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MACHINE LEARNING ASSISTED 2D AIRFOIL SELECTION DURING AIRCRAFT CONCEPTUAL DESIGN PHASE

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ABSTRACT

One of the main design variables in a conceptual design phase is the airfoil geometry. Its properties influence both aerodynamic and structural characteristics of the resultant air vehicle which affect flight performance and safety. Classical methods use a database of airfoils and choose the best performing airfoil according to design requirements by analyzing each airfoil's aerodynamic properties via numerical methods, such as (high-order) finite element methods (CFD), or (low-order) vorticity stream function panel method. In this study, we propose to replace the existing numerical method with a learned model, to improve the computation time. We introduced a geometric parametrization method that is used to generate the input feature trajectory to the support vector machine based regression model (SVR). Preliminary results showed that sectional lift, drag, and pitching moment predictions by the model can be obtained faster than $20\,ms$ *with an accuracy of over* 0.98 *compared to ground truth (Xfoil). Finally, the utility of the airfoil selection method has been demonstrated for two different use cases, each converging less than four seconds for any typical performance metric such as minimum drag, or maximum lift to drag ratio. Related database and code can be reached from :*

https://github.com/mrtbrnz/airfoil_selector/

INTRODUCTION

The aerodynamic performance of a wing/airfoil is of great importance for air vehicle design. In general, the selection of the proper airfoil that meets the design requirements is based on aerodynamic performance indications evaluated by computational fluid dynamics (CFD) or wind tunnel experiments. Although selecting the best performing airfoil using these methods leads to reliable and accurate solutions, these methods are not always cost-effective and easy to implement. This work aims to provide a practical and computationally cost-effective tool that could be used to select an airfoil geometry that meets the design requirements. This proposed tool is believed to be useful especially for those who are concerned about UAV design in terms of saving time. Several prediction

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models have been developed with the increased popularity of machine learning methods. Most of the recent studies regarding the prediction of 2D airfoil design and/or aerodynamic performance, use methods based on deep learning models. These studies differ from one another, depending on the predicted data, the prediction model, and the types and number of input and output data they use. Most of them target to predict the aerodynamic coefficients through airfoil data and flow conditions. Some use the geometric airfoil data as an input [Jihong et al., 2010] whereas others use the airfoil images as input data for the prediction models since it is more convenient for the model they use [Chen et al., 2020; Sekar et al., 2019; Yilmaz and German, 2017; Zhang et al., 2018]. The former method is known as the parametric method while the latter is referred to as the graphical method. Both methods have pros and cons depending on the model.

[Chen et al., 2020] used a prediction model based on a convolutional neural network (CNN) to predict the pitch-moment, drag, and lift coefficients by feeding the airfoil images directly into the prediction model as input. [Yilmaz and German, 2017] developed an approach based on CNN to predict the airfoil pressure coefficient, and the mapping between the input and output data set lead to an accuracy of more than 80%. [Zhang et al., 2018] used CNN prediction model to predict the lift coefficient through airfoil image and flow conditions used as input. [Zelong et al., 2018] also used CNN to predict aerodynamic coefficients of the airfoils by using a signed distance function (SDF) instead of the conventional Kriging surrogate model.

[Sekar et al., 2019] performed a deep CNN to predict the airfoil shape by using the pressure-coefficient distribution as an input in the training phase. In the testing phase, they gave a new pressure-coefficient distribution to the CNN model and generated an airfoil shape that was very close to the related airfoil. However, they used only C_p distribution generated at a fixed angle of attack and Reynolds number as an input.

Besides the aforementioned studies, some studies focus on generative models. [Wang et al., 2021] used a Generative Adversarial Network (GAN) combined with Variational Autoencoder (VAE) and trained their model with gradient-based technique. VAE trains the model to explicitly encode an existing airfoil shape into a low dimensional feature domain while GAN leads to the generation of high-quality new airfoils from random noise [Larsen et al., 2015].

[Karali et al., 2020] developed a deep learning-based surrogate model to predict non-linear aerodynamic characteristics of UAVs. They trained their model using a data set composed of wing-tail geometric parameters and performance coefficients which they previously generated with the non-linear lifting line method. Their results indicate a successful prediction of the maximum lift coefficient, stall angle of attack, total drag, and pitching moment coefficients.

In this paper, we propose an efficient 2D airfoil analysis method based on machine learning which can predict the aerodynamic characteristics of a given airfoil geometry under $20\,ms$ with an accuracy of over 0.98 compared to ground truth (Xfoil).

The main contributions of the present work can be summarized as follows:

- Processed airfoil database is shared publicly (open-source)
- Selection of 2D airfoil is automated with a simple computer program
- An SVR based surrogate model is presented with a small number of airfoils
- The core model has been trained on a database of pre-calculated airfoils and achieves an accuracy of over 98$\%$ on predicting the aerodynamic coefficients C_l, C_d, and C_m of a 2D airfoil.

PROPOSED METHOD

Airfoil selection is an intermediate step during the conceptual design of air vehicles. Classical methods end up with a specific set of design requirements where a database of existing airfoils has to be searched and analyzed to find the best performing geometry that satisfies the requirements and minimize the cost function. This procedure is briefly shown in Figure 1. Here, one can calculate the aerodynamic coefficients of existing airfoils at a given Reynolds number and angle of attack using a software such as XFOIL and choose the best performing airfoil based on these computations. This process is computationally expensive and makes it less favorable during the conceptual design phase. Our goal is to improve this bottleneck with a faster data-driven prediction method that uses a pre-calculated airfoil performance database at different Reynolds numbers and angles of attack.

Therefore, we developed an SVR-based prediction method that would substitute for XFOIL in Figure 1.

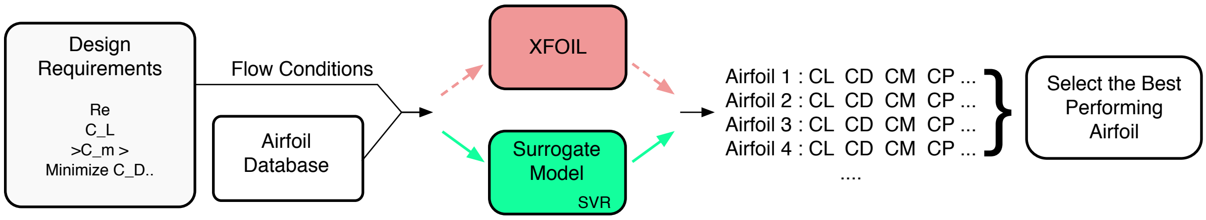


Figure 1: Simplified framework of the airfoil selection during a traditional conceptual design phase.

The proposed method is based on surrogate modeling which is a special case of supervised machine learning. Surrogate modeling builds up a statistical model by assembling the design parameters namely the inputs and their corresponding outputs into a training data set.

Surrogate modeling can substitute for CFD simulations in determining/predicting aerodynamic coefficients of an airfoil which would otherwise be computationally expensive and in carrying out optimizations, uncertainty quantification and/or sensitivity analysis.

Mostly used surrogate modeling approaches are polynomial response surfaces; kriging; gradient-enhanced kriging (GEK); radial basis function; support vector machines; space mapping, artificial neural networks, and Bayesian networks. In this study, we used the SVR model for surrogate modeling.

Database Generation

We used XFOIL to create the aforementioned pre-calculated database for the aerodynamic coefficients of airfoils at Reynolds number ranging from 10^5 to $6\text{x}10^5$ and at the angle of attack values ranging from 0 to 12 degrees. The airfoil coordinates are obtained from UIUC Airfoil database [Selig, M., 1996]. Figure 2 shows arbitrarily selected airfoil geometries taken from the airfoil database that are used in this work. The main difficulties during this tedious work of database generation were mainly coming from geometric problems and sparsity of the coordinates that define the airfoil curvature. Each airfoil is checked for file format issues, and also for the existence of repeated internal point coordinates. Then, the sparse representation is corrected using XFOIL's CADD function and geometry is paneled with a higher number of points, i.e 160 points in our case. Later we used a parallel batch run to analyze the aerodynamic performance of each airfoil at the defined envelope of Reynolds numbers and angle of attack values. Finally, all calculated values are stored in separate directories to be later used on the training of the regression model.

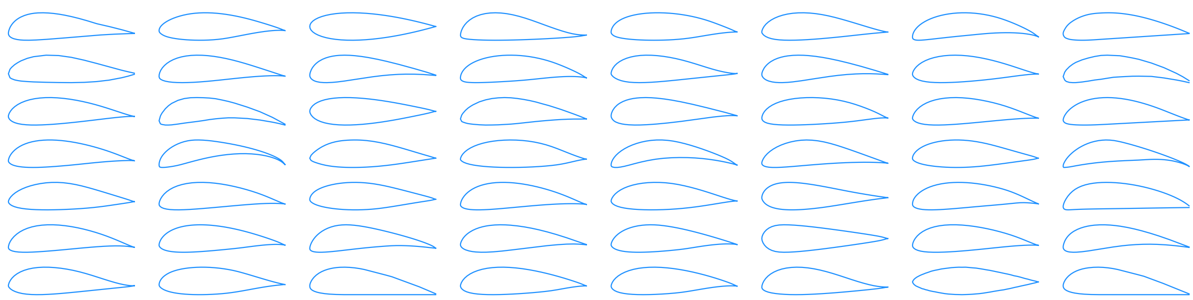


Figure 2: A random sample of airfoil geometries taken from the used airfoil-database [Selig, M., 1996].

Input Trajectory Generation

An alternative way of representing the airfoil geometry and input variables (i.e Reynolds number (Re), and angle of attack (α)) for our regression model is to use direct coordinate trajectory. Each airfoil geometry is considered as a combination of upper and lower curves. These curves are re-sampled with a cosine distribution and then concatenated as depicted in Figure 3. This method has the advantage of representing the airfoil by using only the y-coordinates as every x-coordinate in the database will be identical after the manipulation. In order to add the required input variables, the concatenated geometry vector is extended by adding Reynolds number and angle of attack to the end. The generated feature trajectory is then scaled as the Reynolds number and the geometry coordinates have a big variation. $StandartScaler$ method is used from the Scikitlearn library The input feature trajectory generation details of the proposed learning method are illustrated in Figure 3.

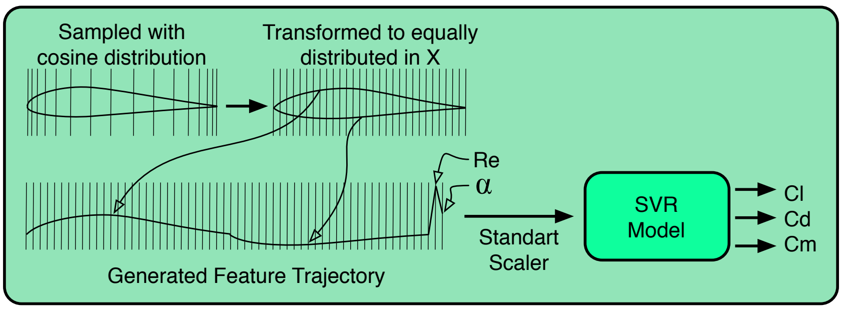


Figure 3: Input feature trajectory generation details of the proposed learning method.

Once, we had all the input data including airfoil geometry and flow conditions, we started training the SVR model for each variable.

Support Vector Machine Regression SVR

SVR is a part of Support Vector Machine (SVM) which is a machine learning tool for classification and regression. SVM is used as a binary classification, whereas SVR is used to predict a value of a continuous variable [Vapnik, V.N., 2019].

SVR performs a linear regression in higher dimensional space. It is a very useful and flexible tool. Also, it is superior to simple linear regression since it can capture non-linearity. In simple regression, the goal is to minimize the error between the data and prediction. However, in SVR, the aim is to keep the error within a certain threshold. Further detailed information regarding SVR algorithm can be found in [Vapnik, V.N., 2019; Awad and Khanna, 2015].

PRELIMINARY RESULTS AND DISCUSSION

Preliminary results clearly show the feasibility of the proposed method. The trained SVR algorithm can predict both sectional lift C_l, drag C_d, and moment C_m coefficients within acceptable error bounds.

SVR Model Training

The model is trained over a small set of 33 airfoils for various Reynolds numbers (100k - 600k), and angle of attack values (0-12 deg). Radial basis function kernel is used in the algorithm with a gamma coefficient of 0.1. Regularization parameter C is selected to be 1. Epsilon parameter which specifies the epsilon-tube within which no penalty is associated with the points is selected as 0.001.

Aerodynamic Coefficient Prediction Capability

Sectional Lift Coefficient C_l: The trained model predicts the sectional lift coefficient values with a very little discrepancy with respect to XFOIL calculations in the linear regime. The obtained accuracy for lift coefficient prediction over validation set is 0.98. The fitting capacity for a randomly chosen airfoil from the database can be seen in Figure 4.

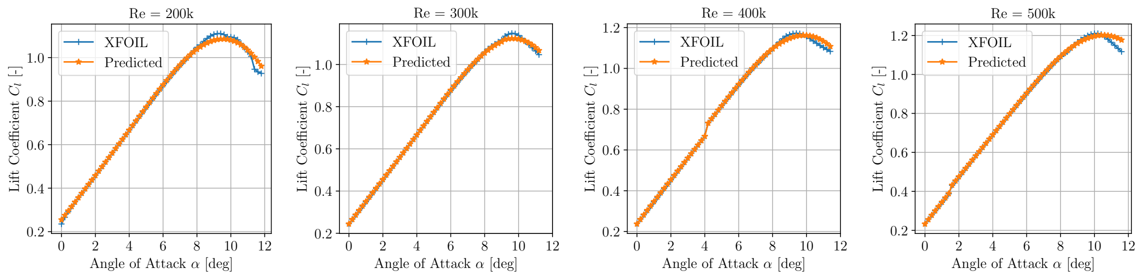


Figure 4: Prediction performance of the learned model on lift coefficient for varying Reynolds number.

In some cases, i.e. for different airfoils, the model can neither capture the stall behavior correctly nor the correct angle of attack where the maximum lift coefficient $C_{l_{max}}$ is obtained, however, the value of $C_{l_{max}}$ is obtained correctly, which is an important issue for design considerations. Those behavior are shown in Figure 5 at different Reynolds numbers.

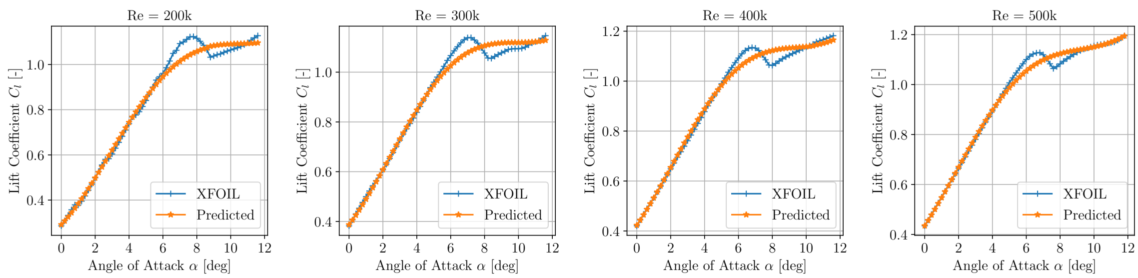


Figure 5: Prediction performance of the learned model on lift coefficient for varying Reynolds number.

Sectional Drag Coefficient C_d: The obtained root mean squared error for drag coefficient prediction accuracy over validation set is 0.98. The representation quality of the model on predicting drag coefficient is visible in Figure 6. It is important to mention that to clearly show only the drag coefficient prediction in the figure, the corresponding lift coefficients are taken from label data.

Sectional Moment Coefficient C_m: Finally, for the sectional moment coefficient prediction, the accuracy obtained over the validation set resulted in 0.99, as it can be seen in Figure 7.

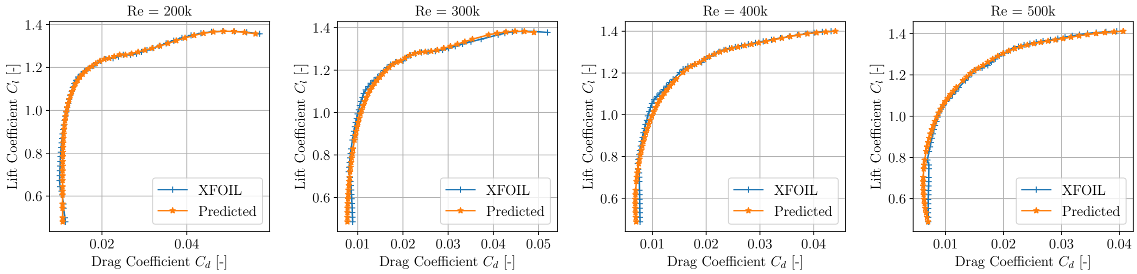


Figure 6: Prediction performance of the learned model on drag coefficient for varying Reynolds number.

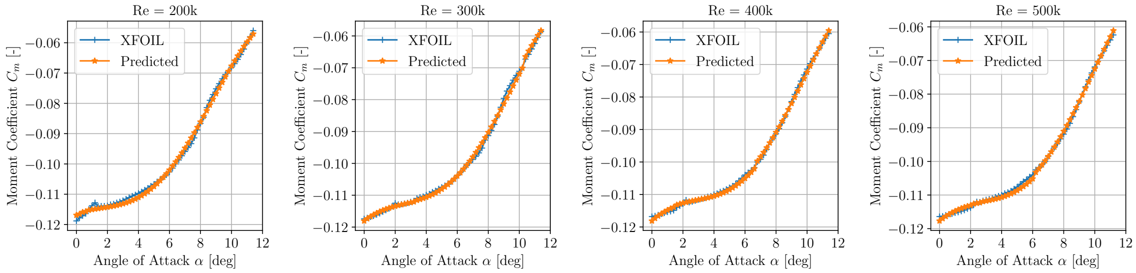
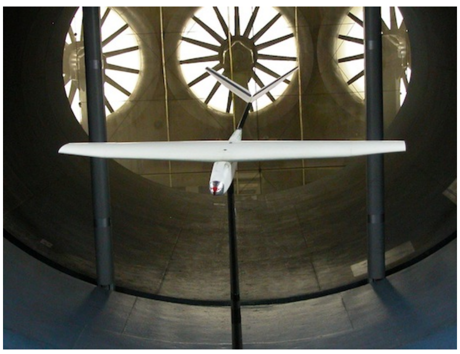


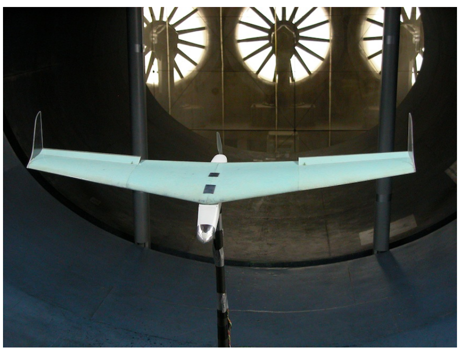
Figure 7: Prediction performance of the learned model on moment coefficient for varying Reynolds number.

DESIGN CASE STUDY

In order to demonstrate the utility of the proposed airfoil selection method, two design cases are selected in this section. The examples are taken from a previous study [Bronz, M. , 2012] where two different aircraft configurations, with identical wing span and weight, were evaluated for their performance on the same mission profile. It is important to note that the selected mission profile does not have any strong relation with the existing projects. In these case studies, we will assume that the main design parameters of the vehicles, such as wing span, surface area, total weight have already been selected and fixed. The concentration will only be on the selection of the wing airfoil geometry for the given mission profile.



Conventional Configuration		
Wingspan	m	1.0
Surface Area	m^2	0.156
Weight	kg	0.6



Flying-Wing Configuration		
Wingspan	m	1.0
Surface Area	m^2	0.176
Weight	kg	0.6

Figure 8: Two example cases that are taken from existing Wind tunnel models of the Conventional and Flying-Wing aircraft configurations Bronz, M. [2012].

Airfoil for a Conventional Aircraft Configuration

Conventional aircraft configuration usually takes advantage of its horizontal tail in order to use more efficient cambered airfoils, and any restriction on the moment coefficient of the selected airfoil can be relaxed. Using the conventional aircraft design specification shown in Figure 8, the required lift coefficient and Reynolds number are calculated to be $C_l = 0.427$ and $Re = 124k$, respectively. It is assumed that the aircraft will be designed for long range mission, therefore increasing the lift to drag ratio (C_l/C_d) is the main selection criteria during the airfoil selection.

Airfoil Name	C_l	C_d	C_m	C_l/C_d
AG27	0.427	0.0104	-0.073	41.22
AG12	0.427	0.0111	-0.046	38.45
AG16	0.427	0.0112	-0.054	38.10
AG36	0.427	0.0119	-0.054	35.73
RG14	0.427	0.0121	-0.050	35.27

Table 1: The output of the airfoil selection program for the conventional aircraft configuration.

Table 1 shows the resultant best five airfoils selected by the presented method among the predefined airfoil database of 33 airfoils. As it has been mentioned in the previous sections, instead of analysing the airfoils by a numerical method such as Xfoil, the method used the trained surrogate model in order to evaluate the performance of each airfoil for the given design conditions (Re, C_l) in less than 4s on a personal laptop computer. For demonstration purpose, the selection criteria has been defined simply to be max C_l/C_d. A more complex selection criteria could have been defined which includes maximum thickness of the airfoil, or relations to other aerodynamic coefficients e.g. C_m if it is necessary.

Airfoil for a Flying-Wing (Tail-less) Aircraft Configuration

Selection criteria for the airfoils on Flying-Wing configuration is modified to include the importance of moment coefficient C_m by simply multiplying the maximum lift to drag ratio with moment coefficient ($C_m\, C_l/C_d$). Using the conventional aircraft design specification shown in Figure 8, the required lift coefficient and Reynolds number are calculated to be $C_l = 0.27$ and $Re = 145k$, respectively.

Airfoil Name	C_l	C_d	C_m	C_l/C_d
S8025	0.270	0.0109	-0.005	24.73
E472	0.273	0.0135	-0.018	20.18
S8036	0.273	0.0192	-0.035	14.17
MH45	0.270	0.0118	-0.023	22.85
MH60	0.270	0.0126	-0.027	21.41

Table 2: The output of the airfoil selection program for the flying-wing aircraft configuration.

Table 2 shows the selected best five airfoils by the method from the same airfoil database as the conventional aircraft configuration example described above. It can be seen that naively defined selection criteria resulted the airfoil *S8036* to **out-perform** airfoils *MH45* and *MH60* although they have higher C_l/C_d values.This known behavior shows the importance of selection criteria definition, and can be easily corrected for example by modifying the selection criteria as filtering out any airfoil with $C_m < 0.04$ while maximizing the C_l/C_d.

Take-Away

As it can be seen from the results shown in Table 3 that the definition of the selection criteria and C_m filtering have a big effect on the final airfoil list, therefore it has to be done more intelligently than what has been demonstrated here. However, it is important to note that the main objective of

Airfoil Name	C_l	C_d	C_m	C_l/C_d
J5012	0.619	0.0142	-0.035	43.68
AG45ct02r	0.270	0.0098	-0.037	27.53
S8025	0.270	0.0109	-0.005	24.73
MH45	0.270	0.0118	-0.023	22.85
MH60	0.270	0.0126	-0.027	21.41
E472	0.273	0.0135	-0.018	20.18
S8036	0.273	0.0192	-0.035	14.17

Table 3: Another output of airfoil selection program for flying-wing aircraft configuration for different selection criteria.

this study is not to discuss the difficulties of selection criteria definition, which is very well known, but to present the use of a faster surrogate based method which reduces the burden of aerodynamic analysis that has to be done at the background of each design problem.

CONCLUSIONS

This study presents an automated airfoil selection method that uses an SVR-based surrogate model of the aerodynamic coefficients that are required during the performance evaluation. The core model has been trained on a database of pre-calculated airfoils and achieves an accuracy of over 98 percent on predicting aerodynamic coefficients C_l, C_d, and C_m of a 2D airfoil. The utility of the proposed method is demonstrated in two example design cases, with the discussion of the importance of selection criteria definition.

With the future goal of a fully automated airfoil generation and selection code, input features are formed as a trajectory of flow conditions and y coordinate points of the airfoils for predefined x coordinates (in cosine distribution). The main objective was to obtain a high generalization of any given airfoil geometry so that unseen, e.g. generated, geometries can also receive reasonably correct aerodynamic coefficient predictions from the model. Although we have achieved high generalization for unseen flow conditions, i.e. angle of attack α and Reynolds numbers, within the database envelope, the model fails to predict satisfactory results for any new unseen airfoil geometry. This issue is going to be addressed in the continuation of this work in a future publication. Both the database and the code has been released as open-source and can be accessed from:

https://github.com/mrtbrnz/airfoil_selector/

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