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RESEARCH ARTICLE

PREDICTION OF NO_x AND FUEL FLOW OF COMMERCIAL HIGH BYPASS AIRCRAFT ENGINES BASED ON CSA-SVR MODEL

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Abstract

Due to the negative effects of emissions caused by fossil fuels used by aircraft engines on the environment and human health, and the fact that fuel consumption is a high cost input for airlines, the aviation community has many studies on both issues. In order to overcome these problems, much space has been devoted to modeling, prediction and optimization studies on emissions and fuel consumption in the literature. Within the scope of this study, a model was created to predict the NOx emission values and fuel flow of high by-pass turbofan engines, which are also used in today's commercial air transportation. 165 different turbofan data taken from the International Civil Aviation Organization (ICAO) emission databank were used for modeling, and the specified parameters were modeled according to the by-pass ratio (BPR), overall pressure ratio (OPR) and rated thrust input parameters. In this context, the Cuckoo search algorithm-support vector regression (CSA-SVR) method for the Landing and Take-off (LTO) cycle, which includes the idle, take-off (T/O), climb out (C/O) and approach (App) phases, was used for the first time in the literature for the above-mentioned purpose. As a result of the error analysis methods, the minimum R^2 value for 4 phases in FF estimation was found to be 0.972763. This value for NO_x was 0.6745 in the idle phase. However, the fact that this value was found to be 0.861497, 0.884984 and 0.792779 for T/O, C/O and App, respectively, shows the success of the model in estimating actual data.

Keywords

Cuckoo search algorithm,
Support vector regression,
Aircraft emission modelling,
Aircraft fuel modelling

Time Scale of Article

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1. INTRODUCTION

Although situations such as the continuous development of technology, industrialization and the constant increase in transportation networks are important developments for humanity, they also bring certain problems. One of these problems is air pollution. It should not be forgotten that this situation, which has a negative impact on the environment and human health, may also be caused by natural factors (volcanic factors, wild fire, etc.) in addition to the anthropogenic factors mentioned above. Transportation, one of the anthropogenic factors, has a significant share in air pollution. Emissions resulting from air, land, sea and rail transportation are also partially responsible for climate change, stratospheric ozone depletion and acid deposition [1,3].

The speed that aviation provides to its customers, especially in international transportation, compared to other types of transportation, causes its rapid growth. As a matter of fact, research predicts that despite the negative effects of Covid-19, air transportation will grow between 3.6% and 3.8% on an annual basis between 2019 and 2041 [4,5]. Increasing air traffic will also increase total fuel consumption and fuel-related emissions. In order to overcome the mentioned problems, aircraft/engine manufacturers are trying to produce more efficient aircraft/engines, relevant authorities are developing different

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procedures and methods to make aircraft stay in the air and on the ground shorter, and also; they have brought solutions such as turning to alternative fuels (Hydrogen) [6–10].

Research shows that aircraft engines account for approximately 2% of global greenhouse gas emissions due to the fossil fuel they use. However, with increasing air traffic, this value is estimated to be around 3% in 2050. Among transportation modes, approximately 10% of global greenhouse gas emissions originate from aircraft engines. In this context, being able to use fuel efficiently and reduce emissions is very important for economic and environmental sustainability [11,12]. Namely; According to International Air Transport Association (IATA) data, fuel costs (271 billion USD) constituted a very large percentage of airline operating costs, approximately 32%, in 2023 [13].

Emissions caused by aircraft engines spread to the environment within and above the troposphere layer of the atmosphere. These are nitrogen oxides (NO_x), carbon dioxide (CO_2), various sulfur oxides (SO_x), water vapor (H_2O), carbon monoxide (CO), various non-methane hydrocarbons (NMHC), other gases and particles [1, 14]. Within the scope of this study, NO_x-related estimation was made. Aviation NO_x emissions have adverse effects on local air quality and human health. NO_x emissions change the levels of methane (CH_4) and atmospheric ozone (O_3), two important greenhouse gases, and thus also affect the climate [15]. In addition, the impact of aviation among all anthropogenic sources in NO_x production is approximately 3% [1]. In this regard, considering the future development of aviation, studies on NO_x are important.

Due to the importance of reducing emissions, there are many studies in the literature on emission estimation, modeling and optimization for different aircraft engines in aviation. Metaheuristic methods are frequently used for this purpose. The basis for this lies in the success of these methods in challenging modeling and optimization problems in many different fields. Modeling work for 51 different mixed-flow turbofan engines can be given as an example of the mentioned studies. A multiple regression model was created for the engines specified within the scope of the study. Afterwards, it was aimed to increase the model accuracy by using the simulated annealing and genetic algorithms (GA) methods. The data used are data published by the International Civil Aviation Organization (ICAO). Model input values are by-pass ratio (BPR), overall pressure ratio (OPR) and fuel flow (FF), which have significant effects on engine performance. Using the 3 specified input values, rated thrust, different exergetic parameters and NO_x emission index (EI) values were predicted. As a result of the analysis, the coefficient of determination (R^2) value was found to be approximately 0.862 for NO_x EI [16]. In another study on the subject, certain exergy parameters were calculated for the take-off phase. Additionally, models estimating emission values and calculated exergy parameters were created. SVR and long short-term memory (LSTM) methods were used to model 171 different high BPR turbofan engines. In the study where FF was also modeled for the take-off phase, HC, NO_x and CO EI parameters were estimated. ICAO data was used for modeling and model input values were determined as rated thrust, BPR, OPR and combustion type. The study stands out as the first study on modeling the emission index and exergetic environmental parameters of high-bypass turbofan engines using the specified methods. The fact that the R^2 values of the models are very close to 1 shows the accuracy of the study [17]. Apart from emissions, there are also many studies on fuel consumption modeling alone. The basis for this lies in the fact that fuel consumption has a significant share in the operating expenses of airlines and is the main source of emissions. Trani et al. (2004) created an aircraft fuel consumption model using the Fokker F-100 aircraft performance manual and the artificial neural network (ANN) method [18]. Other studies on the subject were conducted by Baklacioglu (2015) and Baklacioglu (2016). In his first study, the author created a fuel flow rate model for commercial aircraft for the climbing flight profile using the GA method. True airspeed (TAS) and altitude were used as input values [19]. In the other study, a model was created for the B737-800 aircraft by using ANN and GA methods together. The goal is to create a model that predicts actual data for climb, cruise and descent based on TAS and altitude inputs [6]. Moreover, Ridvan and Baklacioglu conducted two different studies on climb and descent flight profiles, respectively, using CSA and particle swarm optimization (PSO) method. The data set used in the study is flight data recorder (FDR) data of B737-800, one of the most used aircraft in medium-haul commercial air transportation. TAS and altitude, which directly affect flight performance and therefore fuel consumption, were used as model input values. Actual data were predicted with high accuracy in both fuel flow rate models [20, 21].

As a result of the literature research, to the author's knowledge, there is no study using the CSA-SVR method on NO_x emissions and fuel flow for the landing and take-off (LTO) cycle of turbofan engines with high BPR. This study stands out in this context as it is the first in this field. BPR, rated thrust and OPR, which have a significant impact on engine performance, were used as model input values. The created model predicts FF and NO_x with high accuracy according to the input values specified for the LTO cycle, which includes the idle, take-off, climb out and approach phases. In the study, data sets taken from the ICAO emission databank for 165 different high-bypass turbofan engines were used [22]. Although the input parameters and number of engines used are high, the prediction success is quite high, which shows the accuracy of the study. The fact that the engines are used in today's commercial air transportation shows the up-to-dateness of the study; Moreover, modeling for 4 different phases is important for the breadth of the scope.

2. CUCKOO SEARCH ALGORTIHM

Although CSA is a relatively new algorithm, it is frequently used in many areas. The most important reasons for this are that changing the parameters in the algorithm does not have much effect on the solution quality, CSA explores the search space more efficiently by using Lévy flights instead of standard random walks, and the risk of getting stuck in local minima is low. Research shows that the performance of the CSA method is better than GA and PSO, two of the most used metaheuristic methods. The main inspiration for the algorithm is brood parasitism, which is the reproductive strategy of some cuckoo species. CSA is built on 3 basic rules given below [20, 23, 24].

- Each cuckoo lays one egg in a randomly selected nest at one time.
- The best nests with high-quality eggs will be passed on to future generations.
- In CSA, the number of nests is fixed and the egg laid will be found by the host bird with a probability between 0 and 1. If the host bird notices the cuckoo egg, it will either get rid of it or leave its current nest to build a new nest [20,25].

CSA uses a combination of local and global random walk. The extent to which the algorithm's global and local search capabilities will be used is determined by the switching factor (p_a). Local random walk is shown in equation 1.

$$x_i^{t+1} = x_i^t + \alpha s \otimes H(p_a - \in) \otimes (x_j^t - x_k^t) \tag{1}$$

where x_i^t is the current solution and x_i^{t+1} indicates the new solution. From the other terms s and α are step size and step size scaling factor, respectively. While H(u) denotes the heaviside function, x_j^t and x_k^t are two randomly selected different solutions. Finally, ϵ refers to a random number drawn from a uniform distribution, while the symbol ⨂ is the entry-wise product. The global random walk is specified in the equations below.

$$x_i^{t+1} = x_i^t + \alpha L(s,\lambda), \tag{2}$$

and

$$L(s,\lambda) = \frac{\lambda \Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}, (s >> s_0 > 0) \tag{3}$$

The global random walk uses Lévy flights. Therefore, λ is the Lévy flight parameter and the function Γ is a constant given for λ. One of the other terms, αL(s, λ) is the transition probability [20,23,25–27].

3. SUPPORT VECTOR REGRESSION

SVR is a high-dimensional and non-linear mapping machine learning method with low computational complexity that gives very good results in challenging optimization problems [28,29]. The general equations for SVR are shown below:
Consider a series of training points, $\{(x_1, d_1), (x_2, d_2), \ldots, (x_i, d_i)\}$, $x \in R^n$ ve $y \in R$. x are the input values and d expressions are used to specify the output values. The main goal is to define a regression function such as y=f(x) that accurately predicts the outputs d_i corresponding to a new set of input-output samples expressed as (x_i, d_i). The linear regression function (in feature space) is shown below:

$$f(x) = \omega\phi(x) + b$$
$$\phi : R^n \to F, \omega \in F \tag{4}$$

where Φ(x) is the high-dimensional feature space mapped non-linearly from the input space x. Other terms ω and b are coefficients. These coefficients can be estimated by minimizing the basic problem of SVR as follows:

$$\min R(\omega, \xi, \xi^*) = \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{N}(\xi + \xi^*)$$
$$s.t. \quad d_i - f(x_i) \le \varepsilon + \xi^*$$
$$f(x_i) - d_i \le \varepsilon + \xi$$
$$\xi, \xi^* \ge 0, i = 1,2,3...., N, \varepsilon \ge 0 \tag{5}$$

where slack variables ξ and ξ∗ are used to measure the error of the up and down sides, respectively, and C is the regulator. This basic optimization problem is a linearly constrained quadratic programming problem that can be solved by introducing Lagrangian multipliers and applying Karush-Kuhn-Tucker (KKT) conditions for solving the dual problem:

$$\min R(\alpha, \alpha^*) = \sum_{i=1}^{N} d_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{N} d_i(\alpha_i + \alpha_i^*)$$
$$-0.5\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - a_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j)$$
$$s.t.\sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0$$
$$0 \le \alpha, \alpha^* \ge C, i = 1,2,3,...., N \tag{6}$$

Where $K(x_i, x_j)$ is used to denote the kernel function, and the value of this function is equal to the product $\Phi(x_i)$ and $\Phi(x_j)$. Additionally, in equation 6, the terms α and α* associated with the constraints are used to express the Lagrangian multipliers. The kernel function used for SVR modeling in the study is the Radial basis function (Gaussian). The equation used for this is expressed below [17,29–31]:

$$K(x_i, x_j) = e^{-\gamma\|x - x_i\|^2} \tag{7}$$

4. RESULT AND DISCUSSION

The aim of the study is to create a model that will predict NO_x, which has a very negative impact on the environment and human health, and FF, which is one of the largest cost inputs of airline operating expenses and is actually the source of emissions. For modeling, 165 different high-bypass turbofan engines taken from the ICAO emission databank and frequently used in today's commercial air transportation were used. The most commonly used engines today were used in the analyses. CFM56-5B/7B engines and their variants are some of them. These engines are used in aircraft such as A320 and B738, which are frequently preferred in commercial air transportation. Moreover, GE90, CF6, LEAP 1A/1B, GEnx-1B/-2B etc. engines and their variants were used. The areas of use of these engines are again the most preferred aircrafts such as B777, B747, A320 Neo, B737 Max, B787 respectively. The above engines are only a few of the engines used in the analyses. Some of the mentioned engines can be used in other aircrafts in addition to the above aircrafts. In the model, NO_x and FF were estimated according to 3 different input values (BPR, OPR and Rated Thrust) and 4 different phases (Idle, Take-off, Climb out and approach). The large number of engines and input values makes modeling very difficult. To overcome this problem, the CSA-SVR method was used. The basis for this is that the SVR method provides very successful results in complex and challenging problems. However, SVR parameters that affect SVR performance and therefore solution quality need to be adjusted very well. For this, the CSA method was used. Using the CSA method, the SVR performance parameters that would give the best results were found and then modeling was done with SVR. Very good results were obtained as a result of combining the superior features of the two methods. The SVR parameters mentioned are regularization parameter (C), The tube size of e-insensitive loss function (ε) and γ. One of the specified hyper-parameters, C, determines the trade-off cost between minimizing training error and minimizing model complexity. Another important term, γ, is the variance of the Gaussian kernel function. ε is equivalent to the approximation accuracy placed on the training data points [29].

In the CSA-SVR model, the objective function is to find hyper parameters that will minimize the Mean squared error (MSE) value between real values and model values. In this context, the number of nests, or in other words, the number of solutions, for the CSA method was taken as 25, in line with the literature. As a matter of fact, studies on CSA performance show that this parameter gives better results in the range of 15-25. In addition, p_a, which is an important performance indicator for the CSA algorithm and determines the local and global search ability of the algorithm, was taken as 0.25, similar to the literature. This value means that the algorithm allocates 25% of the entire search to local search and the remaining 75% to global search. Performance studies show that p_a values between 0.15 and 0.30 have a positive effect on optimization performance [24]. In the CSA method, the lower limits of the coefficient (C, ε, γ) are determined as 10^{-4} for ε, 10^{-2} for the other two parameters, and the upper limits are 10^{-1} for ε and 10^{4} for the other parameters. A low value of ε is important for the accuracy of the method. Therefore, ε differs in value from the other two parameters. With the idea that expanding the solution range would have a positive effect on the result efficiency, the other two parameters were taken within the ranges mentioned above. Finally, the stopping criterion in the CSA-SVR method was determined as 5000 iterations. The specified value was taken because increasing the number of iterations above this value does not affect the accuracy much and significantly prolongs the solution time.

Although the CSA method is a new metaheuristic algorithm, it can use the search space quite effectively, offer quite different solution suggestions and does not easily get stuck in local minimum. This contributes a lot to giving the best results in the selection of hyperparameters required for SVR. Thanks to these features, it is estimated that it will give better results than grid search, which is one of the most used methods for this purpose. For the SVR part of the CSA-SVR method, the LIBSVM package, which was introduced in 2000, was used. LIBSVM is a widely used and very popular support vector machine (SVM) method [30]. Using a method widely known in the field is important for the accuracy of the results. This article uses a combination of CSA and SVR as a method. The preference of LIBSVM, which allows easy adjustment in hyperparameter selection in SVR usage, provides both the ease of integration of CSA and SVR and the ability to offer different options in hyperparameter selection. Thus, the optimization process can be carried out more effectively, quickly and efficiently. The engines used in the study also cover the engines of the aircraft most frequently used in commercial air transportation today. This means that the scope of this study is quite broad. In addition to the above-mentioned advantages in estimating the specified parameters, the use of the CSA-SVR method for the first time in the literature will provide a new approach to studies on fuel consumption and emission prediction. In order to measure the accuracy of the model, 80% of the 165 data were taken as train and the remaining 20% as test data. The data is randomly separated. The data ratio is taken as 80% and 20%, similar to the literature. A high ratio of train data such as 70-80% is necessary for an accurate model and a test ratio of 20% was deemed sufficient to evaluate the model performance.The ranges of input values are given in Figure 1-2. In addition, the comparison of real NO_x data and model data is shown in Figure 3-6, and the comparison of real FF data and model data is shown in Figures 7-10.

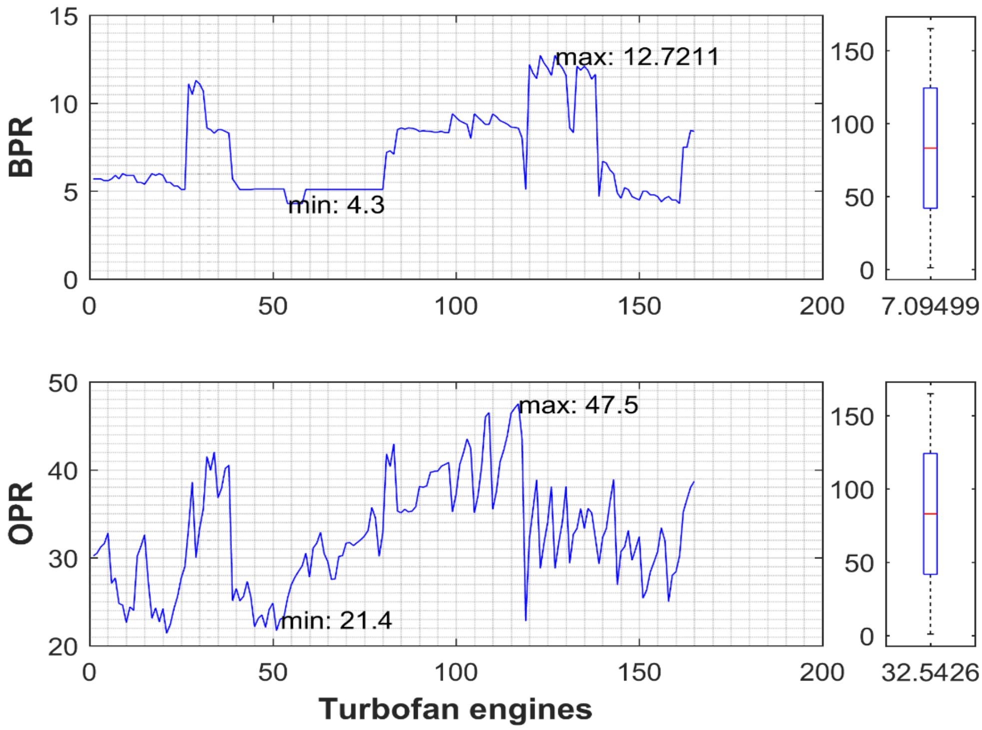

Figure 1. BPR and OPR values of aircraft engines

As can be seen in Figure 2, BPR varies between 4.3 and 12.7211. The average by-pass ratio of turbofan engines is approximately 7.095. At the same time, when the specified figure is examined, the maximum value of OPR is 47.5 and the minimum value is approximately 21.4. The average OPR value is approximately 32.543. In Figure 3, rated thrust values of turbofan engines in kN were given. Unlike BPR and OPR input values, rated thrust varies depending on engine power, so it was shown for 4 different phases.

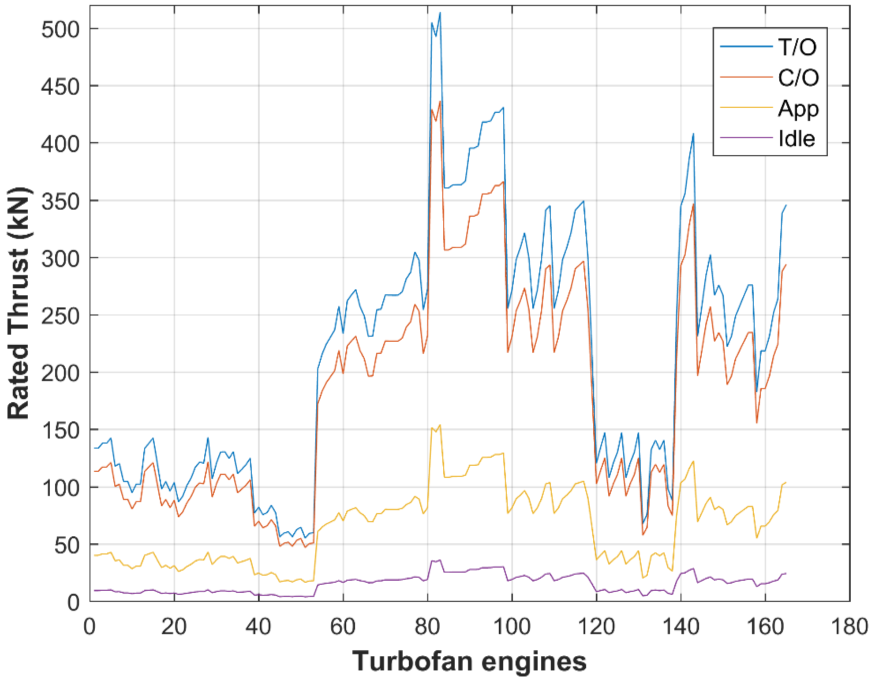

Figure 2. Rated thrust values for 4 different phases

Figure 3-6 shows the comparison of actual data and model NO_x data for 4 different phases. When the specified figures are examined, it is seen that the data are shown separately as train and test data, and the real and model data results largely match in both data sets. The fact that the NO_x values of turbofan engines are quite different reveals a non-linear structure. Despite this, very successful results were obtained with the CSA-SVR model. In the figures shown, it can be seen that the NO_x value is maximum 64.36 (g/kg) for T/O and 6.98 (g/kg) for idle. In addition, the phase with the lowest minimum value is idle (2.86 g/kg), while the phase with the highest value is T/O with 13.51 g/kg. One of the most important reasons for this is the difference in engine power between phases.

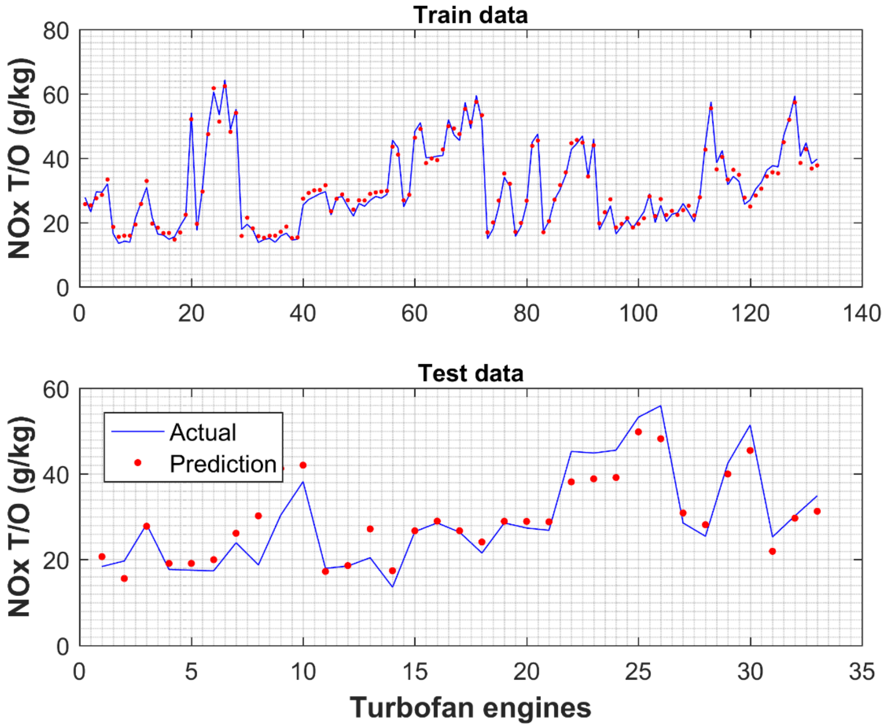

Figure 3. Comparison of actual NO_x values and model values for the T/O phase

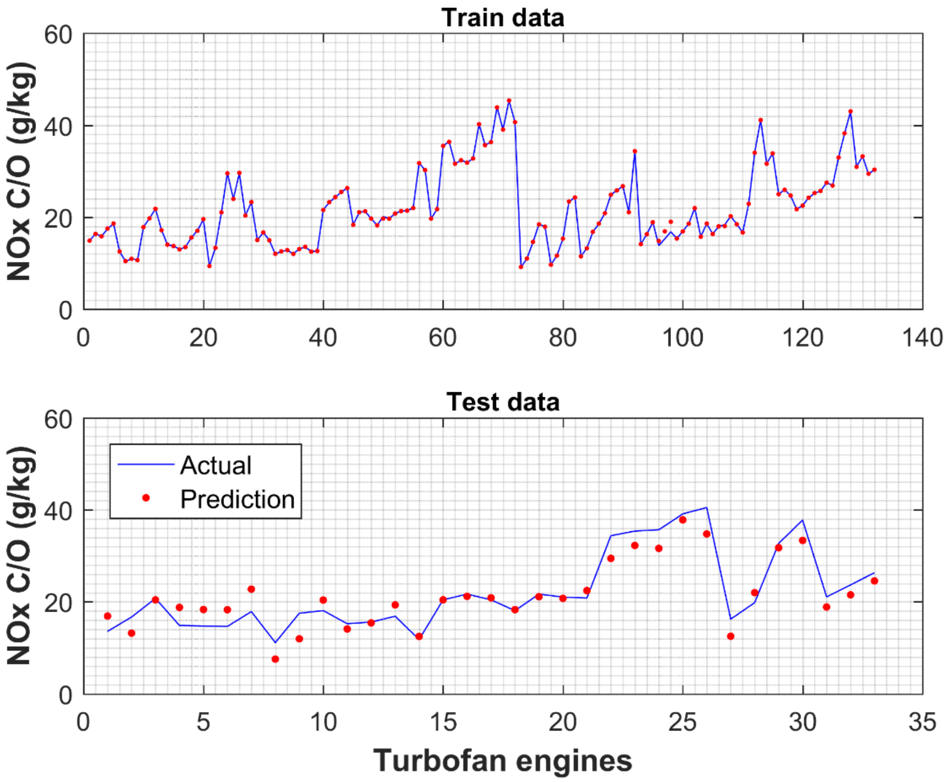

Figure 4. Comparison of actual NO_x values and model values for the C/O phase

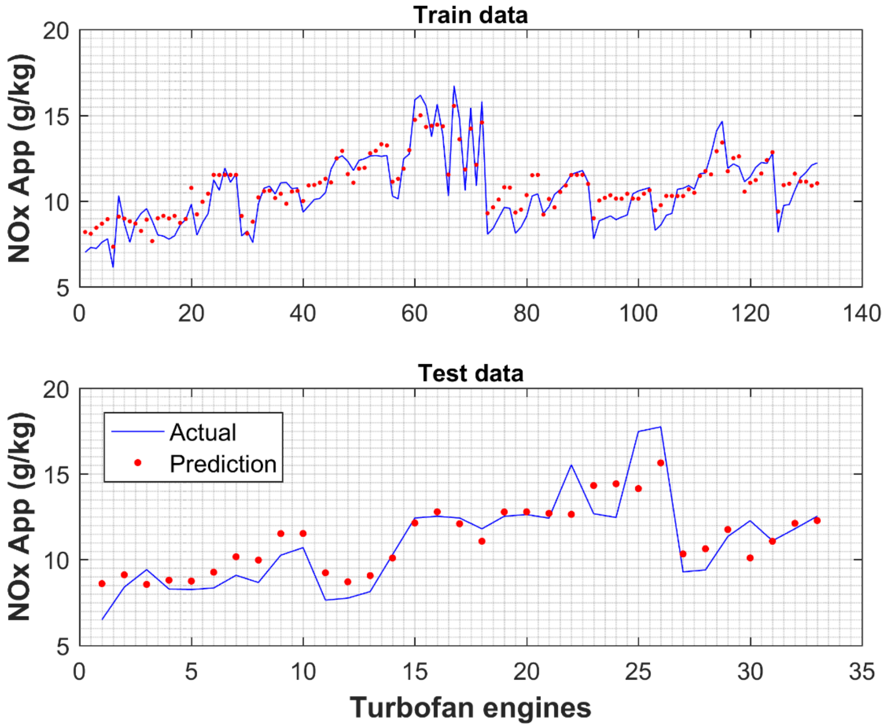

Figure 5. Comparison of actual NO_x values and model values for the app phase

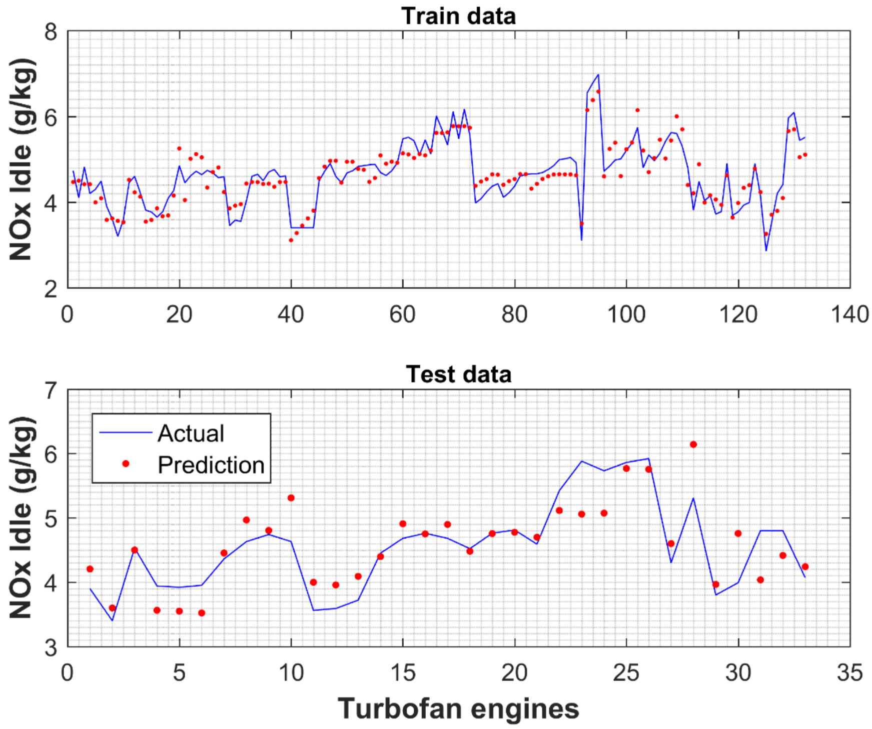

Figure 6. Comparison of actual NO_x values and model values for the idle phase

FF modeling was also performed within the scope of the study. Comparison of model results and actual data is shown in Figures 7-10. It can be seen from the figures that the FF model is in good agreement with the real data, as is the case with the NO_x data. In addition, the phase with the highest FF is T/O and the phase with the lowest is idle.

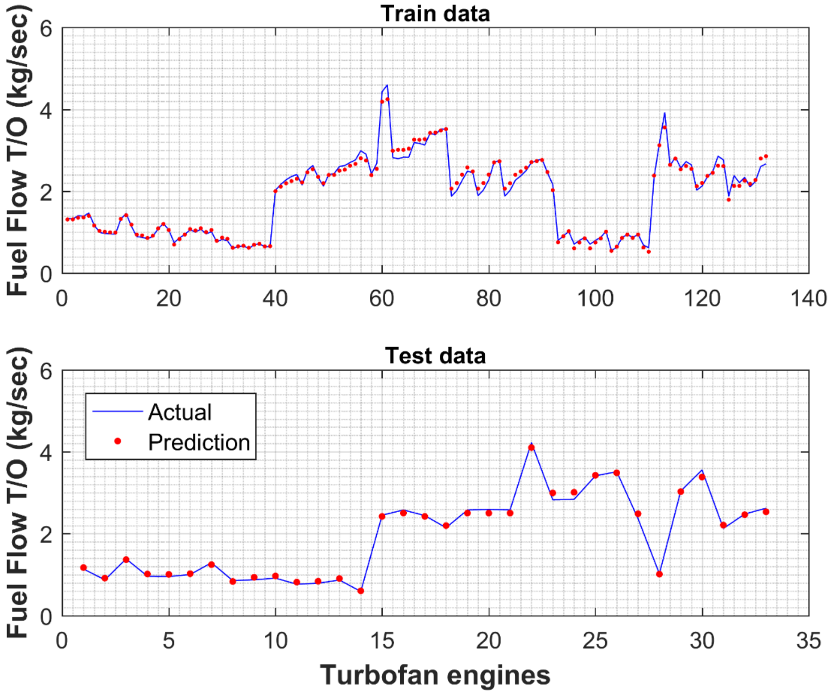

Figure 7. Comparison of actual FF values and model values for the T/O phase

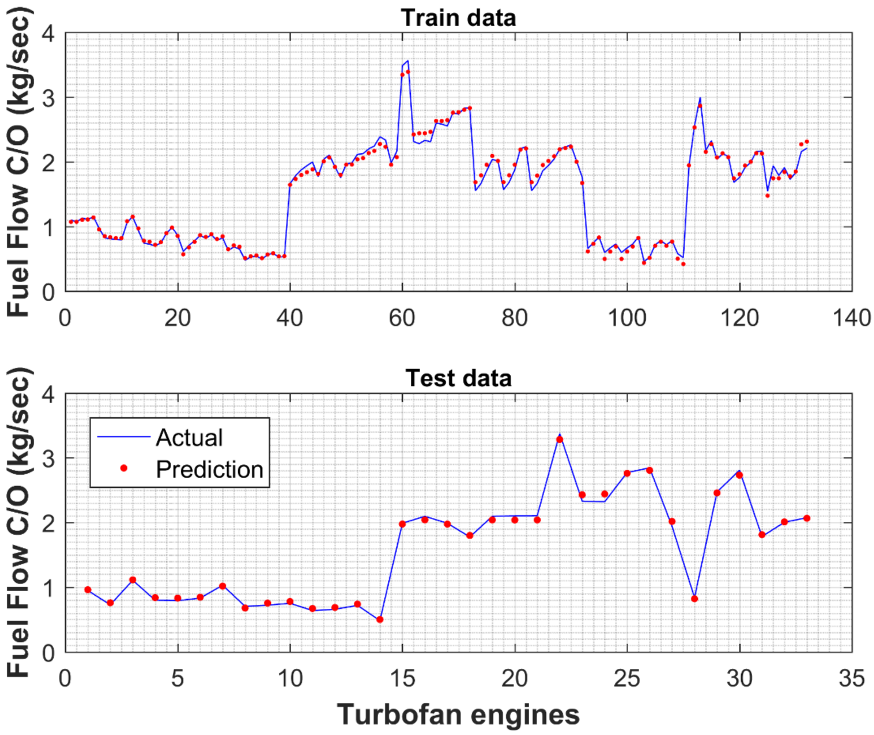

Figure 8. Comparison of actual FF values and model values for the C/O phase

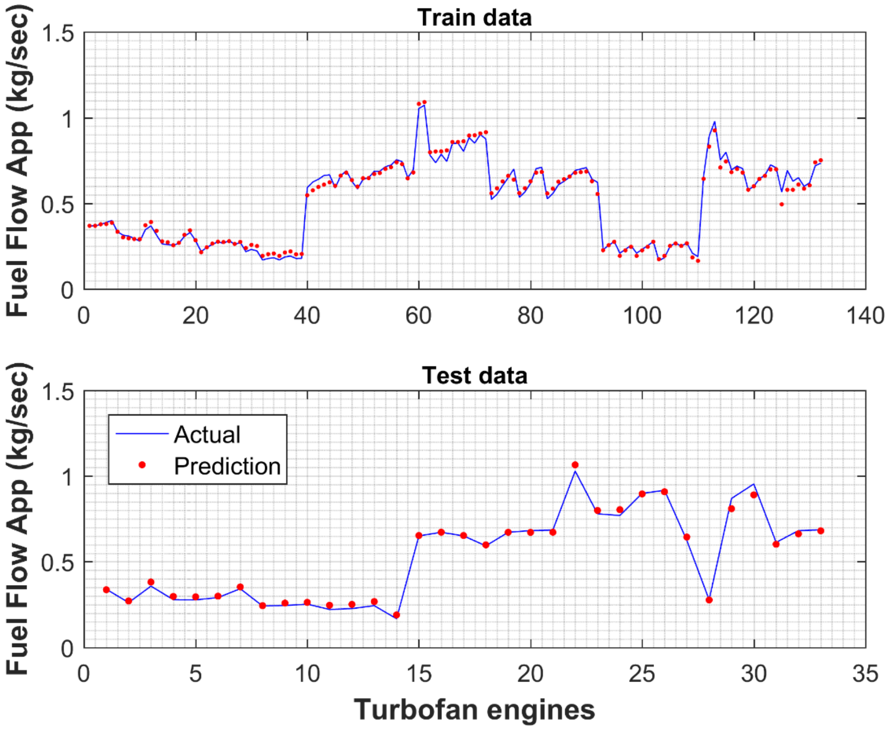

Figure 9. Comparison of actual FF values and model values for the app phase

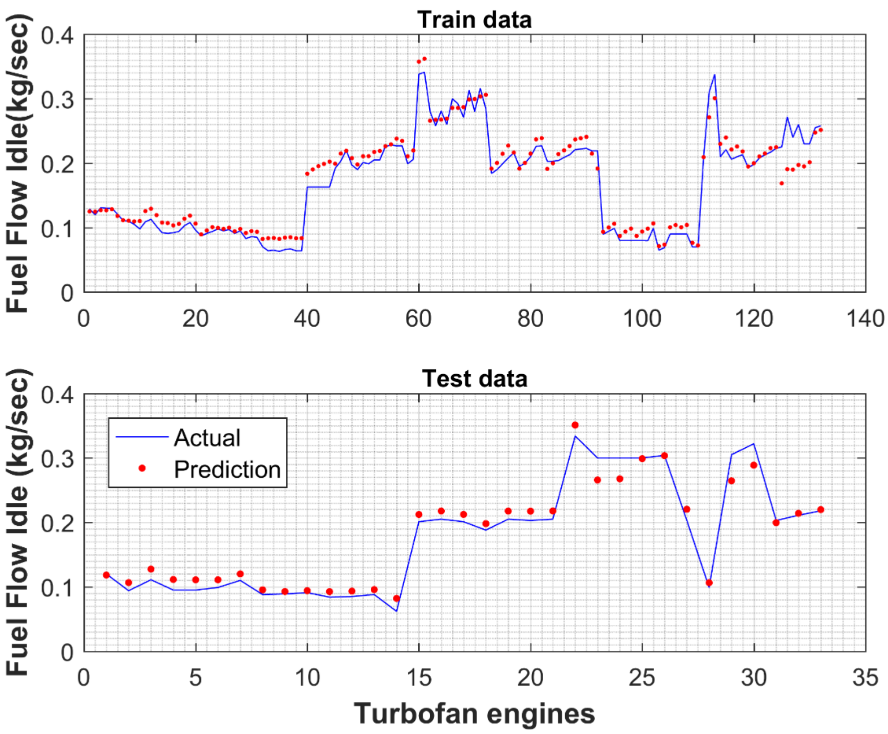

Figure 10. Comparison of actual FF values and model values for the idle phase

SVR performance parameters, in other words CSA model coefficients, were shown in Table 1, and model error rates were shown in Table 2. In Table 2, error rates are given in terms of MSE and Coefficient of Determination (R^2). The R^2 value being close to 1 indicates that there is a good relationship between the data set. In this context, values close to 1 indicate the accuracy of the model.

Table 1. SVR performance parameter values according to NO_x and FF models

		ε	**γ**	**C**
NO_x	T/O	0.0201	2131.7276	8167.9149
	C/O	0.0001	2477.6724	1120.2005
	App	0.0120	5041.9103	9451.5192
	Idle	0.04	614.1491	10000
FF	T/O	0.0001	0.01	10000
	C/O	0.0001	0.01	10000
	App	0.0001	0.01	9559.3102
	Idle	0.0196	0.01	10000

Table 2. Model error values

		Train		**Test**	
		MSE	**R^2**	**MSE**	**R^2**
NO_x	T/O	2.79205	0.986192	19.7715	0.861497
	C/O	6.72358×10^{-2}	0.999061	8.6542	0.884984
	App	0.768855	0.86489	1.68079	0.792779
	Idle	8.83527	0.842976	15.6282	0.6745
FF	T/O	1.01026	0.988502	0.568287	0.994988
	C/O	0.406476	0.992692	0.221538	0.996991
	App	7.32728×10^{-2}	0.986911	4.804×10^{-2}	0.994013
	Idle	3.23715	0.948679	2.59692	0.972763

5. CONCLUSION

The fact that emissions caused by aircraft engines have a significant impact on the environment and human health has caused the aviation community to carry out many studies on the subject. In addition, the fact that fuel consumption is one of the biggest cost items of airline companies increases the importance of this problem and has led to many studies on both subjects in the literature.

Within the scope of this study, a model was created to predict the NO_x emission values and fuel flow of turbofan engines with high by-pass ratio, which are also used in today's commercial air transportation. 165 different turbofan data taken from the ICAO emission databank were used for modeling. The two mentioned parameters were modeled based on BPR, OPR and rated thrust input data. Actual data for 4 different phases were estimated with the CSA-SVR method. The important findings obtained within the scope of the study are listed below:

1. The fact that this study is the first to use the CSA-SVR method on modeling NO_x emissions and fuel flow for the LTO cycle of turbofan engines with high by-pass ratio shows the originality of the method.
2. The use of BPR and OPR design parameters, which have significant effects on engine performance, and rated thrust, which is another important engine performance indicator, as input data shows the accuracy and reliability of the study.
3. For the SVR part of the CSA-SVR method, the LIBSVM package, which was introduced in 2000, was used. LIBSVM is a widely used and very popular support vector machine (SVM) method. Using a method that is widely known in the field is important for the reliability of the results.
4. The fact that today's commercial air transportation engines are used for modeling and the number of engines is quite high, 165, also shows the timeliness and accuracy of the study.
5. As a result of the error analysis methods, the fact that R^2 values are close to 1 in estimating NO_x and FF values, which have a very non-linear structure according to engine types, is another indicator that shows accuracy. Namely; minimum R^2 value for 4 phases in FF estimation was found as 0.972763. This value for NO_X was 0.6745 in the idle phase. However, this value is 0.861497, 0.884984 and 0.792779 for T/O, C/O and App, respectively, and this shows that the values are close to 1.
6. In future studies, different emission parameters will be estimated using different metaheuristic methods.

According to the results obtained, the parameters of bypass ratio, rated thrust and overall pressure ratio affect fuel consumption and NO_X values for different flight phases. Sensitivity analyses can be performed to measure the degree of effect of these parameters. Since the accuracy is high in this method, similar approaches can be applied for different emission indices (HC, CO etc.). Moreover, algorithms such as PSO and GA, which are frequently compared with CSA, can be integrated into the SVR method in emission modeling studies and compared.

CONFLICT OF INTEREST

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

CRediT AUTHOR STATEMENT

Rıdvan Oruç: Formal analysis, Writing - original draft, Visualization, Investigation, Supervision, Conceptualization.

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