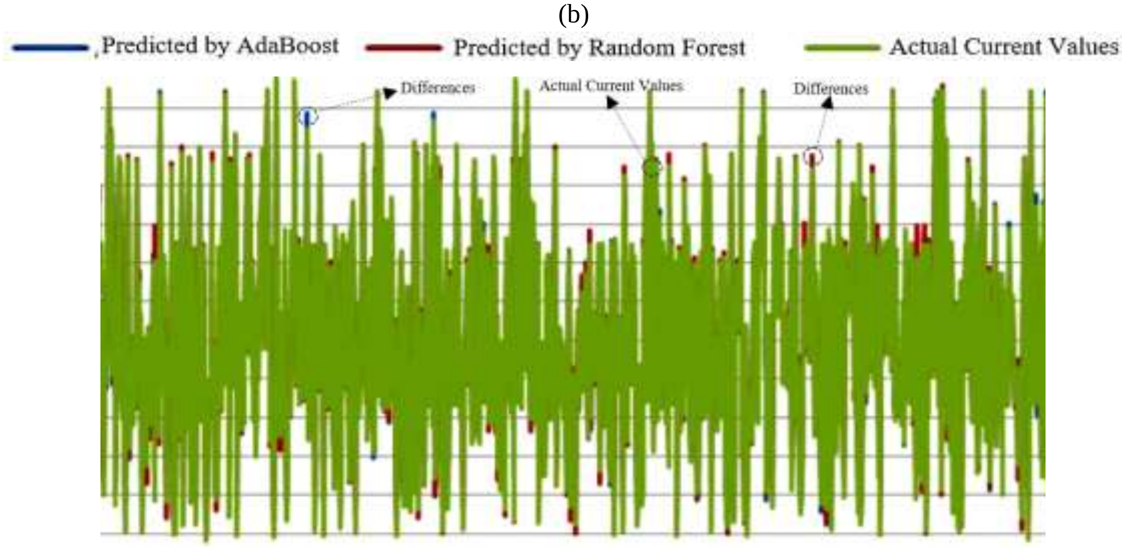
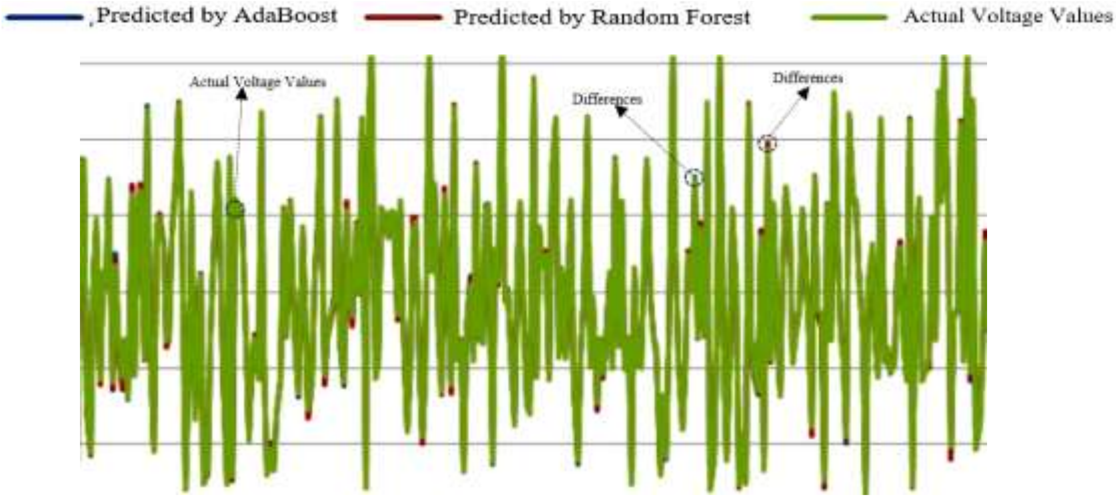
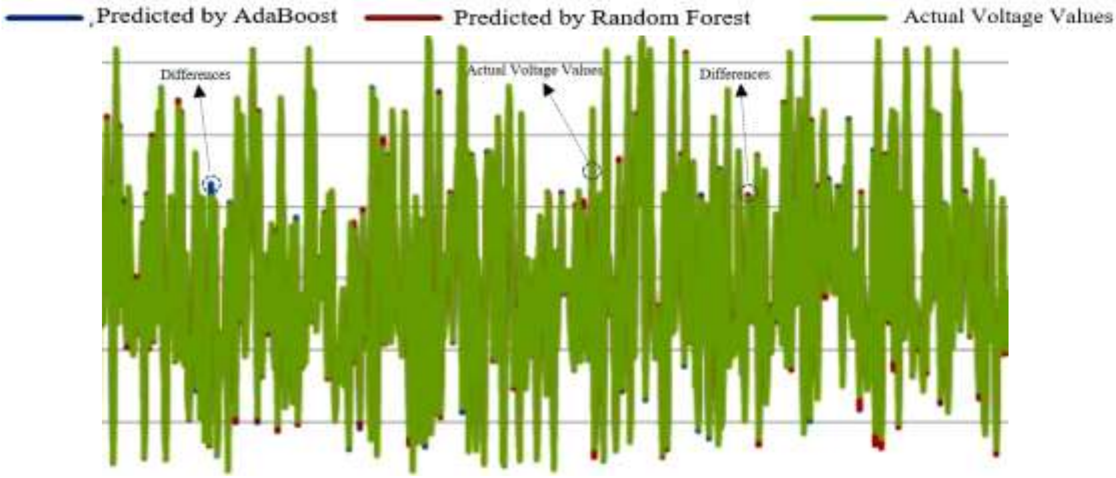


(c)

Figure 6: The differences between actual current values and predicted current values: (a)The predicted current values (for 75% training, 25% test rates) and actual current values; (b)The predicted current values (for 50% training, 50% test rates) and actual current values; (c) The predicted current values (for 25% training, 75% test rates) and actual current values.



(a)



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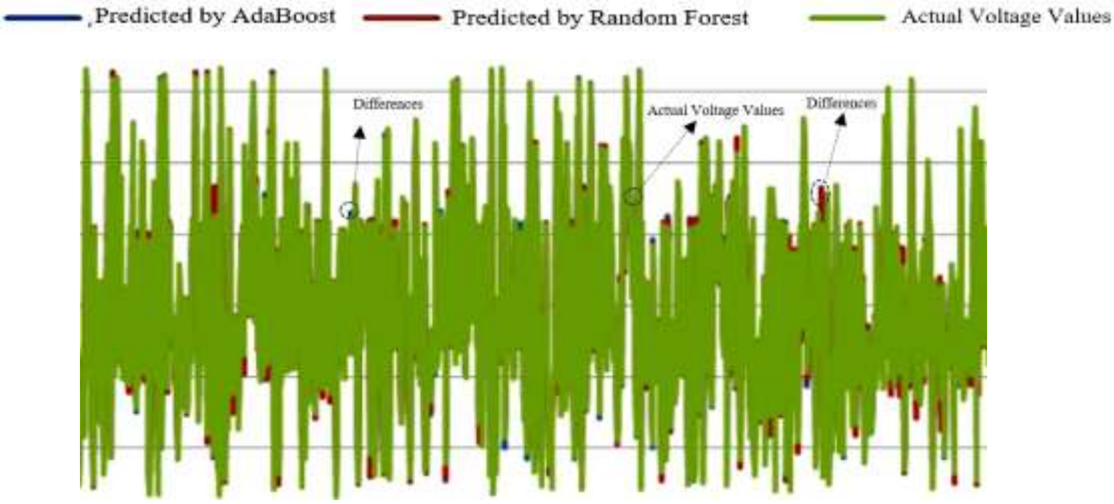

(c)

Figure 7: The differences between actual voltage values and predicted voltage values: (a)The predicted voltage values (for 75% training, 25% test rates) and actual voltage values; (b)The predicted voltage values (for 50% training, 50% test rates) and actual voltage values; (c)The predicted voltage values (for 25% training, 75% test rates) and actual voltage values.

3. EXPERIMENTAL RESULTS

In this study, graphs comparing the current and voltage values estimated according to different training and test data with the actual current and voltage values are shown in Figure 6 and Figure 7. The green plot on the graph shows the actual current values. The blue plot on the graphs shows the values predicted by the AdaBoost algorithm, and the red plot shows the values predicted by the Random Forest algorithm. The intersection of the drawings on the graphs indicates that the forecast success is high. Table 2 shows the data counts and percentages selected for training and testing.

Table 2: The number and percentage ratio of data selected for training and testing.

Train		Test	
Percentage	Number	Percentage	Number
75%	2019	25%	673
50%	1346	50%	1346
25%	673	75%	2019

Figure 6 shows the comparison of the predicted current values obtained by AdaBoost and Random Forest algorithm with the actual (A) values when 75%, 50% and 25% data are selected for training and 25%, 50% and 75% data are selected for testing. In the first model, when 75% data is selected for training and 25% for testing, the difference between the actual current values and the predicted current values is shown in the graph on Figure 6.a. In this model, the highest success is seen because the training data is selected high. In the second model, when the training data is selected at a rate of 50% and the test at a rate of 50%, the difference between the actual current values and the predicted current values is shown in the graph on Figure 6.b. In the third model, when the data is selected at the rate of 25% of the training and 75% of the test, the difference between the actual current values and the predicted current values is shown in the graph on Figure 6.c. In this model, since the training data is selected low, the lowest performance was observed on this graph.

Figure 7 shows the comparison of the actual (A) voltage values with the predicted voltage values by the AdaBoost and Random Forest algorithm when 75%, 50% and 25% data are selected for training and 25%, 50% and 75% data are selected for testing. In the first model, when 75% data is selected for training and 25% for testing, the difference between the actual voltage values and the predicted voltage values is shown in the graph on Figure 7.a. In this model, the highest success is seen because the training data is selected high. In the second model, when the training data is selected at a rate of 50% and the test is selected at a rate of 50%, the difference between the actual voltage values and the predicted voltage values is shown in the graph on Figure 7.b. In the third model, when the training data is 25% and the test is 75%, the difference between the actual voltage values and the predicted voltage values is shown in the graph on Figure 7.c. In this model, since the training data is selected low, the lowest performance was observed on this graph.

In this study, electricity was produced from the heat generated on the exhaust system by using TEG devices. The article provides the test environment, vehicle characteristics, road condition, and load condition. In addition, the basic building blocks of electricity generation are current and voltage values. Therefore, it is of great importance. The comparison of voltage and current estimates produced are showing according to different numbers of training and test data with the actual in the Figure 4 and Figure 5. The red and blue regions on the figures indicate erroneous estimates. From the figures, it can be seen that the error rate is very low. This shows that the results obtained are remarkable.

3.1. Comparison of Results Based on the Performance Metrics

Table 3 shows the success of the current values estimated by AdaBoost and Random Forest algorithms. The MSE metric value was found to be 0.000 in all tests performed on the designed model. The RMSE metric value was found to be 0.004, the highest by the Random Forest algorithm, when 25% data was selected for training and 75% for testing. The MAE metric value was found to be the lowest 0.001 with the AdaBoost algorithm when 75% data was selected for training and 25% data for testing.

Table 3: Success rates of the current estimation.

Model	Train	Test	MSE	RMSE	MAE	MAPE	R^2
AdaBoost	75% (2019)	25% (673)	4×10^{-6}	2×10^{-3}	1×10^{-3}	15×10^{-3}	999×10^{-3}
	50% (1346)	50% (1346)	4×10^{-6}	2×10^{-3}	2×10^{-3}	18×10^{-3}	998×10^{-3}
	25% (673)	75% (2019)	9×10^{-6}	3×10^{-3}	2×10^{-3}	25×10^{-3}	997×10^{-3}
Random Forest	75% (2019)	25% (673)	4×10^{-6}	2×10^{-3}	2×10^{-3}	17×10^{-3}	998×10^{-3}
	50% (1346)	50% (1346)	4×10^{-6}	2×10^{-3}	2×10^{-3}	20×10^{-3}	998×10^{-3}
	25% (673)	75% (2019)	16×10^{-6}	4×10^{-3}	2×10^{-3}	27×10^{-3}	995×10^{-3}

The MAPE metric value was found to be the lowest 0.001 by the AdaBoost algorithm when 75% data was selected for training and 25% data for testing. However, the MAPE metric value was found to be the highest 0.027 by the Random Forest algorithm when 25% of the data was selected for training and 75% for testing. The R2 metric value was found to be the highest 0.999 by the AdaBoost algorithm when 75% of the data was selected for training and 25% for testing. However, the R2 metric value was found to be the lowest 0.995 by the Random Forest algorithm when was selected at a rate of 25% for training and 75% for testing.

Table 4 shows the success of the voltage values estimated by AdaBoost and Random Forest algorithms. The MSE metric value was found to be the lowest 0.010, by the AdaBoost algorithm, when 75% data was selected for training and 25% data was selected for testing on the designed model. However, the MSE metric value was found to be the highest 0.037 by the Random Forest algorithm when 25% of the data was selected for training and 75% for testing. The RMSE metric value was found to be the lowest, 0.098, by the AdaBoost algorithm when 75% of the data was selected for training and 25% for testing. However, the RMSE metric value was found to be the highest, 0.193 by the Random Forest algorithm when 25% The MAE metric value was found to be the lowest 0.070 by the AdaBoost algorithm, when 75% of the data was selected for training and 25% for testing. However, the MAE metric value was found to be the highest 0.130 by the Random Forest algorithm when 25% of the data was selected for training and 75% for testing. The MAPE metric value was found to be the lowest, 0.017, by the AdaBoost algorithm, when 75% of the data was selected for training and 25% for testing. However, the MAPE metric value was found to be the highest 0.033, by the Random Forest algorithm, when 25% data were selected for training and 75% for testing. The R2 metric value was found to be the lowest 0.995, by the Random Forest algorithm, when 25% of the data was selected for training and 75% for testing.

Table 4: Success rates of the voltage estimation.

Model	Train	Test	MSE	RMSE	MAE	MAPE	R^2
	75% (2019)	25% (673)	9604×10^{-6}	98×10^{-3}	70×10^{-3}	17×10^{-3}	999×10^{-3}
AdaBoost	50% (1346)	50% (1346)	11236×10^{-6}	106×10^{-3}	74×10^{-3}	19×10^{-3}	999×10^{-3}
	25% (673)	75% (2019)	26896×10^{-6}	164×10^{-3}	110×10^{-3}	28×10^{-3}	997×10^{-3}
	75% (2019)	25% (673)	10816×10^{-6}	104×10^{-3}	74×10^{-3}	18×10^{-3}	999×10^{-3}
Random Forest	50% (1346)	50% (1346)	13924×10^{-6}	118×10^{-3}	79×10^{-3}	20×10^{-3}	998×10^{-3}
	25% (673)	75% (2019)	37249×10^{-6}	193×10^{-3}	130×10^{-3}	33×10^{-3}	995×10^{-3}

4. DISCUSSION

Artificial intelligence-supported smart models can create very important beneficial results for sustainable energy management and planning. In the literature, many studies have been conducted on energy production and consumption estimations using different models [53]. Energy generation from thermoelectric systems is one of the renewable energy conversion technologies that can convert heat into electricity. In recent years, a large number of model designs have begun to be carried out in the literature to predict and optimize the performance of thermoelectric generator systems [54]. Table 5 presents studies from the literature in which various algorithms have been used for energy production forecasting, as well as regression prediction studies that specifically employ the AdaBoost and Random Forest algorithms. There are important points that distinguish this study from other studies. To the best of our knowledge in existing literature, no other study was found in which real data obtained from thermoelectric generators were used on an automobile exhaust system and current and voltage values estimation using error metrics. In the table, 6 related studies are shown that have been previously conducted using different learning algorithms in the literature. In addition, with the model developed in this study, the achievements obtained in the literature studies were compared with numerical data.

MdShahiduzzaman et al. [16] carried out a renewable energy production forecasting model. It was designed a renewable energy forecasting model for twelve (12) countries in the study. It was used three machine learning model as Support Vector Machine, Linear Regression, and Long Short-Term Memory (LSTM) in the estimation process. According to the results, the Linear Regression algorithm found at least error rate of 2.282 according to the MAE metric measurement, 9.592 according to the MSE metric measurement, and 3.097 according to the RMSE metric measurement.

Cetin et al. [53] used a new geothermal-thermoelectric hybrid system to predict electrical power generation using smart models. In the study, it has been shown that it can be used to predict real-time power production by using artificial intelligence-supported smart models based on machine learning algorithms. In the study, a model was designed to predict energy production from waste geothermal fluid on a real test platform. Support Vector Machine (SVM), Support Vector Regression, k-Nearest Neighbor, Decision Tree (DT), Random Forest, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Categorical Gradient Boosting (CatBoost) algorithms were used in the estimation model. According to the results obtained, power generation estimates were obtained with 98.7% accuracy according to the R2 metric with LightGBM learning algorithms. The study shows that the models used to classify different hot and cold water levels have high classification performance.

Table 5: Comparison with studies in the literature.

Researcher	Estimation process	Algorithm	Success / Error Rate
Angeline et al. [9]	Performance estimation of thermoelectric generator (Matlab simulation)	Artificial Neural Network	MER<0.03
MdShahiduzzaman et al. [16]	Renewable energy production	Linear Regression	MSE=9.592 MAE=2.282 RMSE=3.097
Cetin et al. [53]	Estimation of electrical power generation that can be generated from a geothermal-thermoelectric hybrid system (Real data)	Light gradient boosting machine (LightGBM)	R2=0.987
Belovski et al. [55]	Voltage production estimation of thermoelectric generator (Matlab simulation)	Artificial Neural Network	MSE=0.143
Ozbektas et al. [56]	Current production estimation of thermoelectric generator (Real data)	Artificial Neural Network	R2=0.995 MAE=0.006 MSE= $8.32*10^{-5}$ RMSE=$9.12*10^{-3}$
	Voltage production estimation of thermoelectric generator (Real data)		R2=0.982 MAE=0.061 MSE=0.007 RMSE=0.086
	Power production estimation of thermoelectric generator (Real data)		R2=0.942 MAE=0.025 MSE= 0.001 RMSE=0.037
	Efficiency production estimation of thermoelectric generator (Real data)		R2=0.980 MAE=$5.1*10^{-4}$ MSE= $4.22*10^{-7}$ RMSE=$6.4.10^{-5}$
Celik et al. [57]	Electric power production prediction and classification of thermoelectric generator (Real data)	Random Forest	Accuracy=96.6%
Proposed Model	Current production estimation of thermoelectric generator (Real data)	AdaBoost	MSE=0.000 RMSE=0.002 MAE=0.001 MAPE=0.015 R2=0.999
	Voltage production estimation of thermoelectric generator (Real data)	AdaBoost	MSE=0.010 RMSE=0.098 MAE=0.070 MAPE=0.017 R2=0.999

Angeline et al. [9] performed performance estimation of a hybrid thermoelectric generator using the artificial neural networks tool on the simulation created on MATLAB software under various temperature, load and series conditions. The simulated parameters (up to an inlet heater temperature of approx. 250 °C) were compared with the experimental results. For all parameter values, the mean error rate (MER) between the experimental approach and the ANN-based approach was found to be less than 0.03.

Belovski et al. [55] designed the Seebeck module on the Matlab. In the study, they performed voltage production estimation with the ANN algorithm using the data they received from the thermoelectric generator simulation. In the study, the direct conversion of temperature differences into electrical energy was modeled using the Seebeck module. Using this model, the electrical voltage values generated from the thermoelectric generator simulation were obtained. Then, the voltage values produced by the thermoelectric generator simulation module were compared with the voltage estimation values obtained by the ANN algorithm and the estimation error rates were compared. According to the results, it was found an error rate of 0.143 in the MSE metric measurement.

Ozbektas et al. [56] performed performance comparison by estimating the effects of load resistance and heat input on TEG performance using ANN models on an experimental set. In the study, three-dimensional finite volume methods were applied using ANSYS software and the results were compared with experimental and ANN estimation results in terms of voltage, current, power output and efficiency. According to the study, according to the correlation of determination (R2), mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) performance metrics, 0.9958, 0.0061, 0.0000832, 0.00912 for current; 0.982, 0.0611, 0.0075, 0.086 for voltage; 0.9422, 0.025, 0.0014, 0.037 for power and 0.98056, 0.00051, 4.22*10-7, 0.000064 for efficiency results were obtained. According to the results obtained; the results of the ANN forecast model and the actual data are very close to each other.

Celik et al. [57] designed a model for prediction seven electric power classification using Random Forest, Support Vector Machine and Naive Bayes machine learning algorithms. In the model, 76% of the dataset was used for training and 24% was used for testing process. In the study, classification prediction success was achieved rate of 96.6% by Random Forest algorithm, 94.6% using the Support Vector Machine algorithm and 76.7% using the Naive Bayes algorithm. In the study accuracy success metric was used for classification prediction. According to the obtained results; electrical power classification process was predicted more successfully by Random Forest machine learning algorithm.

In the proposed model, the current and voltage values that can be produced from the thermoelectric generator on an automobile exhaust system were estimated with AdaBoost and Random Forest algorithms.

According to the results obtained, it was seen that the AdaBoost algorithm made a more successful prediction. When the current estimation was made with the AdaBoost algorithm, 0.000 values were obtained according to the MSE metric measurement, 0.002 according to the RMSE metric measurement, 0.001 according to the MAE metric measurement, 0.015 according to the MAPE metric measurement and 0.999 according to the R2 correlation coefficient. In addition, when voltage estimation was made with the AdaBoost algorithm, values of 0.010 were obtained according to the MSE metric measurement, 0.098 according to the RMSE metric measurement, 0.070 according to the MAE metric measurement, 0.017 according to the MAPE metric measurement and 0.999 according to the R2 correlation coefficient. When compared with all studies in the literature, it is seen that the R2 correlation coefficient in the proposed model is the highest. In addition, it is seen that the estimation is made with the least error rate compared to other studies with an error rate of 0.000 according to the MSE metric in the current production estimation. When compared with other metrics, it is seen that the error rates are small. The results obtained show that artificial intelligence models can effectively use waste thermal energy and contribute to electrical energy production. Unlike the study by Ozbektas et al. [56], this research employs alternative forecasting models. Furthermore, it differs from the work of Celik et al. [57] in terms of the predicted and classified output variables.

5. CONCLUSION

In the study, a dataset consisting of the current and voltage values obtained from the TEG mounted on the exhaust system was created which is the waste heat source of an automobile. In the study, the data obtained from the thermoelectric generator on the exhaust system in the real driving environment on the determined route were recorded with the help of a data recorder. In the data set consisting of 2692 records, there are 10 attribute data for each record, including speed, engine speed, gear, outdoor temperature and temperature values of the 6 channels of the TEG. Using this data set, current and voltage estimations were made by machine learning algorithms for future states. AdaBoost and Random Forest machine learning algorithms were used for prediction. In the study different training and test rates were used for comparing and verifying prediction performance results. When 75% for training and 25% for the test records were selected from this data set randomly, the estimation was performed more successful with the AdaBoost machine learning algorithms. MSE, RMSE, MAE, MAPE error metrics and R2 correlation coefficient success metrics were used as estimation measurement parameters. The limited number of TEGs and the application of only one vehicle to the exhaust system can be seen as the limit of the study. TEG performance is achieved through effective cooling of cold surfaces. In our study, cooling is achieved with fans. Liquid cooling systems are being considered for future studies, allowing for more effective and stable cooling. In future studies, it is planned to make voltage and current estimates that can be produced with TEG devices on the waste heat systems of different vehicles/machines using others types of learning algorithms. In addition, it is thought that our study, which is a new topic in the literature, will help the future applications of exhaust gas waste heat recovery prediction of automobiles using TEGs.

Authors' Contributions

In this study, authors contributed equally to the study.

Competing Interests

The authors declare that they have no conflict of interest.

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