Prediction of electricity energy consumption including COVID-19 precautions using the hybrid MLR-FFANN optimized with the stochastic fractal search with fitness distance balance algorithm

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Abstract
The increase in energy consumption is affected by the developments in technology as well as the global population growth. Increasing energy consumption makes it difficult to ensure electrical energy supply security. Meeting the energy demand can be achieved with the right planning. Proper planning is critical for both economical use of resources and low cost for the end consumer. On the other hand, erroneous estimation of demand may cause waste of resources and energy crisis. Accurate estimation is possible by accurately modeling the factors affecting electricity consumption. Apart from known factors such as seasonal conditions, days of the week and hours, modeling in extreme events such as pandemics that affect all our behaviors increases the success in modeling the future projection. This ensures that the security of electrical energy supply is carried out effectively with limited resources. For this purpose, in this study, a hybrid multiple linear regression-feedforward artificial neural network (MLR-FFANN) based algorithm model was proposed, taking into account the estimated impact of the COVID-19 pandemic on the energy consumption values of Bursa, an industrial city in Turkey. The aim of the hybrid MLR-FFANN approach was to simultaneously optimize the polynomial for multiple linear regression and the weight and bias coefficients for the forward propagation neural network using the adaptive guided differential evolution, equilibrium optimizer, slime mold algorithm, and stochastic fractal search with fitness distance balance (SFSFDB) optimization algorithms. The success of the model whose parameters were optimized using the optimization algorithms was determined according to mean absolute error, mean absolute percentage error, and root mean square error evaluation criteria and statistical analysis of these results. According to the results of the analysis, the MLR-FFANN approach whose parameters were optimized with the SFSFDB algorithm was more successful in the training of the dataset containing the COVID-19 precautions.

KEYWORDS
COVID-19 precautions, energy consumption, MLR-FFANN algorithm, optimization, SFSFDB algorithm
1 | INTRODUCTION

1.1 | Background, definitions, and motivation

Today, meeting electrical energy demands is a very difficult problem considering the increasing population, industrialization, depletion of fossil resources, and increasing environmental concerns. In addition to fossil fuels, there is a need to meet increasing energy demands with low-cost and environmentally friendly renewable resources. However, as renewable energy sources are dependent on nature and exhibit seasonal characteristics, such energy production requires planning. Therefore, today, diversifying energy and ensuring supply security play a critical role for countries. Successful planning of resources means efficient use of energy and preventing waste of resources. By using estimation methods, short-, medium-, and long-term electricity consumption amounts can be determined and necessary measures can be taken to ensure a secure energy supply. The consumption of electric energy is affected by human activities and seasonal factors such as air temperature and humidity. However, the presence of unexpected circumstances also affects the success of the plans. The COVID-19 pandemic has affected the activities of the global community and as a result, has been reflected in the impact on the electricity consumption sector. The demand for electric energy is affected by human activities and mobility. Therefore, the restrictions brought about by countries during pandemic periods will affect their electricity consumption.1,2

1.2 | Related work

Prediction of electricity consumption over the short, medium, and long term can be carried out in any city, country, building, or structure. Consumption estimation can be performed with mathematical modeling such as least squares, regression analysis, artificial intelligence, or machine learning approaches including the genetic algorithm and fuzzy logic.3,4 In the literature, many estimation methods have been presented comparatively for different time periods. Regression methods, Kalman filter-based forecasting, artificial intelligence techniques, deep recurrent neural networks, and hybrids of these techniques have been used successfully in the forecasting of electricity demand.5–7 Chen and Lee proposed an adaptive network-based fuzzy system (ANFIS) method for estimating electricity consumption in public buildings. In their study, a multiple ANFIS approach was presented to predict electricity consumption based on human activities and weather conditions. Temperature, precipitation, sunshine duration, insolation radiation, humidity, working days, school days, and holidays were determined as inputs to the ANFIS model. The performance of the proposed method was compared with the Levenberg–Marquardt back propagation (LM-BP) neural network, single ANFIS model, and linear and nonlinear regression. Although the method outperformed simple regression models, it underperformed compared to the single ANFIS and LM-BP.8 Similar to consumption in buildings, electricity consumption estimates have been carried out within cities, countries, and areas directly affected by human use. The support vector regression (SVR) model was used to estimate the daily electricity consumption of a metro station. In this model, similar to the previous model, meteorological data such as air temperature and relative humidity were used as input data that affected consumption. Five-fold-cross-validation with the genetic algorithm was used to optimize the hyper-parameters of the SVR to improve its performance.9 In addition to the aforementioned input parameters, wind speed and direction, day, and time information have also been used in the estimation of electricity consumption.10 Parametric and nonparametric AutoRegressive (AR, NPAR), Smooth Transition AutoRegressive (STAR), and AutoRegressive Moving Average (ARMA) models were used in a study in which the medium-term electricity consumption estimation of Pakistan was carried out. It was stated that among the proposed methods, ARMA performed better than the other models.11 A multivariate gray estimation model based on first-order linear difference equations was proposed for long-term electricity consumption estimation for Shanxi City (China). In that study, it was stated that electricity consumption was affected by factors such as seasons, holidays, political conditions, technological development level, and the economy.12 In addition to daily and annual forecasts, hourly forecasts can be made over a much shorter term. The hourly electricity consumption of a building was estimated using artificial neural network (ANN) and case-based reasoning (CBR) methods. It was determined that the performance of the ANN was better than that of the CBR. Although a relatively large dataset is needed for ANNs to be successful, it has been stated that CBR can perform estimation with relatively less data.13 It has also been determined in similar studies that in order to provide acceptable accuracy, an ANN should have a sufficient number of samples.14 Estimation of electricity consumption was also carried out for different areas such as polymer material production15 and electric vehicle charging stations.16 Wang et al. proposed a model called ESN-DE, which uses an improved echo state network (ESN) to perform the estimation of electrical energy consumption. In the proposed model, the differential evolution (DE) algorithm is used to find the optimal values of three important parameters of the ESN. According to the results obtained, it has been determined that the ESN-DE algorithm gives better results than the basic ESN and ESN-GA. Therefore, the ESN-DE is a potential candidate for the estimation of electrical energy consumption due to its easy implementation and stability.17 In another study by the authors, the ESN and fruit fly optimization algorithm (FOA) approach were designed to predict medium-term industrial electricity consumption in China. Numerical results indicate that adaboostsp-ESN with FOA is successful in predicting future industrial electricity consumption.18 Zhou et al. proposed a new model for electricity consumption named panel semi-parametric quantile regression NN (PSQRNN). The PSQRNN estimation results have been reported to perform better when compared to back propagation NN (BPNN), support vector machine (SVM) and quantile regression neural network (QRNN).19 Artificial intelligence algorithms,
such as neural network models based on various neural networks and optimization algorithms, have been applied in a variety of science fields. For example, these methods have been successfully used to calculate the viscosity of natural gas, the MMP of pure and impure CO$_2$ flux, the density of CO$_2$ adsorption on activated carbon, and the estimation of the viscosity of self-diverting acids.\textsuperscript{20–23}

The COVID-19 pandemic, which swept throughout the globe before the end of 2019, prompted countries around the world to take immediate anti-pandemic measures in all sectors of life. The epidemic period, which continues until today, is affected every sector both commercially and scientifically. In the literature, the impact of the pandemic on many sectors in different countries has been examined. In scientific studies, Chen et al., used mixed data sampling (MIDAS) and extension models to estimate the variability of China’s crude oil futures with high frequency data. It was determined that the MIDAS-RV-CJ model was more successful in the short term, while the MIDAS-RV-L model gave better results in long-term predictions. Furthermore, it has been reported that the leverage effect is the strongest predictor of the COVID-19 pandemic based on the samples collected during the pandemic.\textsuperscript{24} In another study, Wu et al. analyzed the US oil markets based on social media information using convolutional NN (CNN) during the COVID-19 process. The results obtained from the experimental studies showed that although social media information contributes to the estimation of oil price, production and consumption, the oil inventory does not affect the estimation accuracy.\textsuperscript{25} Considering the electricity consumption in terms of the energy sector worldwide, it is seen that electricity consumption is affected like other sectors due to the restrictions applied during the COVID-19 pandemic period.\textsuperscript{1} In order to examine the impact of COVID-19 in Turkey, the effect of the number of daily cases on electricity consumption was examined. In the analysis, it was determined that there was an inverse relationship between the number of cases and electricity consumption.\textsuperscript{26} Similar to the example of Turkey, the electricity consumption of Spain, one of the countries most affected by the pandemic, has been examined in detail. In the March–April period, a decrease of approximately 13.49% was determined by taking the average of the previous 5 years as a reference.\textsuperscript{1} A similar analysis was carried out in nine European countries and the USA, and the consumption differences between countries were examined. It was determined that the differences were the result of the different restrictions carried out in those countries.\textsuperscript{27} From this point of view, the degree of restrictions imposed by countries is an important factor in electricity consumption. Almost no reduction in electricity demand was detected in Norway, which took a much less strict stance in terms of restrictions. Whereas electricity demand decreased by 8% in the USA, decreases by 20%, 25%, and 28%, respectively, were observed in France, Spain, and Italy, which had tight lockdown policies.\textsuperscript{28}

1.3 Contribution of the article

Accurate realization of demand forecasting is important for economical generation of electric energy. An overestimation of demand may waste resources, whereas underestimation may lead to energy crises. In this context, energy supply security could be ensured through government policies and maintenance-investment plans.\textsuperscript{2} In the literature, parameters that affect electricity consumption include the economy, industry, climate, ambient temperature, solar radiation, humidity, wind speed, working days, and the gross domestic product.\textsuperscript{29,30} However, apart from these classical studies, no examination of extraordinary situations such as pandemics has been carried out. Moreover, for countries that have followed a partial closure system, regional or city-based studies are important in obtaining critical results.

The main contributions of the study can be listed as follows.

- This study discusses in a comparative way the effect of the COVID-19 pandemic, which has impacted the whole world with an unexpected speed, on electricity consumption and the estimation of this effect using flexible calculation methods.
- One of the most important contributions of the study is to reveal the electricity consumption behavior under the influence of COVID-19 in Bursa, an industrial city of Turkey, and to create a strategy for future pandemic periods.
- For the first time, the stochastic fractal search with fitness distance balance (SFSFDB) algorithm was adapted and simulated for the proposed hybrid multiple linear regression-feedforward artificial neural network (MLR-FFANN).
- The design of the optimal structure of the feedforward artificial neural network (FFANN) and the determination of the $\beta$ polynomial coefficients of the (multi-linear regression) MLR were carried out during the training process, and these can be defined as the most important factors for training the proposed hybrid MLR-FFANN.
- Combinations of hyperbolic tangent and sigmoid activation functions were used in the hidden and output layers of the FFANN and the success of these combinations in the training and learning process of the proposed hybrid MLR-FFANN approach was investigated.
- The SFSFDB algorithm was broadly compared to and outperformed the adaptive guided differential evolution algorithm (AGDE),\textsuperscript{31} equilibrium optimizer (EO),\textsuperscript{32} and slime mold algorithm (SMA).\textsuperscript{33}
- The SFSFDB algorithm successfully trained the hybrid MLR-FFANN in a minor number of iterations and found the optimal value of weight, bias, and $\beta$ polynomial coefficients of both simultaneously.
- The simulation results were analyzed statistically and according to the results, the SFSFDB algorithm was proven to be more successful in training the MLR-FFANN algorithm proposed in the prediction dataset compared to the other optimization algorithms.
1.4 Organization of the study

The rest of the study article is organized as follows:

- The progress of the pandemic in Turkey and its effect on energy consumption is discussed in Section 2.
- In Section 3, MLR-FFANN, SFS, and SFSFDB algorithms are explained.
- Section 4 provides detailed information on the application of the SFSFDB optimization algorithm to the hybrid MLR-FFANN model.
- Section 5 focuses on the analysis of the experimental results under different operational scenarios.
- Finally, Section 6 provides the conclusions drawn from this study and ideas for future works.

2 PROGRESS OF THE PANDEMIC IN TURKEY AND ITS EFFECT ON ENERGY CONSUMPTION

In this section, Turkey’s energy outlook and Bursa’s electric energy production and consumption are detailed. The course of the pandemic in Turkey and the measures taken by the government against the pandemic are examined.

2.1 Situation of the city of Bursa

According to the 2020 data, the population of Bursa is 3,101,832, making it the fourth largest city in Turkey in terms of population. For a clearer understanding of Bursa’s position in Turkey, data on industry and electricity consumption are given in Table 1.

The total electricity consumption value per person in Bursa is above the national average. Similarly, industrial electricity consumption per person for Bursa is high in all of the years mentioned. The number of enterprises, as an important parameter of the industry indicator, realized in Bursa corresponds to approximately 3.88% of the number of enterprises realized in Turkey. In addition, an average of 6.29% of the exports produced in Turkey for the specified years originated from Bursa. Considering all these indicators, Bursa is seen as an important industrial city.

2.2 Electricity energy outlook in Turkey

Turkey has a growing population and strong economic growth. This is also reflected in the energy requirements. In the last 10 years, the Turkish economy has grown around 5% on average. This growth also increases energy consumption and makes it difficult to ensure energy supply security. Consequently, in order to ensure energy supply security, installed power has been continuously increasing, especially after 2000. The installed power, which was 27,264.1 MW in 2000 and 49,524.1 MW in 2010, reached 96,709.6 MW as of February 2021. As of February 2021, the installed power values according to their sources are given in Figure 1.

| Table 1 Indicators of Bursa and Turkey |
|----------------------------------------|
| Indicator                              | Bursa 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
| Exports (thousand $)                   | Bursa 9,970,943 | 9,140,463 | 10,364,727 | 11,066,414 | 11,716,921 | 10,371,117 | 9,076,069 |
|                                        | Turkey 166,504,862 | 150,982,114 | 149,246,999 | 164,494,619 | 177,168,756 | 171,464,945 | 160,514,811 |
| The number of enterprises              | Bursa 126,554 | 128,169 | 131,407 | 136,322 | 140,633 | 147,618 | 153,435 |
|                                        | Turkey 3,397,724 | 3,434,912 | 3,498,586 | 3,608,470 | 3,696,004 | 3,845,951 | 3,954,698 |
| Gross domestic product per person ($)  | Bursa 14,282 | 13,829 | 12,537 | 12,270 | 12,132 | 11,451 | 10,382 |
|                                        | Turkey 12,582 | 12,178 | 11,085 | 10,964 | 10,696 | 9792 | 9213 |
| Total electricity consumption per person (kWh) | Bursa 3427 | 3455 | 3733 | 3726 | 4106 | 4246 | 3094 |
|                                        | Turkey 2583 | 2669 | 2760 | 2897 | 3082 | 3149 | 4155 |
| Industrial electricity consumption per person (kWh) | Bursa 2135 | 2087 | 2310 | 2251 | 2574 | 2649 | - |
|                                        | Turkey 1216 | 1258 | 1315 | 1357 | 1441 | 1435 | - |
Between 2000 and 2009, oil prices increased by 76% and natural gas prices by 114%. According to the projections made for the years 2015–2040, an increase of 186.3% in oil prices and 85.7% in natural gas prices is expected. Considering the price instability in fossil fuels and the depletion of resources, renewable energy sources come to the fore as an alternative. Figure 1 shows that 50.05% of Turkey’s installed power consists of renewable resources. Among renewable resources, hydraulic resources take the first place, with 31,177.9 MW. With the licensed power plant investments that were temporarily accepted in 2020, the amount of additional installed power is 5430.31 MW. Only 60.80 MW of this additional power amount is from fossil fuel. The investments made can be evaluated as an indicator of the importance given to renewable energy in Turkey. In addition, with these investments, the energy supply will not be secured with imported resources, but with clean and renewable resources without fuel costs.

According to the market development report published by the Energy Market Regulatory Authority, the total licensed electricity generation amount in Turkey in 2019 was 294,251,318.65 MWh, with Bursa contributing at a rate of 2.49%, or 7,322,483.15 MWh. Whereas the total licensed installed power of Turkey was 84,957.72 MW as of 2019, that of Bursa constituted 3.07% of this power, with 2607.03 MW. The unlicensed installed power was 6309.27 MW in Turkey for 2019, whereas in Bursa it was 70.54 MW, making up 1.12%. Unlicensed electricity generation in Turkey amounted to 9,829,447.73 MWh in total for 2019, with Bursa contributing 97,251.79 MWh (0.99%). When the electricity consumption values are examined, the total consumption billed for 2019 was 229,597,913.65 MWh in Turkey and 11,813,549.28 MWh in Bursa. With a share of 5.15%, Bursa was the city with the fourth highest electricity consumption in Turkey. Consumption amounts billed on a consumer basis are given in Table 2.

Considering the consumption amounts for Bursa, the highest was realized in the industrial section, followed by the commercial establishments. Considering its share in total consumption and the amounts by type of consumer, Bursa is seen as a robust industrial city.

2.3 Course of the COVID-19 pandemic

The World Health Organization (WHO) gave the first notification for the coronavirus pandemic on December 31, 2019, by reporting that the disease was seen in China. On March 11, WHO declared the outbreak a pandemic. As of March 13, 2021, according to the data announced by WHO, the number of cases in the world was 118,754,336 and the number of deaths was 2,634,370. These figures forced governments to take strict actions. The measures taken caused difficulties for people and countries both socially and economically.

There were significant changes in the work, education, shopping, and entertainment habits during the pandemic period. Societies were forced to carry out many activities remotely or in accordance with social distancing rules. It was important to provide uninterrupted health services during these critical measures. In order for all these services to be carried out safely, electric energy had to be provided without any problems. Gradual restrictions were introduced in Turkey with the occurrence of cases in March 2020. Due to these restrictions, periodic closures or capacity reductions were experienced in the manufacturing sector. These restrictions and slowdowns in activities were also reflected in the electricity consumption. Figure 2 presents the change in consumption for the years 2019 and 2020.

Especially in April and May, a significant decrease was observed in consumption amounts, followed by a recovery. In August, as a continuation of this recovery, 2020 consumption increased compared to the same time period of the previous year, and this trend continued until the end of the year.
FIGURE 2   Electricity consumption amounts

COVID-19 has caused a decrease in electricity demand in many countries and an increase in the share of renewable energy sources in electricity production. In a study carried out in Germany, energy production from renewable sources increased by 8% in the first quarter of 2020, taking the same period of 2019 as a reference.41 Similarly, in a study conducted in Italy, the effect of COVID-19 on electricity consumption was examined by taking into account its environmental dimensions. It was determined that the significantly reduced electricity consumption was supported by wind-based generation, resulting in a 30% decrease in wholesale energy prices. This has also had a positive impact on reducing carbon dioxide emissions. In addition, the researchers observed that the decrease in consumption affected the amount of energy supplied from traditional (thermal) sources.42

In order to reduce and control the impact of the pandemic, governments have applied different restrictions. These policies can cause disadvantageous situations in many sectors. The detection of these situations is important, especially in the later stages of the pandemic or similar pandemics that may occur later, in terms of precautions to be taken. The first case in Turkey was seen on March 11, 2020, after which, various measures were taken to control the pandemic. The steps taken during the pandemic process are summarized in Table 3.

3 | METHODS

3.1 | Multi-linear regression

Regression analysis is a statistical technique used to investigate and model the relationship between variables in order to obtain an approximate function between the relevant response (output) and independent variables (inputs).43 If there is more than one independent variable in the regression analysis, it is called MLR. In most MLR problems, it is not known how the independent variables relate to the dependent variables. Therefore, the first step and the main problem are to find an approximation method to relate them.44 Generally, first-order and second-order polynomial models are used, as given in Equations (1) and (2).

\[ y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \epsilon, \quad (1) \]

\[ y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^2 + \sum_{i=1}^{k} \sum_{j=i}^{k} \beta_{ij} x_i x_j + \epsilon, \quad (2) \]

where \( \beta \) denotes the polynomial coefficients and \( x \) the independent variables, \( y \) is defined as the dependent variable, and \( \epsilon \) identifies other forms of variation, such as errors or lack of numerical convergence. The \( k \) index represents the total number of variables. The \( i \) and \( j \) indices represent a certain variable between 1 and \( k \).

If Equations (1) and (2) are written in a matrix form, Equation (3) is obtained.

\[ Y = X\beta + \epsilon. \quad (3) \]
### TABLE 3 Milestones of COVID-19 and the steps taken in Turkey

| Date               | Event                                                                 |
|--------------------|----------------------------------------------------------------------|
| February 3, 2020   | Turkey suspends all flights from China.                              |
| March 11, 2020     | The first coronavirus case was announced in Turkey.                 |
| March 14, 2020     | Passenger transportation banned with 16 countries, 9 of which were European countries. |
| March 18, 2020     | The first death due to coronavirus occurred.                         |
| March 20, 2020     | With the Presidential circular, all scientific, cultural, artistic, and similar meetings and activities were stopped until the end of April. |
| March 21, 2020     | Curfew restrictions were imposed on citizens aged 65 and over.       |
| March 22, 2020     | With the Presidential circular, flexible and remote working was allowed in public institutions and organizations. |
| March 23, 2020     | Formal education was interrupted and distance education programs were started. |
| March 27, 2020     | International flights were completely suspended. Intercity transportation was subject to the permission of the Governorship. Entrance to places such as picnic areas, forests, and historical sites was prohibited at the weekend. |
| April 3, 2020      | Curfews were imposed on those under 20 years old throughout the whole country. 30 metropolitan areas and 1 province were closed to entry and exit of vehicles with some exceptions. |
| April 11–12, 2020  | The Government declared curfew in 30 metropolitan areas and 1 province (2 days) |
| April 18–19, 2020  | The Government declared curfew in 30 metropolitan areas and 1 province (2 days) |
| April 23–26, 2020  | The Government declared curfew in 30 metropolitan areas and 1 province (4 days) |
| May 1–3, 2020      | The Government declared curfew in 30 metropolitan areas and 1 province (3 days) |
| May 10, 2020       | The curfew for 65 years and older has been lifted between 12:00 and 18.00. |
| May 13, 2020       | The curfew for children aged 0–14 has been lifted between 11:00 and 15.00. |
| May 15, 2020       | The curfew for young people between the ages of 15 and 20 has been lifted between 11.00 and 15.00. |
| May 23–26, 2020    | A curfew was imposed during the Ramadan Holiday (4 days). |
| May 24, 2020       | The curfew for 65 years and older has been lifted between 12:00 and 18.00. |
| June 1, 2020       | The intercity travel restriction has been lifted. Flexible and remote working in the public sector has come to an end. |
| June 3, 2020       | The curfew imposed on people over the age of 65 has been lifted.      |
| June 20, 2020      | A curfew was imposed during the university entrance exam (first step).  |
| June 27–28, 2020   | A curfew was imposed during the university entrance exam (second step). |
| August 26, 2020    | Flexible and remote working in public institutions and organizations was allowed. |
| November 17, 2020  | A curfew will be imposed on weekends outside of 10.00–20.00. Restaurants will only provide takeaway service, shopping malls and markets will be closed at 20:00. (First starting on 04.12.2020.) |
| November 30, 2020  | A curfew will be imposed, starting at 21:00 on Fridays and ending at 05:00 on Mondays. |
| November 30, 2020  | Until a new decision, a curfew will be applied between 21.00 and 05.00 on weekdays throughout the country. (First started on 01.12.2020.) |
| December 31, 2020–January 4, 2021 | A curfew will be imposed, starting from 21:00 on Thursday, December 31, 2021, and ending at 05:00 on Monday, January 4, 2021. |
| February 2, 2021   | Face-to-face education will begin gradually in village schools as of February 15, 2021 and for other classes as of March 1, 2021. |
| February 3, 2021   | The South African and Brazilian variants were also seen in Turkey.    |
| March 1, 2021      | As of March 2, 2021, pre-school education institutions, primary school, secondary school 8th and 12th grades will start education in all cities and will start at other levels, including secondary and high schools, in low and medium risk provinces. The scope of the curfews has been changed according to the provinces with the new Controlled Normalization Process announced on March 1, 2021. The provinces have been divided into four different risk groups (low, medium, high, and very high) and the level of precaution has been determined according to the risk group. |
| March 2, 2021      | BURSA: In the medium risk group. According to this:  |
|                    | • A curfew will be applied between 21.00 and 05.00 on weekdays.  |
|                    | • A curfew will be applied between 21.00 and 05.00 on weekends.  |
|                    | • For our citizens aged 65 and over and under the age of 20, the curfew will be lifted outside the hours stated above.  |
|                    | • The food and beverage sector, which will operate between 07:00 and 19:00, will serve with a 50% capacity limitation.  |
The related matrices and vectors can be elaborated as in Equation (4).

\[
Y = \begin{bmatrix}
Y_1 \\
Y_2 \\
\vdots \\
Y_n
\end{bmatrix}, \quad \beta = \begin{bmatrix}
\beta_0 \\
\beta_1 \\
\vdots \\
\beta_k
\end{bmatrix}, \quad \omega = \begin{bmatrix}
\omega_1 \\
\omega_2 \\
\vdots \\
\omega_n
\end{bmatrix},
\]

\[
X = \begin{bmatrix}
1 & x_{11} & \cdots & x_{1k} & x_1^2 & \cdots & x_{1k}^2 & \cdots & x_{11}x_{1k} & \cdots & x_{12}x_{1k} & \cdots & x_{1k-1}x_{1k} \\
1 & x_{21} & \cdots & x_{2k} & x_2^2 & \cdots & x_{2k}^2 & \cdots & x_{21}x_{2k} & \cdots & x_{22}x_{2k} & \cdots & x_{2k-1}x_{2k} \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & x_{n1} & \cdots & x_{nk} & x_{n1}^2 & \cdots & x_{nk}^2 & \cdots & x_{n1}x_{nk} & \cdots & x_{n2}x_{nk} & \cdots & x_{nk-1}x_{nk}
\end{bmatrix},
\]

(4)

To estimate the coefficients of MLR models, the least squares method given for the vector sample \( \beta \) in Equation (5) is generally used. Thus, MLR models can be developed according to the existence of errors.\(^{45}\)

\[
\beta = (X'X)^{-1}X'Y.
\]

(5)

### 3.2 Feedforward artificial neural networks

ANNs are a distributed computing technology, inspired by the information processing technique of the human brain that can record the experimental information of systems. The ANN topology is divided into two types: feedforward (FF) and backpropagation neural networks (BPNN).\(^{46}\) The FFANN is used more widely because it requires less memory in the implementation phase. The FFANN allows a one-way signal flow. In addition, feedforward neural networks are organized in multiple layers: the input layer, the hidden layer, and an output layer. The neurons of each layer are interconnected by the weights and bias terms of the other neurons in the previous layers.\(^{47}\) This system is represented by the mathematical expression given in Equation (6).

\[
y_j = \sum_{i=1}^{n} \omega_{ij}x_i + \theta_j, \quad j = 1, 2, 3, \ldots, h.
\]

(6)

where \( n \) is the number of input nodes and \( \omega_{ij} \) is the connection weight of the \( j \)th node in the hidden layer from the \( i \)th node in the input layer; \( \theta \) denotes the \( j \)th hidden node bias and \( x_i \) denotes the \( i \)th input. Accordingly, Equation (7) is used to calculate the output of each hidden node.

\[
Y_j = \text{Hyperbolic tangent} \ (y_j) = \frac{e^{y_j} - e^{-y_j}}{e^{y_j} + e^{-y_j}}, \quad j = 1, 2, 3, \ldots, h,
\]

\[
Y_j = \text{Sigmoid} \ (y_j) = \frac{1}{1 + e^{-y_j}}, \quad j = 1, 2, 3, \ldots, h.
\]

(7)

The final outputs are defined as given in Equations (8) and (9).

\[
o_k = \sum_{i=1}^{n} \omega_{ik}Y_i + \theta_k, \quad k = 1, 2, 3, \ldots, m,
\]

(8)

\[
o_k = \text{Hyperbolic tangent} \ (o_k) = \frac{e^{o_k} - e^{-o_k}}{e^{o_k} + e^{-o_k}}, \quad k = 1, 2, 3, \ldots, m,
\]

\[
o_k = \text{Sigmoid} \ (o_k) = \frac{1}{1 + e^{-o_k}}, \quad k = 1, 2, 3, \ldots, m.
\]

(9)

where \( \omega_{ik} \) is the connection weight from the \( j \)th hidden node to the \( k \)th output node and \( \theta_k \) represents the bias value of the \( k \)th output node.

As can be understood from the equations, the most important parts of these structures are the weights and bias values because they determine the final value of the output. In order to find these values at the optimum value, the training of the neural network is very important.\(^{48}\) The aim is to obtain the minimum error value at the end of both the training process and the testing process of the neural network. Based on calculating the difference between the actual and predicted values, the mean square error (MSE) is used to evaluate the forward propagation neural network. This mathematical expression is given in Equation (10).
where $e_i$ represents the error value of the $i$th data, $x_i$ and $o_i$ are defined as the actual and estimated value of the $i$th data, respectively, and $n$ is the total number of data. The FFANN model with the structure of 4-5-1 is illustrated in Figure 3.

3.3 Proposed optimization algorithm

3.3.1 Stochastic fractal search algorithm

The stochastic fractal search (SFS) algorithm was developed because there was no information exchange between fractals and the many parameters that needed to be determined according to the problem to be optimized by the fractal search algorithm. The SFS algorithm is constituted of two basic processes: the propagation and update processes. The update process also consists of two parts: the first and second update processes. The propagation process performs the local search feature in the algorithm, and the update processes perform the global search functions. The two functions given in Equations (11) and (12) are proposed for the propagation process of fractals.

$$GW_1 = \text{Gaussian}(\mu_{BP}, \sigma) + (\epsilon x BP - \epsilon x P_i).$$ (11)

$$GW_2 = \text{Gaussian}(\mu_P, \sigma).$$ (12)

In Equation (12), $\mu_{BP}$ represents the position of the fractal that gives the best fitness value found up to that generation, $BP$ is the fractal that gives the best fitness value, and $P_i$ denotes the propagating fractal; the $\epsilon$ expression defines randomly generated numbers in the range of [0, 1]. In addition, $\mu_P$ in Equation (12) represents the position of the spreading fractal. The $\sigma$ value is the standard deviation value that expresses the step length of the Gaussian walking function. The standard deviation expression is calculated as given in Equation (13).

$$\sigma = \frac{\log(g)}{g} x (P_i - BP).$$ (13)

Equation (13) shows that the difference between the fractal with the best fitness value and the spreading fractal is obtained by multiplying the expression $\log(g)/g$. The $g$ in the $\log(g)/g$ expression added to Equation (13) represents the generation value and creates a damping effect in the standard deviation function, that is, the value of the standard deviation decreases as the number of generations progresses. Although this causes a more local search, it increases the probability of finding a solution with an even better fitness value in the immediate vicinity of the found solution point. After the propagation process is performed, the first and second update processes are run. For these operations, first of all, a probabilistic value is given to each fractal by taking into account the order of the fitness values, using the expression given in Equation (14).
\[ P_n = \frac{\text{rank}(P_i)}{N}. \] (14)

where \( N \) is the number of fractals in the generation and the expression \( \text{rank}(P_i) \) expresses the rank of the fractal in the generation according to its fitness value.

The first update process starts after the probabilistic value is calculated. Depending on whether the randomly generated \( \epsilon \) expression is smaller or larger than the probabilistic value, the relevant dimension of the relevant fractal is updated. This process is as given in Equation (15).

\[
P'_i(j) = \begin{cases} 
  P_i(j) - \epsilon x (P_i(j) - P_r(j)), & \epsilon > P_n, \\
  P_i(j), & \epsilon \leq P_n.
\end{cases}
\] (15)

The \( r \) and \( t \) subindices given in Equation (15) represent randomly selected fractals from within the generation.

After the first update process, Equation (14) is reordered and the fractals are assigned probabilistic values. For fractals entering the second update process, the position of the fractal is changed according to whether a randomly generated number between 0 and 1 is smaller or larger than 0.5. The second update process is performed with the expression given in Equation (16).

\[
P''_i = \begin{cases} 
  P'_i - \epsilon x (P'_i - P_t), & \epsilon' \leq 0.5, \\
  P'_i - \epsilon x (P'_i - P_r), & \epsilon' > 0.5.
\end{cases}
\] (16)

The algorithm continues to generate a new generation and generate new solution points until it meets the termination criterion.

### 3.3.2 Fitness distance balance selection method

The purpose of the fitness distance balance (FDB) method is to effectively guide meta-heuristic search (MHS) algorithms in the search process.\(^5^0\) The feature that distinguishes the FDB method from other selection methods is the calculation of the score values of the solution candidates and the selection process according to the score values. In the calculation of the score, the fitness values of the solution candidates and their distance from the best solution candidate in the population are taken into account. This ensures that the solution candidate with a high fitness value is selected. On the other hand, this prevents the selection of a solution candidate that is very close to the best solution in the population. This selection strategy of the FDB method contributes to the solution of the early convergence problem frequently encountered in the MHS process.\(^5^1-5^3\) The steps to implement the FDB method are as follows:

i. The score values of the solution candidates in the \( P \) population should be calculated. If \( X_{\text{best}} \) is assumed to be the best solution in population \( P \), the scores of the solution candidates in population \( P \) are expressed by the vector \( S_P \) given in Equation (17).

\[
S_P \equiv \begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix}_{1 \times n}. \] (17)

ii. While calculating the score of each solution candidate, the values of fitness and distance are taken into account. In population \( P \), the distance between the \( i \)th solution candidate and \( X_{\text{best}} \) (the best solution in \( P \)) is calculated using the Euclidean metric as given in Equation (18).

\[
\forall_{i=1}^{n}, P_i \neq P_{\text{best}}, D_{pi} = \sqrt{ (x_{1pi} - x_{1p_{\text{best}}})^2 + (x_{2pi} - x_{2p_{\text{best}}})^2 + \ldots + (x_{mpi} - x_{mp_{\text{best}}})^2}. \] (18)

iii. The distance vector \( D_P \) of the solution candidates in the population \( P \) can be represented as given in Equation (19).

\[
D_P \equiv \begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix}_{1 \times n}. \] (19)
iv. Another parameter used in calculating the scores of the solution candidates is the fitness value. The fitness values of the solution candidates in the population $P$ are represented by the vector $p$. The $p$ and $D_P$ vectors are normalized so that the two parameters do not dominate each other in the score calculation. The score calculation of the $i$th solution candidate is given in Equation (20).

$$\forall_{i=1}^n P_i, S_P = \omega \cdot \text{norm} F_P + (1 - \omega) \cdot \text{norm} D_P.$$ (20)

The $\omega$ parameter given in Equation (20) is used to weight the effects of $p$ and $D_P$ parameters. The $\omega$ parameter can have an infinite number of values in the range $[0,1]$. A larger value of the $\omega$ parameter increases the effect of the fitness value on the score. In this case, the effect of the distance value on the score decreases. When $\omega = 1$, the score value of the solution candidate depends only on the fitness value. When $\omega = 0$, the solution candidate’s score depends only on the distance value. This ensures that the solution candidate farthest from $P_{\text{best}}$ is selected in the population. Therefore, the variation in the population increases as the $\omega$ parameter is close to zero. This provides discovery capability for MHS algorithms. This parameter gives the FDB the ability to adapt. The $\omega$ parameter has the important function of switching and balancing between operating and reconnaissance tasks.

3.3.3 FDB based stochastic fractal search algorithm

A step-by-step explanation can be given for improving the search performance of MHS algorithms using the FDB method. Before applying the FDB method to an MHS algorithm, the search process lifecycle of the MHS algorithm should be analyzed and the process in which the algorithm provides diversity should be determined. Therefore, the SFS algorithm needs to be rearranged based on the general steps of the MHS process. The purpose of rearranging the algorithm is to reveal the exploration and exploitation processes, and the step in which the FDB method is applied. After the exploration process, the diffusion process is carried out, and the tasks of searching for a neighborhood and providing diversity in the update process are fulfilled. In the next step, reference positions that guide the search process lifecycle in the SFS algorithm are examined. Thus, reference positions and the methods used to select them are determined. In this process, three reference positions are selected, one using the turn-based method and the other two randomly. According to the information obtained here, the FDB selection method was applied. Thus, the process of ensuring diversity in the population was realized. Equations (17)–(20) are taken into account in the FDB selection method. The SFSFDB flowchart is given in Figure 4.

4 SFSFDB ALGORITHM APPLIED TO HYBRID MLR-FFANN

In the training of ANNs, a large number of uncertainties occur with the relationship between different datasets and the combination of many solutions. This uncertainty and different relationship status make their training process difficult. Moreover, ANNs have a nonlinear structure, which affects the behavior of the network in the learning process. Therefore, the importance is increasing of determining the most appropriate values of the weight and bias coefficients used in the training of the network and the activation functions used in the neurons. Considering this situation, the weight and bias coefficients of FFANN and the $\beta$ polynomial coefficients of MLR in the proposed MLR-FFANN model were determined simultaneously by optimization algorithms. In this study, the application of the SFSFDB algorithm described in Section 3.3 to the training of the proposed MLR-FFANN model is explained step by step as follows.

Step 1: In this step, the prepared dataset is read from the relevant file and the values of the dataset are normalized between 0 and 1 using Equation (21).

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}.$$ (21)

The maximum number of iterations of the SFSFDB algorithm, the size of the population and the number of dimensions are entered into the system by the user. In addition to this step, the initial population is created within the minimum and maximum values determined for the parameters (weight, bias, and $\beta$ polynomial coefficients) of the proposed MLR-FFANN model to be optimized.

Step 2: The fitness function values of the initial population are calculated and the position value with the best fitness value is determined.

Step 3: The algorithm checks whether the current iteration number has reached the determined maximum number of iterations. If not, the natural process of the algorithm continues. If reached, the best value and best position values of the fitness function are displayed.

Step 4: Depending on the structure of the algorithm, the maximum diffusion number is determined. Depending on the maximum diffusion number, the steps of the diffusion process in Figure 4 are applied.

Step 5: According to Step 4, after the condition in the diffusion process is met and the necessary operations are performed, the algorithm performs the first updating process step in the flow diagram. The algorithm checks whether each ordered $P_i$ value is less than the randomly generated number. Depending on this condition, the necessary processing is carried out.
Step 6: When the condition step in Step 5 is completed, the second updating process is started. In this step, all solution candidates in the population are ranked. Depending on the specified condition, either the selection method of the SFS algorithm is applied or the FDB selection method is applied, depending on Equations (17)–(20). After the selection steps are performed depending on the specified conditions, the position of the $P_i$ solution candidate in the population is updated.

Step 7: The current iteration number of the algorithm is increased and the algorithm goes to Step 3 and checks whether the condition there is met.

Figure 5 shows the application of the SFSFDB algorithm to the training of the proposed MLR-FFANN model. Here, the input dataset is expressed as environmental conditions, days of the week, COVID-19 pandemic precautions, the average electrical energy consumption values for the MLR method, and the average electric energy consumption estimated error values for FFANN, whereas the output dataset shows the daily average energy consumption of the city of Bursa. By using the normalization expression shown in Equation (21) for the input and output datasets, the values of the data are transformed into a dataset varying between 0 and 1.

5 EXPERIMENTAL RESULTS

In this study, a multiple linear regression and feedforward neural network-based hybrid algorithm was proposed to predict the electric energy consumption of the city of Bursa during the COVID-19 pandemic, and the design of this algorithm was carried out using AGDE, EO, SMA, and SFSFDB optimization algorithms. Although the optimization algorithms used minimized the mean squared error, they aimed to find the most appropriate weight and bias coefficients of the FFANN model and the $\beta$ polynomial coefficients of the multiple linear regression algorithm.

Furthermore, the success of the following design structures in training of the FFANN model was examined in the optimization process. The case studies of the FFANN structural designs were carried out as follows.
FIGURE 5  Flowchart of SFSFDB algorithm applied to MLR-FFANN

TABLE 4  FFANN structures used in study cases

| Case 1       | Case 2       | Case 3       | Case 4       |
|--------------|--------------|--------------|--------------|
| FFANN structures | Hidden layer  | Output layer | Hidden layer  | Output layer |
| 21 x 5 x 1  | Hyperbolic tangent | Hyperbolic tangent | Hyperbolic tangent | Sigmoid |
| 21 x 6 x 1  | ✓            | ✓            | ✓            | ✓            |
| 21 x 7 x 1  | ✓            | ✓            | ✓            | ✓            |
| 21 x 8 x 1  | ✓            | ✓            | ✓            | ✓            |
| 21 x 9 x 1  | ✓            | ✓            | ✓            | ✓            |
| 21 x 10 x 1 | ✓            | ✓            | ✓            | ✓            |

- Case 1: Using the hyperbolic tangent function in the hidden and output layers for the FFANN model.
- Case 2: Using the hyperbolic tangent function in the hidden layer and the sigmoid function in the output layer for the FFANN model.
- Case 3: Using the sigmoid function in the hidden layer and the hyperbolic tangent function in the output layer for the FFANN model.
- Case 4: Using the sigmoid function in the hidden and the output layers for the FFANN model.

Each of the structures for the FFANN model case studies is shown in Table 4. The simulation studies were conducted according to these network structures.

The input and output parameters of the proposed hybrid MLR-FFANN model are as follows.

Input parameters of the hybrid MLR-FFANN model

- Days of the week
- COVID-19 pandemic process precautions
- Environmental conditions
- Average electric energy consumption values for MLR \( y(t - 1), y(t - 2) \)
- Predicted error values of average electric energy consumption for FFANN \( er(t - 1), er(t - 2) \)
Output parameters of the hybrid MLR-FFANN model

- Electricity energy consumption values of the Bursa Metropolitan Province

During the COVID-19 pandemic, 80% of the dataset created for the estimation of the electric energy consumption of the Bursa Metropolitan Province was used in the training of the hybrid MLR-FFANN model and 20% in the testing of the model. The mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) criteria were used to evaluate the success of the proposed model in training and testing data. These evaluation criteria are shown in Equations (22)-(24). The MAE, MAPE, and RMSE evaluation criteria results from the training and testing data of different FFANN structures for all working cases of the AGDE algorithm are given in Table 5. Depending on these results, all working cases and the ranking of the network structures are shown in Table 6 in order to identify which working condition among the network structures used in the different working cases was more successful in the FFANN training process of the AGDE algorithm.

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |e_i| = \frac{1}{n} \sum_{i=1}^{n} |x_i - o_i|,
\]

\[
\text{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{x_i - o_i}{x_i} \right|.
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} e_i^2} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - o_i)^2}.
\]

Figure 6 shows that the training of the proposed MLR-FFANN model was carried out in 250 iterations by all optimization algorithms. During the training of the MLR-FFANN model in different operational situations, it is clearly seen that the SFSFDB algorithm in Cases 1 and 3, and the AGDE algorithm in Cases 2 and 4 compared to the other algorithms, were more successful in finding the optimal value of the objective function. Moreover, it can be seen from Figure 6B that the SFSFDB algorithm was as successful as the AGDE algorithm in the training method proposed for Case 2.

The results of MAE, MAPE, and RMSE evaluation criteria obtained from the training and testing data of different FFANN structures for all working cases of EO, SMA, and SFSFDB algorithms are given in Tables 7–9, respectively. The ranking of the evaluation criteria results obtained for the training and testing data at the end of the optimization process of the FFANN design structures by the EO, SMA, and SFSFDB optimization algorithms in the different study cases is shown in Tables 10–12. The comparative analysis and ranking of FFANN structures in simulation cases for all optimization algorithms are given in Table 13. These rankings are shown depending on the sum of the ranking results, mean values of these results, and standard deviation values given in Tables 6 and 10–12. According to these ranking results, the FFANN structure that completed the training and testing process the most successfully was determined among the simulation cases for each optimization algorithm. The identified FFANN structures are denoted in Table 13 in different colors for each optimization algorithm.

In Table 14, the average values of the evaluation criteria obtained for the FFANN structures used in all cases are calculated and the sorting studies of the algorithms according to these values are indicated in both the training and test datasets. In this table, the most successful cases of the AGDE algorithm can be expressed as Cases 2 and 3. The most successful cases for EO, SMA, and SFSFDB algorithms are defined as Cases 2, 4, and 3, respectively. The results of the evaluation criteria obtained in both training and test data for each case (Table 14) are shown in detail in the bar graphs in Figure 7.

The results of the evaluation criteria of the best cases in each optimization algorithm (Figure 7 and Table 14) are shown in bar graph form in Figure 8 for both training and test data so that the results can be better interpreted. After determining the best cases used in the training process of FFANN for each optimization algorithm (Table 14), the results of the evaluation criteria of the best FFANN structures in the cases, the ranking of these results for both training and test data, and the sum of these ranking results, mean value, and standard deviation values are shown in Table 15. In other words, the final ranking in Table 15 clearly shows that the EO algorithm was the first in the training of the dataset, followed by the SFSFDB and SMA algorithms.

The FFANN structures determined for all optimization algorithms were adapted to the proposed hybrid MLR-FFANN model. By using MLR-FFANN algorithms, where the most appropriate weight, bias, and \( \beta \) polynomial coefficients were determined by the optimization algorithms, the electric energy consumption of the Bursa Metropolitan Province was predicted during the COVID-19 pandemic period until September 2020. As a result of the prediction process, the evaluation criteria, the ranking of these criteria, and the final ranking of the algorithms are shown in Table 16. According to the final ranking of the algorithms, the MLR-FFANN method trained with the SFSFDB algorithm was more successful than other algorithms in estimating the electric energy consumption values of Bursa during the COVID-19 pandemic. When Tables 15 and 16 were evaluated together for the final rankings of the optimization algorithms, the MLR-FFANN, whose training process was completed with the SFSFDB algorithm, was more successful than the MLR-FFANN trained with the other (EO, SMA, and AGDE) algorithms.
Table 5 MAE, MAPE and RMSE values obtained from the different FFANN structures optimized by AGDE algorithm

| Algorithm | FFANN structures | Data type | Evaluation criteria | Case 1 | Case 2 | Case 3 | Case 4 |
|-----------|------------------|-----------|---------------------|--------|--------|--------|--------|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
| AGDE      | 21 × 5 × 1       | Training data |                     | 27.3941| 26.1891| 30.2360| 30.1717|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 5.2678 | 5.1011 | 5.9940 | 5.9849 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 38.7474| 38.8531| 44.0428| 44.1025|
|           |                  | Test data |                     | 56.7584| 53.1980| 44.8230| 42.6288|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 10.8761| 10.5233| 8.9435 | 8.5632 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 98.5928| 78.2590| 64.4790| 61.7684|
| 21 × 6 × 1| Training data    |           |                     | 27.5425| 27.7760| 28.6354| 30.0492|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 5.3205 | 5.3031 | 5.5539 | 5.9714 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 39.7643| 38.4424| 41.2921| 44.0109|
|           |                  | Test data |                     | 52.5854| 54.7330| 49.2259| 42.6781|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 10.3154| 10.7155| 9.8232 | 8.5095 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 78.6412| 76.5316| 73.4692| 61.5986|
| 21 × 7 × 1| Training data    |           |                     | 25.3562| 26.9770| 27.3865| 25.8093|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 4.8113 | 5.3183 | 5.3252 | 4.9777 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 35.1984| 42.2227| 39.6723| 36.9277|
|           |                  | Test data |                     | 58.7017| 42.7280| 45.3613| 50.1409|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 11.4637| 8.6879 | 9.2956 | 9.9568 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 93.8435| 60.8729| 68.7305| 71.9617|
| 21 × 8 × 1| Training data    |           |                     | 26.4724| 27.7247| 25.8503| 25.2653|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 5.0011 | 5.3367 | 4.9074 | 4.9397 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 36.9890| 39.8150| 36.2223| 36.9891|
|           |                  | Test data |                     | 51.1938| 52.9556| 52.8339| 60.1406|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 10.1769| 10.3547| 10.4806| 11.5400|
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 79.5222| 75.2103| 78.2415| 97.8941|
| 21 × 9 × 1| Training data    |           |                     | 26.6057| 26.2527| 27.5657| 31.0802|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 5.0962 | 5.0866 | 5.3265 | 6.1767 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 37.7601| 38.1095| 39.3924| 45.5558|
|           |                  | Test data |                     | 47.7024| 53.5154| 54.5175| 41.0055|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 9.4646 | 10.4809| 10.7926| 8.3016 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 73.3299| 80.3011| 80.9939| 59.6515|
| 21 × 10 × 1| Training data   |           |                     | 24.3042| 26.2617| 26.8161| 28.0184|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 4.5708 | 5.0730 | 5.1697 | 5.4671 |
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 34.7527| 36.8862| 38.2322| 39.9554|
|           |                  | Test data |                     | 63.1113| 50.4191| 51.8507| 50.8396|
|           |                  |           |                     | MAE    | MAE    | MAE    | MAE    |
|           |                  |           |                     | 12.3587| 9.8081 | 10.1927| 10.0942|
|           |                  |           |                     | RMSE   | RMSE   | RMSE   | RMSE   |
|           |                  |           |                     | 99.3556| 76.0028| 76.3146| 74.0462|
TABLE 6  Ranking of results of simulation studies of the AGDE algorithm for different operational cases

| Algorithm | Cases | Layers | Activation functions | Data type | Evaluation criteria | FFANN structures |
|-----------|-------|--------|----------------------|-----------|--------------------|------------------|
| AGDE      | Case 1| Hidden layer/output layer | Hyperbolic tangent/hyperbolic tangent | Training data | MAE 5 6 2 3 4 1 | $21 \times 5 \times 1$ |
|           |       |        |                      |           | MAPE 5 6 2 3 4 1 | $21 \times 6 \times 1$ |
|           |       |        |                      |           | RMSE 5 6 2 3 4 1 | $21 \times 7 \times 1$ |
|           |       |        |                      | Test data | MAE 4 3 5 2 1 6 | $21 \times 8 \times 1$ |
|           |       |        |                      |           | MAPE 4 3 5 2 1 6 | $21 \times 9 \times 1$ |
|           |       |        |                      |           | RMSE 5 2 4 3 1 6 | $21 \times 10 \times 1$ |
| Case 2    | Hidden layer/output layer | Hyperbolic tangent/sigmoid | Training data | MAE 1 6 4 5 2 3 | $21 \times 5 \times 1$ |
|           |       |        |                      |           | MAPE 3 4 5 6 2 1 | $21 \times 6 \times 1$ |
|           |       |        |                      |           | RMSE 4 3 6 5 2 1 | $21 \times 7 \times 1$ |
|           |       |        |                      | Test data | MAE 4 6 1 3 5 2 | $21 \times 8 \times 1$ |
|           |       |        |                      |           | MAPE 5 6 1 3 4 2 | $21 \times 9 \times 1$ |
|           |       |        |                      |           | RMSE 5 4 1 2 6 3 | $21 \times 10 \times 1$ |
| Case 3    | Hidden layer/output layer | Sigmoid/hyperbolic tangent | Training data | MAE 6 5 3 1 4 2 | $21 \times 5 \times 1$ |
|           |       |        |                      |           | MAPE 6 5 3 1 4 2 | $21 \times 6 \times 1$ |
|           |       |        |                      |           | RMSE 6 5 4 1 3 2 | $21 \times 7 \times 1$ |
|           |       |        |                      | Test data | MAE 1 3 2 5 6 4 | $21 \times 8 \times 1$ |
|           |       |        |                      |           | MAPE 1 3 2 5 6 4 | $21 \times 9 \times 1$ |
|           |       |        |                      |           | RMSE 1 3 2 5 6 4 | $21 \times 10 \times 1$ |
| Case 4    | Hidden layer/output layer | Sigmoid/sigmoid | Training data | MAE 6 4 2 1 5 3 | $21 \times 5 \times 1$ |
|           |       |        |                      |           | MAPE 5 4 2 1 6 3 | $21 \times 6 \times 1$ |
|           |       |        |                      |           | RMSE 5 4 1 2 6 3 | $21 \times 7 \times 1$ |
|           |       |        |                      | Test data | MAE 2 3 4 6 1 5 | $21 \times 8 \times 1$ |
|           |       |        |                      |           | MAPE 3 2 4 6 1 5 | $21 \times 9 \times 1$ |
|           |       |        |                      |           | RMSE 3 2 4 6 1 5 | $21 \times 10 \times 1$ |

In other words, the SFSFDB algorithm had a value of 33.2284 for the MAE evaluation criterion, which is 36.7355%, 19.3358%, and 50.7798% less than the results of the AGDE, EO, and SMA algorithms, respectively. When the results were evaluated in terms of the MAPE criterion, the SFSFDB algorithm had a value of 7.0958, a value that is 36.9133%, 13.9798%, and 51.6825% less than the results of the system trained by the other optimization algorithms. Considering the RMSE values, the result of the model designed with the SFSFDB optimization algorithm was 23.8159%, 8.0017%, and 43.358% less than the results of the other algorithms, respectively.

Figure 9A gives the comparison of the most suitable MLR-FFANN structures, determined according to the results obtained from all optimization algorithms, in estimating the electric energy consumption values of the city of Bursa until September 2020 during the COVID-19 pandemic process, according to the evaluation criteria. Figure 9B shows the difference between the actual and estimated electric energy consumption values. Actual and predicted electricity energy consumption data are detailed in Figure 9C.

5.1  Accuracy and reliability of the developed SFSFDB based MLR-FFANN

5.1.1  Outlier detection

Outlier detection is critical in the development of appropriate models for recognizing individual data that may differ from the data chunk contained in a dataset. In the literature, the methods consisting of both numerical and graphical algorithms have been proposed for this purpose. Leverage approach is an algorithm that is considered quite good for detecting these different values. This method considers the deviations of a model from the experimental data, a matrix of experimental data known as the Hat matrix, and the predicted values. The main criterion in the application
of this method is to use a model that can calculate or estimate the relevant data within acceptable limits. Leverage or hat indices (hat matrix \((H)\)) are calculated using Equation \((25)\):

\[
H = X (X^t X)^{-1} X^t, \tag{25}
\]

where \(X\) is a \((n \times k)\) matrix consisting of \(n\) data (rows) and \(k\) parameters (columns) of the model and \(t\) denotes the transpose matrix. Hat values of the data form the diagonal elements of the \(H\) value. The Williams plot is created by calculating the \(H\) values in Equation \((25)\). Outliers or suspicious data are graphically identified in this plot. This graph shows the correlation of the Hat indices with the standardized cross-validated residuals \((\hat{R})\). A warning leverage \((\hat{H}^*)\) is usually fixed at a value equal to \(3p/n\), where \(n\) represents the number of data points and \(p\) represents one more than the number of model parameters. A leverage set to three is normally considered a cut-off value to accept points within \(\pm 3\) standard deviations from the mean. The fact that the majority of data points are in the range of \(0 \leq H \leq \hat{H}^*\) and \(-3 \leq \hat{R} \leq 3\) indicates that both the model development and its predictions are within the applicability limits. Thus, a statistically valid model is presented. "Good high leverage" points must be in the \(\hat{H}^* \leq H\) and \(-3 \leq \hat{R} \leq 3\) fields. Points greater than \(\hat{H}^*\) or within the specified value range \((\hat{R} < -3\) or \(3 < \hat{R})\) are defined as model outliers or "bad high leverage" points. These erroneous representations/predictions are called as the doubtful data.

In this study, the statistical hat matrix, Williams plot, and leverage approach, which enables outliers to be recognized in the model results, were used to check the reliability of the proposed model. \(^{55-60}\) \(H\) values were calculated with Equation \((25)\) and the evaluation steps were
| Algorithm | FFANN structures | Data type | Evaluation criteria | Case 1 | Case 2 | Case 3 | Case 4 |
|-----------|-----------------|-----------|---------------------|--------|--------|--------|--------|
|           |                 |           | Hidden layer         | Output layer | Hidden layer | Output layer | Hidden layer | Output layer |
|           |                 |           | Hyperbolic tangent  | Hyperbolic tangent | Hyperbolic tangent | Sigmoid | Hyperbolic tangent | Sigmoid |
| EO        | 21 × 5 × 1      | Training data | MAE                 | 30.4668 | 29.8874 | 31.3811 | 31.8208 |
|           |                 |           | MAPE                | 5.9711  | 5.8785  | 6.2732  | 6.3167  |
|           |                 |           | RMSE                | 43.8322 | 43.3388 | 46.7406 | 45.9720 |
|           |                 | Test data  | MAE                 | 44.7642 | 8.8721  | 9.0075  | 8.4246  |
|           |                 |           | MAPE                | 62.3096 | 60.0308 | 59.1625 | 59.7926 |
|           |                 | Training data | MAE                | 21 × 6 × 1 | 29.3265 | 30.3324 | 30.6505 | 30.9127 |
|           |                 |           | MAPE                | 5.7169  | 5.9751  | 5.9525  | 6.1542  |
|           |                 |           | RMSE                | 41.6963 | 42.6786 | 44.3530 | 45.5809 |
|           |                 | Test data  | MAE                 | 50.8371 | 9.5335  | 10.1827 | 8.2865  |
|           |                 |           | MAPE                | 74.7142 | 71.3203 | 63.2783 | 59.3978 |
|           |                 | Training data | MAE                | 21 × 7 × 1 | 28.2143 | 27.7485 | 30.0383 | 29.5706 |
|           |                 |           | MAPE                | 5.4786  | 5.4395  | 5.9537  | 5.8674  |
|           |                 |           | RMSE                | 41.0958 | 40.2583 | 43.4762 | 43.6306 |
|           |                 | Test data  | MAE                 | 42.5659 | 53.8792 | 48.8363 | 42.6071 |
|           |                 |           | MAPE                | 8.5576  | 10.4588 | 9.7582  | 8.6709  |
|           |                 |           | RMSE                | 63.3066 | 79.3093 | 69.8616 | 64.3107 |
|           |                 | Training data | MAE                | 21 × 8 × 1 | 28.6195 | 29.0233 | 30.5674 | 30.9093 |
|           |                 |           | MAPE                | 5.4598  | 5.6943  | 5.9648  | 6.1330  |
|           |                 |           | RMSE                | 38.5721 | 40.6563 | 42.8045 | 44.4658 |
|           |                 | Test data  | MAE                 | 61.6132 | 51.9173 | 45.9266 | 45.8902 |
|           |                 |           | MAPE                | 12.1829 | 10.3261 | 9.1488  | 9.2047  |
|           |                 |           | RMSE                | 86.7060 | 73.3204 | 67.5272 | 66.7979 |
|           |                 | Training data | MAE                | 21 × 9 × 1 | 28.6827 | 27.5769 | 29.9710 | 30.0967 |
|           |                 |           | MAPE                | 5.5448  | 5.3586  | 5.8727  | 5.8982  |
|           |                 |           | RMSE                | 40.0931 | 39.1470 | 42.8298 | 42.6977 |
|           |                 | Test data  | MAE                 | 54.3271 | 44.2227 | 45.5620 | 49.3985 |
|           |                 |           | MAPE                | 10.5901 | 8.9883  | 9.1701  | 9.6140  |
|           |                 |           | RMSE                | 77.5188 | 66.2420 | 68.7613 | 69.9643 |
|           |                 | Training data | MAE                | 21 × 10 × 1 | 26.3307 | 24.9453 | 26.8037 | 29.1426 |
|           |                 |           | MAPE                | 5.0676  | 4.7770  | 5.1726  | 5.7892  |
|           |                 |           | RMSE                | 37.2934 | 36.1464 | 37.8466 | 42.4553 |
|           |                 | Test data  | MAE                 | 49.0802 | 47.4105 | 55.0736 | 44.3604 |
|           |                 |           | MAPE                | 9.7212  | 9.3795  | 10.7414 | 8.9299  |
|           |                 |           | RMSE                | 74.5325 | 70.9335 | 86.7372 | 65.7630 |
| Algorithm | FFANN structures | Data type | Evaluation criteria | Case 1 | Case 2 | Case 3 | Case 4 |
|-----------|----------------|-----------|---------------------|--------|--------|--------|--------|
| SMA       | 21 × 5 × 1     | Training data | MAE 33.7515 32.1509 34.9322 35.0882 | MAPE 6.7271 6.4573 6.9716 7.0292 | RMSE 49.4351 46.5082 50.2342 50.9672 |
|           |                | Test data  | MAE 38.6627 46.7917 41.1690 37.9265 | MAPE 7.9884 9.4161 8.4393 7.8526 | RMSE 57.0402 65.4499 58.6201 55.8728 |
|           | 21 × 6 × 1     | Training data | MAE 36.0985 34.1528 35.2396 36.255 | MAPE 7.2939 6.8609 7.0943 7.2331 | RMSE 53.2378 50.1897 51.1227 51.4780 |
|           |                | Test data  | MAE 41.1084 40.7327 42.4998 43.9866 | MAPE 8.4412 8.3030 8.6026 8.8966 | RMSE 56.4548 58.7742 59.1442 61.4382 |
|           | 21 × 7 × 1     | Training data | MAE 33.0708 32.6873 32.7321 32.6362 | MAPE 6.6120 6.5353 6.5624 6.5491 | RMSE 48.9362 47.4181 48.3851 48.8187 |
|           |                | Test data  | MAE 39.6327 41.7810 39.6390 37.0926 | MAPE 8.1020 8.4235 8.1305 7.6234 | RMSE 58.5108 59.8181 58.1576 54.8335 |
|           | 21 × 8 × 1     | Training data | MAE 33.0936 34.9420 33.9971 34.3282 | MAPE 6.6271 6.9643 6.8000 6.8296 | RMSE 48.1543 49.2945 49.3698 49.5032 |
|           |                | Test data  | MAE 42.0874 44.1913 40.3400 38.3903 | MAPE 8.6223 9.1382 8.2148 7.8880 | RMSE 61.7824 63.0710 58.8103 56.4119 |
|           | 21 × 9 × 1     | Training data | MAE 32.5330 32.6000 32.0428 33.0650 | MAPE 6.4707 6.4883 6.8125 6.6219 | RMSE 46.9966 47.2959 49.1337 48.5220 |
|           |                | Test data  | MAE 44.2997 42.8522 39.2549 38.5194 | MAPE 8.9143 8.7290 8.0704 7.8535 | RMSE 62.6968 60.9679 50.847 56.4597 |
|           | 21 × 10 × 1    | Training data | MAE 31.6898 32.4855 35.2936 33.8145 | MAPE 6.3566 6.4431 7.0546 6.7522 | RMSE 46.9098 45.7092 50.2625 48.8474 |
|           |                | Test data  | MAE 36.7966 47.8138 40.2164 42.9139 | MAPE 7.6497 9.4573 8.3951 8.7180 | RMSE 55.3233 69.9524 59.6641 60.5452 |
| Algorithm | FFANN structures | Data type | Evaluation criteria | Case 1 | Case 2 | Case 3 | Case 4 |
|-----------|-----------------|-----------|---------------------|--------|--------|--------|--------|
|           |                 |           |                     | Hidden layer | Hyperbolic tangent | Hyperbolic tangent | Hidden layer | Sigmoid | Hyperbolic tangent | Sigmoid | Hidden layer | Sigmoid | Hyperbolic tangent | Sigmoid |
| SFSFDB    | 21 × 5 × 1      | Training data | MAE                | 29.7848 | 26.3936 | 25.0693 | 25.8692 |
|           |                 |           | MAPE               | 5.7796  | 5.0850  | 4.8339  | 5.0302  |
|           |                 |           | RMSE               | 41.6004 | 37.3705 | 35.9982 | 38.1307 |
|           |                 | Test data | MAE                | 51.5971 | 49.7136 | 54.0009 | 55.3014 |
|           |                 |           | MAPE               | 10.3010 | 9.7947  | 10.7137 | 10.8689 |
|           |                 |           | RMSE               | 77.2815 | 69.1236 | 86.6259 | 85.7601 |
|           | 21 × 6 × 1      | Training data | MAE                | 26.4507 | 27.2546 | 27.7269 | 29.7217 |
|           |                 |           | MAPE               | 5.0356  | 5.2810  | 5.3298  | 5.8510  |
|           |                 |           | RMSE               | 37.8495 | 39.0741 | 39.7307 | 42.3777 |
|           |                 | Test data | MAE                | 59.9968 | 53.4792 | 53.6484 | 48.2257 |
|           |                 |           | MAPE               | 11.6997 | 10.5107 | 10.6577 | 9.7180  |
|           |                 |           | RMSE               | 88.5541 | 78.1406 | 80.7798 | 69.5811 |
|           | 21 × 7 × 1      | Training data | MAE                | 25.3758 | 26.7794 | 27.3811 | 28.3706 |
|           |                 |           | MAPE               | 4.8527  | 5.2326  | 5.2293  | 5.5572  |
|           |                 |           | RMSE               | 35.4393 | 38.7671 | 38.5420 | 40.9998 |
|           |                 | Test data | MAE                | 60.1612 | 48.0063 | 51.6829 | 47.8107 |
|           |                 |           | MAPE               | 11.9726 | 9.6096  | 10.0116 | 9.4816  |
|           |                 |           | RMSE               | 89.8189 | 70.8651 | 84.3398 | 70.8205 |
|           | 21 × 8 × 1      | Training data | MAE                | 24.7913 | 26.5393 | 27.2681 | 28.3706 |
|           |                 |           | MAPE               | 4.6964  | 5.1637  | 5.1986  | 5.4324  |
|           |                 |           | RMSE               | 35.3336 | 37.5864 | 37.9751 | 40.4902 |
|           |                 | Test data | MAE                | 66.8222 | 52.5460 | 55.5138 | 45.6329 |
|           |                 |           | MAPE               | 13.3227 | 10.3486 | 11.0176 | 9.0612  |
|           |                 |           | RMSE               | 106.6947| 75.4689 | 81.1272 | 69.7324 |
|           | 21 × 9 × 1      | Training data | MAE                | 23.3997 | 23.2679 | 22.7836 | 23.5089 |
|           |                 |           | MAPE               | 4.3995  | 4.4133  | 4.2657  | 4.4659  |
|           |                 |           | RMSE               | 33.3388 | 33.2138 | 32.3052 | 33.6666 |
|           |                 | Test data | MAE                | 63.8802 | 62.8841 | 56.8832 | 54.1425 |
|           |                 |           | MAPE               | 12.6739 | 12.2250 | 11.3105 | 10.6307 |
|           |                 |           | RMSE               | 105.3484| 95.0279 | 86.8698 | 84.1150 |
|           | 21 × 10 × 1     | Training data | MAE                | 22.3310 | 21.9726 | 22.0975 | 21.7047 |
|           |                 |           | MAPE               | 4.0906  | 4.1294  | 4.1256  | 4.1347  |
|           |                 |           | RMSE               | 32.1979 | 31.0354 | 31.2159 | 32.0118 |
|           |                 | Test data | MAE                | 69.5505 | 61.4864 | 55.8286 | 56.7811 |
|           |                 |           | MAPE               | 13.6395 | 11.9117 | 11.2382 | 11.1619 |
|           |                 |           | RMSE               | 103.0115| 92.5567 | 85.6887 | 82.4051 |
TABLE 10  Ranking of results of simulation studies of the EO algorithm for different operational cases

| Algorithm Cases | Layers        | Activation functions Data type | Evaluation criteria | FFANN structures |
|-----------------|---------------|--------------------------------|---------------------|------------------|
| EO              | Hidden layer/output layer | Hyperbolic tangent/hyperbolic tangent | Training data MAE 6 | 5 2 3 4 1 |
|                 |               |                                | Test data MAE 6 | 5 3 2 4 1 |
|                 |               |                                | MAPE 6          | 5 3 2 4 1 |
|                 |               |                                | RMSE 6         | 5 3 2 4 1 |
|                 |               |                                | Test data MAE 2 | 4 1 6 5 3 |
|                 |               |                                | MAPE 2          | 4 1 6 5 3 |
|                 |               |                                | RMSE 2         | 4 1 6 5 3 |

Case 2 Hidden layer/output layer Hyperbolic tangent/sigmoid Training data MAE 5 | 6 3 4 2 1 |
| Test data MAE 1 | 4 6 5 2 3 |
| MAPE 5          | 6 3 4 2 1 |
| RMSE 6         | 5 3 4 2 1 |

Case 3 Hidden layer/output layer Sigmoid/hyperbolic tangent Training data MAE 6 | 5 3 4 2 1 |
| Test data MAE 1 | 2 5 4 3 6 |
| MAPE 6          | 3 4 5 2 1 |
| RMSE 6         | 4 5 2 3 1 |

Case 4 Hidden layer/output layer Sigmoid/sigmoid Training data MAE 6 | 5 2 4 3 1 |
| Test data MAE 2 | 1 3 5 6 4 |
| MAPE 6          | 5 2 4 3 1 |
| RMSE 2         | 1 3 5 6 4 |

followed step by step according to the procedure mentioned above. Thus, the Williams plot for the results from the SFSFDB model is plotted in Figure 10. The cyan color line in Figure 10 is the critical $H^*$ value or the leverage constraint which is computed as 0.1317 in this study. Moreover, the red line of $R = \pm 3$ is defined as the suspected limits. It can be seen that the majority of data points lie in the range $0 \leq H \leq H^*$ and $-3 \leq R \leq 3$. As a result, the points corresponding to 96.3068% of the total number of data in the data set fall into the domain, while the remaining 3.6932% can be expressed as points outside the domain. These results show that the applied model is statistically acceptable and valid.

5.1.2 Analysis of the cumulative frequency versus absolute percent relative error

The cumulative frequency graph can be consulted for further comparison of the accuracy of the proposed models. This statistical methodology gives an idea of the average absolute percent relative error or absolute percent relative error models below a certain value. Equation (26) is explained as a relative percent error:

$$E_i = \left[ \frac{x_i - o_i}{x_i} \right] \times 100 \quad \rightarrow \quad i = 1, 2, 3, \ldots, n,$$

(26)
### TABLE 11  Ranking of results of simulation studies of SMA for different operational cases

| Algorithm | Cases | Layers                  | Activation functions                  | Data type    | Evaluation criteria | FFANN structures |
|-----------|-------|-------------------------|--------------------------------------|--------------|---------------------|------------------|
| SMA       | Case 1| Hidden layer/output layer | Hyperbolic tangent/hyperbolic tangent | Training data MAE 5 | 6 | 3 | 4 | 2 | 1  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |
|           |       |                         |                                      |              |                     | 21 × 6 × 1         |
|           |       |                         |                                      |              |                     | 21 × 7 × 1         |
|           |       |                         |                                      |              |                     | 21 × 8 × 1         |
|           |       |                         |                                      |              |                     | 21 × 9 × 1         |
|           |       |                         |                                      |              |                     | 21 × 10 × 1        |
|           |       |                         |                                      | Test data    MAPE 5 | 6 | 3 | 4 | 2 | 1  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |
|           |       |                         |                                      |              |                     | 21 × 6 × 1         |
|           |       |                         |                                      |              |                     | 21 × 7 × 1         |
|           |       |                         |                                      |              |                     | 21 × 8 × 1         |
|           |       |                         |                                      |              |                     | 21 × 9 × 1         |
|           |       |                         |                                      |              |                     | 21 × 10 × 1        |
|           | Case 2| Hidden layer/output layer | Hyperbolic tangent/sigmoid           | Training data MAE 1 | 5 | 4 | 6 | 3 | 2  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |
|           |       |                         |                                      |              |                     | 21 × 6 × 1         |
|           |       |                         |                                      | Test data    MAPE 5 | 1 | 2 | 4 | 3 | 6  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |
|           |       |                         |                                      |              |                     | 21 × 6 × 1         |
|           | Case 3| Hidden layer/output layer | Sigmoid/hyperbolic tangent           | Training data MAE 4 | 5 | 1 | 2 | 3 | 6  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |
|           |       |                         |                                      | Test data    MAPE 5 | 6 | 2 | 4 | 1 | 3  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |
|           | Case 4| Hidden layer/output layer | Sigmoid/sigmoid                      | Training data MAE 5 | 6 | 1 | 4 | 2 | 3  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |
|           |       |                         |                                      | Test data    MAPE 5 | 6 | 2 | 4 | 1 | 3  |
|           |       |                         |                                      |              |                     | 21 × 5 × 1         |

where $E_i$ is identified as the relative deviation of a represented/predicted value from an experimental value. $x_i$ and $o_i$ are defined as the actual and estimated/predicted value of the $i$th data, respectively, and $n$ is the total number of data. The mean absolute percentage relative errors given in Equation (27) are used to calculate the absolute deviation of the experimental data.

\[
E_p = \frac{1}{n} \sum_{i=1}^{n} |E_i|.
\]  

(27)

In this study, the cumulative frequency curve given in Figure 11, in which absolute percent relative error values are plotted against the cumulative frequency values, provides further comparisons regarding the accuracy of the proposed models. As can be seen from Figure 11, 90% of the predictions made by the optimized models by the SFSFDB, SMA, AGDE, and EO algorithms have absolute percent relative errors smaller than 27.1328%, 79.6028%, 53.9706%, and 32.6391%, respectively. These results represent another validation analysis of the superiority of the SFSFDB model over other models. Moreover, when the results of all proposed soft calculation methods are evaluated in themselves, they can be expressed as methods that provide fair enough accuracy for estimating electrical energy consumption data involving COVID-19 precautions.
| Algorithm Cases | Layers | Activation functions | Data type | Evaluation criteria |
|-----------------|--------|----------------------|-----------|--------------------|
|                 |        |                      | Training data |                      |
| SFSFDB Case 1   | Hidden layer/output layer | Hyperbolic tangent/hyperbolic tangent | MAE: 6 5 4 3 2 1 |                      |
|                 |        |                      | MAPE: 6 5 4 3 2 1 |                      |
|                 |        |                      | RMSE: 6 5 4 3 2 1 |                      |
|                 |        |                      | Test data: MAE: 1 2 3 5 4 6 |                      |
|                 |        |                      | MAPE: 1 2 3 5 4 6 |                      |
|                 |        |                      | RMSE: 1 2 3 5 4 6 |                      |
| Case 2          | Hidden layer/output layer | Hyperbolic tangent/sigmoid | MAE: 3 6 5 4 2 1 |                      |
|                 |        |                      | MAPE: 3 6 5 4 2 1 |                      |
|                 |        |                      | RMSE: 3 6 5 4 2 1 |                      |
|                 |        |                      | Test data: MAE: 2 4 1 3 6 5 |                      |
|                 |        |                      | MAPE: 2 4 1 3 6 5 |                      |
|                 |        |                      | RMSE: 1 4 2 3 6 5 |                      |
| Case 3          | Hidden layer/output layer | Sigmoid/hyperbolic tangent | MAE: 3 6 5 4 2 1 |                      |
|                 |        |                      | MAPE: 3 6 5 4 2 1 |                      |
|                 |        |                      | RMSE: 3 6 5 4 2 1 |                      |
|                 |        |                      | Test data: MAE: 3 2 1 4 6 5 |                      |
|                 |        |                      | MAPE: 3 2 1 4 6 5 |                      |
|                 |        |                      | RMSE: 6 1 3 2 5 4 |                      |
| Case 4          | Hidden layer/output layer | Sigmoid/sigmoid | MAE: 3 6 5 4 2 1 |                      |
|                 |        |                      | MAPE: 3 6 5 4 2 1 |                      |
|                 |        |                      | RMSE: 3 6 5 4 2 1 |                      |
|                 |        |                      | Test data: MAE: 5 3 2 1 4 6 |                      |
|                 |        |                      | MAPE: 5 3 2 1 4 6 |                      |
|                 |        |                      | RMSE: 6 1 3 2 5 4 |                      |

5.1.3 Sensitivity analysis

The robust predictions can be made as a result of the proposed algorithm being a sufficiently successful model. Therefore, it is necessary to determine whether it is a sufficiently successful model. The important thing here is that accuracy should not be evaluated alone when determining the adequacy of the model. Considering this situation, the degree of effectiveness of the independent variables affecting the model should be investigated by performing a sensitivity analysis. The cosine amplitude method (CAM), which is defined as one of the best sensitivity analyzes in the literature, was used in this study. The variable \( R_{ij} \), which affects the electrical energy consumption the most, is used to measure the degree of sensitivity among the independent variables. The higher the \( R_{ij} \), the more the independent variables affect the electrical energy consumption. If the relationship between the independent variables and electrical energy consumption is positive, the \( R_{ij} \) value is positive, and if the relationship between them is negative, the \( R_{ij} \) value is also negative. X array with \( n \) arguments is \( X = [x_1, x_2, x_3, \ldots, x_m] \), each element of this array as "\( x_i \)" and if there are "\( m \)" of each argument, the elements of the data set are \( X_i = [x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}] \). If the relationship between the dependent and independent variables in the data set is called \( x_i \) and \( x_j \), the \( R_{ij} \) value is calculated as in Equation (28):

\[
R_{ij} = \left( \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}} \right), \quad 0 \leq R_{ij} \leq 1.
\]
| Algorithm | Cases | FFANN structures | Final rank | Sum | Mean | Standard deviation | Algorithm | Cases | FFANN structures | Final rank | Sum | Mean | Standard deviation |
|-----------|-------|-----------------|------------|-----|------|-------------------|-----------|-------|-----------------|------------|-----|------|-------------------|
| AGDE      | Case 1 | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | EO        | Case 1 | 21×5×1          | 3          | 24  | 4.0000 | 2.1909          |
|           | Case 2 | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | Case 2    | 21×5×1 | 3          | 19         | 3.1667 | 2.4014          |
| Case 3    |       | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | Case 3    | 21×5×1 | 3          | 19         | 3.1667 | 2.4014          |
| Case 4    |       | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | Case 4    | 21×5×1 | 3          | 19         | 3.1667 | 2.4014          |
| SMA       | Case 1 | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | SFSDB     | Case 1 | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           |
|           | Case 2 | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | Case 2    | 21×5×1 | 3          | 19         | 3.1667 | 2.4014          |
| Case 3    |       | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | Case 3    | 21×5×1 | 3          | 19         | 3.1667 | 2.4014          |
| Case 4    |       | 21×5×1          | 3          | 24  | 5.6667 | 0.5164           | Case 4    | 21×5×1 | 3          | 19         | 3.1667 | 2.4014          |

Comparison analysis of the ranking results of the FFANN structures for optimization algorithms.
TABLE 14: Comparison analysis of the ranking results of study cases for optimization algorithms

| AGDE | EO |
|------|----|
| **Cases** | **Mean values of the results for all of cases** | **Mean values of the results for all of cases** |
|        | **Training data results** | **Test data results** | **Training data results** | **Test data results** |
|        | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| Case 1 | 26.279183 | 5.011283 | 37.201983 | 55.008833 | 10.7759 | 87.2142 | 12.80675 | 5.5398 | 40.430483 | 50.531283 | 10.040333 | 73.851283 |
| Case 2 | 26.862353 | 5.203133 | 39.054816 | 51.258183 | 10.095066 | 74.529616 | 28.2523 | 5.5205 | 40.3709 | 48.515933 | 9.663016 | 70.52605 |
| Case 3 | 27.748333 | 5.379456 | 39.809016 | 49.768716 | 9.921366 | 73.7047 | 39.914833 | 5.864916 | 43.00845 | 46.106183 | 9.221083 | 69.22135 |
| Case 4 | 28.399016 | 5.58625 | 41.2569 | 47.905583 | 9.494216 | 71.153416 | 30.408783 | 6.02645 | 44.133716 | 44.080466 | 8.8551 | 64.337716 |

| **Ranking of the results for all cases** | **Ranking of the results for all cases** |
|-----------------------------------------|-----------------------------------------|
| **Cases** | **Training data results** | **Test data results** | **Training data results** | **Test data results** |
|        | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| Case 1  | 2  | 1  | 1 | 1 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| Case 2  | 2  | 2  | 2 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| Case 3  | 3  | 3  | 3 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| Case 4  | 4  | 4  | 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

| **Comparison analysis of the ranking results for all cases** | **Comparison analysis of the ranking results for all cases** |
|-------------------------------------------------------------|-------------------------------------------------------------|
| **Cases** | **Final rank** | **Sum** | **Mean** | **Standard deviation** | **Cases** | **Final rank** | **Sum** | **Mean** | **Standard deviation** |
| Case 1    | 2             | 15        | 2.5000   | 1.6432          | Case 1    | 4             | 18        | 3.0000   | 1.0954          |
| Case 2    | 1             | 15        | 2.5000   | 0.5477          | Case 2    | 1             | 12        | 2.0000   | 1.0954          |
| Case 3    | 1             | 15        | 2.5000   | 0.5477          | Case 3    | 2             | 15        | 2.5000   | 0.5477          |
| Case 4    | 2             | 15        | 2.5000   | 1.6432          | Case 4    | 3             | 15        | 2.5000   | 1.6432          |

| **SMA** | **SFSFDB** |
|---------|------------|
| **Cases** | **Mean values of the results for all of cases** | **Mean values of the results for all of cases** |
|        | **Training data results** | **Training data results** | **Training data results** | **Test data results** | **Training data results** | **Test data results** |
|        | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| Case 1  | 33.372866 | 6.81233 | 48.944966 | 40.43125 | 8.286316 | 58.634716 | Case 1 | 25.522216 | 4.809066 | 36.027033 | 60.334666 | 12.26073 | 95.118183 |
| Case 2  | 33.16977 | 6.624866 | 47.735933 | 44.027116 | 8.911833 | 63.005583 | Case 2 | 25.387000 | 4.884166 | 36.174550 | 54.685933 | 10.733383 | 80.197133 |
| Case 3  | 34.3699 | 6.882566 | 49.751333 | 40.51985 | 8.308783 | 58.580166 | Case 3 | 25.387750 | 4.830483 | 35.961183 | 54.592966 | 10.824883 | 84.517866 |
| Case 4  | 34.192333 | 6.83585 | 49.689266 | 39.804883 | 8.138683 | 57.59355 | Case 4 | 26.163316 | 5.078566 | 37.946133 | 51.315716 | 10.153716 | 77.069033 |

| **Ranking of the results for all cases** | **Ranking of the results for all cases** |
|-----------------------------------------|-----------------------------------------|
| **Cases** | **Training data results** | **Test data results** | **Training data results** | **Test data results** |
|        | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| Case 1  | 2  | 1  | 1 | 2 | 2 | 3 | 4 | 2 | 4 | 4 | 4 | 4 |
| Case 2  | 1  | 1  | 1 | 4 | 4 | 4 | 3 | 3 | 2 | 2 | 2 | 2 |
| Case 3  | 4  | 4  | 4 | 3 | 3 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| Case 4  | 3  | 3  | 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

| **Comparison analysis of the ranking results for all cases** | **Comparison analysis of the ranking results for all cases** |
|-------------------------------------------------------------|-------------------------------------------------------------|
| **Cases** | **Final rank** | **Sum** | **Mean** | **Standard deviation** | **Cases** | **Final rank** | **Sum** | **Mean** | **Standard deviation** |
| Case 1    | 2             | 13        | 2.1667   | 0.4082          | Case 1    | 4             | 18        | 3.0000   | 1.2649          |
| Case 2    | 3             | 15        | 2.5000   | 1.6432          | Case 2    | 2             | 14        | 2.3333   | 0.8165          |
| Case 3    | 4             | 20        | 3.3333   | 0.8165          | Case 3    | 1             | 13        | 2.1667   | 0.7528          |
| Case 4    | 1             | 12        | 2.0000   | 1.0954          | Case 4    | 3             | 15        | 2.5000   | 1.6432          |
Figure 7  (A–D) Evaluation criteria for all optimization algorithms

Figure 12 shows the results of the sensitivity analysis according to the CAM performed within the scope of this study. $er(t - 1)$ is defined as the error value between the previous prediction and the true value, and $er(t - 2)$ represents the error value between the two previous prediction and the true value. As can be seen from the results of the analysis, the factor that affects the electrical energy consumption estimation the most is the average humidity value with 0.9271. Average wind speed value follows the average humidity value with 0.9206. Average pressure with 0.8555 and average temperature with 0.8326, which are very close to these values, are seen as the most the other influencing factors. It is seen that the previous error value, $er(t - 1)$ and the two previous error values, $er(t - 2)$, also highly affect the estimation process. It is seen that the days of the week and COVID-19 precautions have a less effect than the others.

6  CONCLUSION

In this study, the recently proposed SFSFDB algorithm was used for the first time as a trainer of the hybrid MLR-FFANN algorithm for the estimation of the energy consumption values of the city of Bursa during the COVID-19 pandemic. The SFSFDB algorithm has the ability to search both locally and globally and optimizes the weight, bias, and $\beta$ polynomial coefficients of the proposed hybrid MLR-FFANN model. The design of the network and the activation functions to be used in the training of the FFANN are among the factors affecting the success percentage of the network in training. Considering this situation, network structures with different hidden layer numbers were considered in the FFANN design of the hybrid model.
FIGURE 8  Evaluation criteria for the best case of all optimization algorithms

TABLE 15  Determination of the best network structures for all optimization algorithms

| Algorithms | Cases | FFANN structures | Training data results | Test data results |
|------------|------|-------------------|-----------------------|------------------|
|            |      |                   | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| AGDE       | Case 3 | 21×7×1            | 27.3865 | 5.3252 | 39.6723 | 45.3613 | 9.2956 | 68.7305 |
| EO         | Case 2 | 21×9×1            | 27.5769 | 5.3586 | 39.1470 | 44.2227 | 8.9883 | 66.2420 |
| SMA        | Case 4 | 21×7×1            | 32.6362 | 6.5491 | 48.8187 | 37.0926 | 7.6234 | 54.8335 |
| SFSFDB     | Case 3 | 21×10×1           | 22.0975 | 4.1256 | 31.2159 | 55.8286 | 11.2382 | 85.6887 |

| Algorithms | Cases | FFANN structures | Training data results | Test data results |
|------------|------|-------------------|-----------------------|------------------|
|            |      |                   | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| AGDE       | Case 3 | 21×7×1            | 2   | 2   | 3    | 3   | 3   | 3    |
| EO         | Case 2 | 21×9×1            | 3   | 3   | 2    | 2   | 2   | 2    |
| SMA        | Case 4 | 21×7×1            | 4   | 4   | 4    | 1   | 1   | 1    |
| SFSFDB     | Case 3 | 21×10×1           | 1   | 1   | 1    | 4   | 4   | 4    |

Final ranking of all optimization algorithms for the training and testing process

| Algorithms | Cases | FFANN structures | Final rank | Sum | Mean | Standard deviation |
|------------|------|-------------------|------------|-----|------|--------------------|
| AGDE       | Case 3 | 21×7×1            | 3          | 16  | 2.6667 | 0.5164 |
| EO         | Case 2 | 21×9×1            | 1          | 14  | 2.3333 | 0.5164 |
| SMA        | Case 4 | 21×7×1            | 2          | 15  | 2.5000 | 1.6432 |
| SFSFDB     | Case 3 | 21×10×1           | 2          | 15  | 2.5000 | 1.6432 |
Moreover, the activation functions in the hidden and output layers used in these network structures were discussed in different study cases as combinations of hyperbolic tangent and sigmoid functions. Whereas the training process of traditional ANNs is carried out by the subjective experience of the researcher or through many iterations, the training process of the hybrid model proposed for different cases in this study was carried out in 250 iterations. In order to show the success of the proposed hybrid MLR-FFANN approach in the training process, the simulation results obtained from the SFSFDB algorithm were compared with the AGDE, EO, and SMA heuristic optimization methods used in the optimization problems of different science fields in the literature. The MAE, MAPE, and RMSE evaluation criteria obtained from the comparison results were statistically examined to evaluate the success of the algorithms in the training of the proposed method. Among the heuristic optimization approaches used in the training process of the hybrid MLR-FFANN, the SFSFDB algorithm was more successful in Cases 1 and 3, the SFSFDB and AGDE algorithms for Case 2, and the AGDE algorithm in Case 4, compared to other algorithms. The simulation results in terms of the evaluation criteria in both training and testing processes and the success ranking of the algorithms showed that the EO and SFSFDB algorithms were more successful than the other algorithms. Furthermore, during the 2020 COVID-19 pandemic, the electric energy consumption values of Bursa were estimated and at the end of the estimation process, the hybrid MLR-FFANN, which was trained by optimizing the parameters via the SFSFDB algorithm, was more successful in the prediction process than the MLR-FFANN structures trained with the other optimization algorithms. The following conclusions were reached as a result of this research:

- When the results of the proposed method based on SFSFDB are examined, statistically MAE, MAPE and RMSE values have the best values with 33.2284, 7.0958, and 48.9234, respectively.
- The validity of the suggested method was demonstrated by outlier analysis, which shows that all data points are within an acceptable range.
- Environmental factors had a more pronounced effect on the estimation of electrical energy consumption than days of the week, error values, and COVID-19 precautions, according to the results of the sensitivity analysis.
- As a result, COVID-19 pandemic precautions were used as input data in the dataset for the estimation of electric energy consumption, and the hybrid MLR-FFANN approach, whose parameters were optimized with the SFSFDB algorithm, successfully carried out the training and learning processes.

| Algorithms | Cases | FFANN structures | MAE | MAPE | RMSE |
|------------|-------|------------------|-----|------|------|
| AGDE       | Case 3 | $21 \times 7 \times 1$ | 52.5230 | 11.2477 | 72.7393 |
| EO         | Case 2 | $21 \times 9 \times 1$ | 41.1935 | 8.2490 | 56.9251 |
| SMA        | Case 4 | $21 \times 7 \times 1$ | 67.5097 | 14.6852 | 92.2592 |
| SFSFDB     | Case 3 | $21 \times 10 \times 1$ | 33.2284 | 7.0958 | 48.9234 |

| Algorithms | Cases | FFANN structures | MAE | MAPE | RMSE |
|------------|-------|------------------|-----|------|------|
| AGDE       | Case 3 | $21 \times 7 \times 1$ | 3 | 3 | 3 |
| EO         | Case 2 | $21 \times 9 \times 1$ | 2 | 2 | 2 |
| SMA        | Case 4 | $21 \times 7 \times 1$ | 4 | 4 | 4 |
| SFSFDB     | Case 3 | $21 \times 10 \times 1$ | 1 | 1 | 1 |

| Algorithms | Cases | FFANN structures | Final rank | Sum | Mean | Standard deviation |
|------------|-------|------------------|------------|-----|------|-------------------|
| AGDE       | Case 3 | $21 \times 7 \times 1$ | 3 | 9 | 3 | 0.0000 |
| EO         | Case 2 | $21 \times 9 \times 1$ | 2 | 6 | 2 | 0.0000 |
| SMA        | Case 4 | $21 \times 7 \times 1$ | 4 | 12 | 4 | 0.0000 |
| SFSFDB     | Case 3 | $21 \times 10 \times 1$ | 1 | 3 | 1 | 0.0000 |
FIGURE 9  For the year 2020: (A) Prediction for the year 2020, (B) error values between actual and predicted consumption values, and (C) actual and predicted electric energy consumption values of the city of Bursa for the year 2020.
FIGURE 10  Detection of potentially suspect data and the domain of applicability of the developed SFSFDB model

(A) (B)

FIGURE 11  For the cumulative frequency versus absolute percent relative error: (A) The results of the different models and (B) zoom version of the results

(A) (B)

FIGURE 12  The sensitivity analysis of dataset
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CONFLICT OF INTEREST
The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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