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A review of the artificial neural network surrogate modeling in aerodynamic design

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Abstract

Artificial neural network surrogate modeling with its economic computational consumption and accurate generalization capabilities offers a feasible approach to aerodynamic design in the field of rapid investigation of design space and optimal solution searching. This paper reviews the basic principle of artificial neural network surrogate modeling in terms of data treatment and configuration setup. A discussion of artificial neural network surrogate modeling is held on different objectives in aerodynamic design applications, various patterns of realization via cutting-edge data technique in numerous optimizations, selection of network topology and types, and other measures for improving modeling. Then, new frontiers of modern artificial neural network surrogate modeling are reviewed with regard to exploiting the hidden information for bringing new perspectives to optimization by exploring new data form and patterns, e.g. quick provision of candidates of better aerodynamic performance via accumulated database instead of random seeding, and envisions of more physical understanding being injected to the data manipulation.

Keywords

Artificial neural network, surrogate modeling, aerodynamic design, machine learning, optimization

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Introduction

The sector of commercial aeronautics is meeting the challenges of public expectation of cheaper fares and reduced environmental impact upon community noise around airports and global warming.[1] The European Union Vision For 2025 requires progress in low-emission energy to secure a sustainable development. The Advisory Council for Aviation Research (ACARE) has set a 2050 goal for civil aeronautical industry to allow a 75% reduction in CO_2 emissions per passenger kilometer, a 90% reduction in NO_x emission, and a 65% reduction in the perceived noise emission of flying aircraft.[2] Therefore, many institutions are dedicated to research and technical exploration in aerodynamic design and optimization.[3] For example, flight tests of the BLADE laminar wing boast a 50% wing friction reduction and up to 5% less CO_2 emissions; Clean Sky and SESAR projects introduce a new generation of aircraft reducing emissions by 15–20%.[4]

Aerodynamic design is related to airfoil, aircraft wing, turbine engine blades, unmanned aerial vehicle (UAV), etc. Generally, typical aerodynamic designs and optimizations formulate objectives, optimization algorithms, constraint functions, and design variables. One major obstacle is the right optimization pattern/approach for the project. The traditional solution to aerodynamic design problems tends to be a top-down approach that relies on physics modeling. For example, the inverse design of pressure distribution designating, as one of the many methods proposed in wing drag reduction problems, modifies the geometry via iterations until the designated pressure distribution over surface is obtained.[5] This method is later challenged by new alternatives in terms of computational resources consumption, e.g. heuristic algorithms combined with the parametric geometry description method.[6] Also, nonlinearity features the aerodynamic optimization problems not only in the physics behind flow phenomena, but also in the influence of geometry description approach on corresponding aerodynamic performance. Furthermore, many aerodynamic design problems require time-consuming evaluations, compared with the duration of operation of the

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optimization algorithm. The computational resource consumption grows rapidly with the utilization of high-fidelity tools for simulations.[7] In addition, most aerodynamic design problems require an appropriate amount of sample points generated via distributing approaches of design of experiment (DoE) methods, e.g. D-optimality, Monte Carlo, and Latin hypercube in multivariable design space, before the set of experimental points is sent to simulator for responses. For example, large numbers of analyses have to be carried out in constructing Hessian at the design point by sampling the design space when there are many variables, particularly when using finite difference methods to evaluate gradients.[8] In fact, many optimizations depend on some forms of internal model for design space exploration.[9] For example, simulations of flow field around new airfoils for different set of shape variables[10] or newly morphed geometry[11] have to be conducted to populate the design space in order to find the optimal candidate. That is to say, obtaining enough information to predict a design landscape in a hypercube of increasing dimensions is a barrier in many optimizations.[12] Approaches including abstraction of problem dimensions and simplification of geometry topology have been adopted in many studies to relieve this difficulty, which yet leads to the inevitable deviation from real design.[13] A strategy of optimization is demanded to be efficient, intelligent, and credible for balancing the modeling efforts and design space scope.[14]

The rapid advance in data science has brought new insights into aerodynamic design and optimization by constructing surrogate models (also termed as metamodel or response surfaces). The "aerodynamic design" refers to the design of airfoil, wing, engine nacelles, etc. that are components of an aircraft. A surrogate model is proposed as a data-driven and bottom-up approach used when an outcome of interest cannot be easily obtained or the inner mechanism of simulation is not assumed to be known. It can be viewed as the response of simulator to the data points in design space comprehensively harnessing high-fidelity simulations and experiments to aid the optimization, sometimes dominating the whole optimization process, and sometimes functioning just as a supplementary aid.[15] The rise of surrogate model comes with the application of inverse design. Traditionally, airfoil design is important for aircraft wings, helicopter rotor blades, etc.[16] Given the boundary conditions of coming flow, the airfoil shape determines its aerodynamic performance including the pressure distribution over the surface. Navier–Stokes equations are applied for obtaining the pressure distribution of specified airfoil shape. Then, the pressure distribution is specified and the airfoil shape is obtained as an output of complex aerodynamic shape optimization procedure.[11] In this circumstance, a surrogate model can be introduced to comprehensively harness data from high-fidelity simulations and experiments to aid the optimization. Meanwhile, reduced-ordered modeling is a similar method that focuses on abstract regeneration of complex flowfield by modeling.[17] For example, the curse of the dimensionality can be relieved with reduced-order modeling in unsteady aerodynamics at varying flow conditions.[18] Comparatively, surrogate modeling is more applicable than reduced-order modeling, because the former is more related to the input and output data of optimization problem and is less involved in detailed aerodynamics.[19] Therefore, this paper focuses on surrogate model thereafter.

Artificial neural network (ANN) is proposed as a data-driven method to transform engineering analysis and design.[20] It emulates biological information processing detouring the need of any objective functions; thus it offers a feasible solution to the technological needs in aerodynamic optimization, which will be discussed in the following section. It can be considered as an interpolation tool for obtaining data that are not originally present in the training data. For example, data-fit models are generated using regression of high-fidelity simulation data from the input to the output.[7] ANN has been widely applied in modern surrogate modeling with its advantage of consuming trivial computational effort; thus, it can be used as the assistant for computational fluid dynamics (CFD) calculation for a large number of designed geometry in a short time, which greatly increases the optimization efficiency.[21] Its accurate generalization and parallel computation capabilities in complex engineering design problems are helpful in the rapid investigation of design space and searching for optimalities.[12] For example, ANN has been used to expedite decision-making process in early stages of aircraft design process and to select proper combination of engine thrust, wing area, and the aircraft weight without going through elaborate details of other direct approaches.[22] The applications and prospects in some new frontiers of ANN surrogate modeling will be discussed in a later section in detail.

Artificial neural network

The advanced intellectual capability and processing power of human brains come from the biological neural network that are composed of numerous chemically connected neurons.[12] A neuron is connected to one another with axons and dendrites; the connecting regions between them are synapses.[23] A neuron receives input from many sources, and then generates a unique output that can be passed on to other neurons in turn.[24] The complexity of biological neural network determines the level of intelligence.[24] The architecture and strengths of synaptic connections often adapt to external stimuli, which is how learning takes place in organisms.[25] Similarly, ANN propagates the computed values from the input neurons to the output neurons, where learning takes place by changing the weights representing the connections between neurons.[26] In many applications, ANN is needed to adjust their internal structure to produce correct outputs for sample inputs, thus approximating the implicit relationship.[27]

Various input–output functions and learning methods can be implemented in realizing neural networks. The configuration of neural network is usually one of the biggest problems in optimization. Figure 1 shows the structure of perceptron as fundamental component of ANN architecture, which contains one input node, one hidden node, and an output node. Generally, the paradigm of ANN is composed of a multi-layer perceptron (MLP) based on feed-forward, supervised learning, and an error back-propagation training algorithm. Consider a situation where each training instance is of the form $(\bar{X}, o)$: each $\bar{X} = [x_1, \ldots, x_d]$ contains d feature variables, and $o \in \{-1, +1\}$ contains the observed value (which is given to the designer as a part of the training data). The input layer contains d nodes that transmit d features $\bar{X} = [x_1, \ldots, x_d]$ with edges of weight $\bar{W} = [w_1, \ldots w_d]$ to an output node. The input layer does not perform any computation in its own right, and the linear function $\bar{W} \cdot \bar{X} = \sum_{i=1}^{d} w_i x_i$ is computed at the output nodes.

Subsequently, an activation function *sign* of this value in form of real number predicts the dependent variable of $\bar{X}$. The activation function as the source of nonlinearities determines the input–output relationships of each processing unit as well as the form of the final solution. Therefore, the prediction $\hat{o}$ is computed as: $\hat{o} = sign(\bar{W} \cdot \bar{X}) = sign\{ \sum_{i=1}^{d} w_i x_i \}$ where the sigmoidal function *sign* maps a real value to either –1 or + 1, which is a common approach in the ANN configuration. Appropriate activation function can provide the desired nonlinear relationship between the input and output vectors. The circumflex on top of the variable o indicates a predicted value instead of an observed one. The primary objective for ANN training is to reduce the error of prediction $E(\bar{X}) = o - \hat{o}$ between the observed value in the training sample and the predicted outcome. Recurrent connections can also be utilized where the predicted outputs become part of the next input vector. When the error value $E(\bar{X})$ is nonzero, the weights in the neural network need to updating in the negative direction of error gradient.

The configuration of the value set to each neuron and weights is the result of neural network training. The operation of a perceptron lays foundation of ANN; its interpretation as a computational unit is useful because it allows to put together multiple units in order to create powerful models in neural network training.[25] Thereby, the basic ANN architecture comprises an input layer, hidden layer(s), and an output layer. Information processing, proceeding from left to right within each layer of the ANN, occurs at many simple processing units or elements.

ANN topology is established/modified according to the detailed situation of the optimization problem: In single-layer neural networks (Figure 1), the training process is straightforward because the error can be computed as a direct function of the weights, which allows easy gradient computation. In multilayer networks (Figure 2), the error is a complicated composition function of the weights in earlier layers. The gradient of a composition function is computed using back-propagation algorithm, which leverages the chain rule of differential calculus, computing the error gradients with respect of weights in terms of summations of local-gradient products over the various paths from nodes to outputs. The principle of weight adjusting is as follows

$$\frac{\partial L}{\partial w_{(h_{r-1}, h_r)}} = \frac{\partial L}{\partial o} \cdot \left[\sum_{[h_r, h_{r+1}, \ldots, h_k, o] \in P} \frac{\partial o}{\partial h_k} \prod_{i=r}^{k-1} \frac{\partial h_{i+1}}{\partial h_i} \right] \times \frac{\partial h_r}{\partial w_{(h_{r-1}, h_r)}}, \quad \forall r \in 1 \ldots k$$

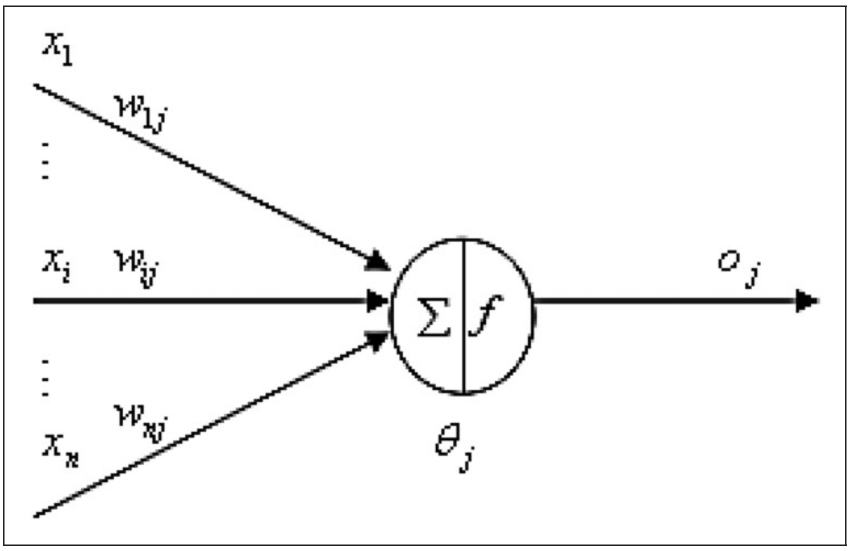

Figure 1. Basic architecture of a perceptron.

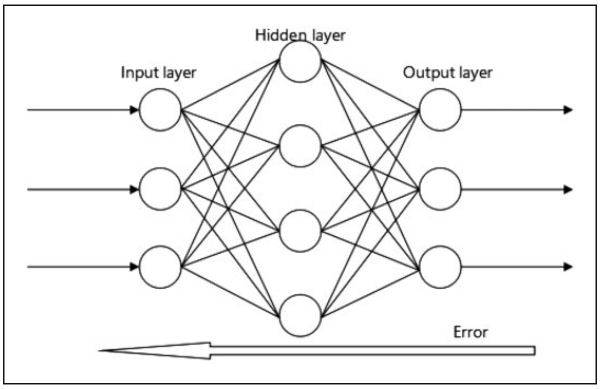

Figure 2. Basic architecture of a multilayer perceptron.

where L is the error function; h is the hidden layer, with subscript indicating layer sequence; $w_{(h_{r-1},h_r)}$ is the weight value connecting layers h_r and h_{r-1}.[25]

The initialization of weight and biases for ANN is investigated to select the effective starting points for training network efficiently and accelerating the convergence.[12] The optimal number of nodes in the hidden layer and the optimal number of hidden layers is problem-dependent. Networks with different numbers of neurons were evaluated to minimize the regression error; however, these numbers should be kept low for the computational efficiency. The number of nodes and layers should be increased if convergence difficulties are encountered, but should not exceed the total number of input and output variables. A simpler network with no hidden layers may be computationally efficient, but it represents only linear mapping between input and output quantities, known as flat networks and can be inadequate to model nonlinear relationships.

ANN modeling of learning from the accumulation of expertise have found their way into practical applications in many areas.[25] The developed techniques assist in addressing a wide range of complex problems in aerodynamic design, where an ANN is fed with CFD simulation during training. For example, an aerodynamic database consisting of approximately 100,000 cases calculated with a full-potential code with computation of viscous effects was used for the neural network training, with the aid of backpropagation algorithm, scaled gradient algorithm, and Nguyen–Wridow weight initialization.[28] Among the techniques, a surrogate model established/aided by neural network method attracts many scientists due to its potential to automatically give the reference geometry according to the design target.[29] The following section will discuss in detail the implementation of ANN in surrogate modeling in the field of aerodynamic design.

Surrogate model in aerodynamic design with ANN

A surrogate model is aimed at reducing computational resource consumption in aerodynamic design and optimization. Efforts have been put so that designers get immediate feedback within design iterations. With surrogate modeling, CFD can be saved during optimization except for final design validation. ANN is used in many applications of surrogate models due to its huge convenience available for problems with large amount of data. The principle behind surrogate modeling is that data at input and output is related through the pattern of the trained neural network.

Direct applications of ANN surrogate modeling in aerodynamic design

Many ANN surrogate modeling have been applied in optimization. ANN has been implemented efficiently to interpolate the aerodynamic pressure loads for one-way UAV fluid structure interaction.[30] The result shows good agreement with the actual pressure profile on aircraft compared against two-dimensional curve fitting with higher order polynomials. With data training, ANN is able to learn active control strategy from experiments of mass flow rates of two jets on sides of a cylinder.[31] Its predictive capability is shown insensitive to numerical instabilities and convergence difficulties typically associated with computational processes.[24] Turbomachinery uncertainty analysis requires performing a large number of simulations, the computational cost of which can be greatly alleviated with ANN surrogate modeling.[32] ANN has successfully helped to estimate the separation point and stall speed of cascaded fins from the relationship with the number of fins in the cascade.[33] Surrogate models with ANN have been shown a good alternative to conventional solution with regard to the prediction of aerodynamic coefficients of airplanes of high accuracy.[28] ANN has been used for space mapping for transonic airfoil aerodynamic shape optimization.[34] ANN has been trained by the data of fuselage drag coefficient obtained by accumulated experimental results conducted in wind tunnel to be capable of fuselage drag coefficient estimation for each parameter values of fuselage shape with respect to inputs without rigorous computations.[20] It has also helped to achieve optimal profiles for minimizing time-averaged drag and buffet magnitude in the supercritical airfoil design.[10]

The numerical search for the optimum shape is of great interest for aircraft and turbomachinery designers. The authors of this paper have both been dedicated to an applicable airfoil/wing inverse design method with the help of ANN and database (Figure 3) in a design for a transonic swept wing of a passenger jet.[16] It can directly generate profiles fitting the requested aerodynamic performance with trained neural network, avoiding the repetitive cut-and-try.[35]

Variation, improvement, and development of ANN surrogate modeling

Selection of type of neural network. The type of neural network is an important option that lays influence

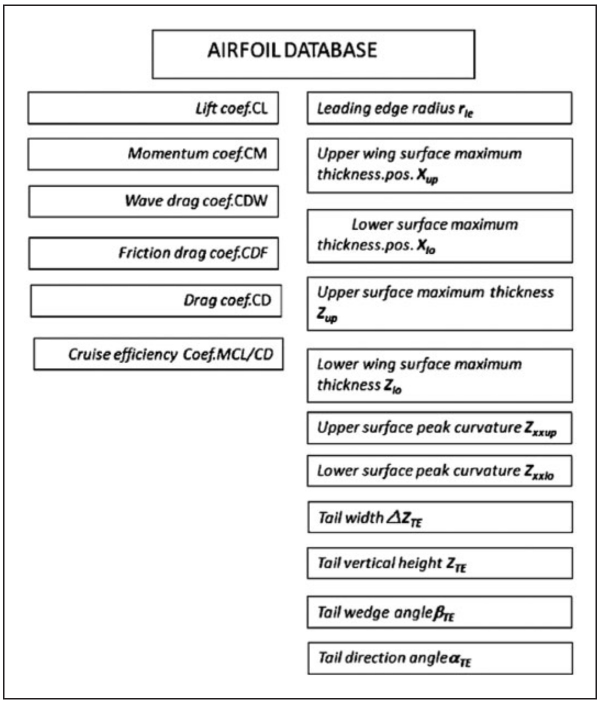

Figure 3. An airfoil database for inverse design.

on the effect of the ANN surrogate modeling. There was an intensive comparative study on the approximation performance of three prospective surrogate models: ANN, radial basis function (RBF), and support vector regression.[32] The result shows that ANN outperforms others, but it may alter if the problem is changed because ANN needs a certain data set to be effectively trained. A data set is an assembly of data. Different surrogate modeling approaches, e.g. RBF, Kriging, and support vector regression, etc., have been compared to bring the efficient global optimization closer to reality.[8] It is certain that the best selection of ANN architecture always accomplishes with different data sets of problem.[20] The outcomes can be influenced by many factors, and therefore there is no simple deduction to which type of surrogate model outperforms others. The main approaches in the frontiers of ANN surrogate modeling proposed to enhance the estimating abilities by recent studies are discussed as follows.

Treatment to the input and output data for neural network training. Conventionally, the input data to the ANN is simply geometric parameters in geometry-aerodynamic performance surrogate modeling, e.g. wing planform, airfoil geometry and flight condition, etc.[28] For example, wing planform parameters of UAV design were determined through an aerodynamic optimization process using both genetic algorithms (GAs) and ANNs.[36] The number of parameters should be kept as little as possible; otherwise the sufficiency of sample data would be difficult to be satisfied in the network training. A class/shape function transformation (CST) geometry parametrization method represents an accurate UAV aerofoil with 10 geometry design variables.[12] Parametric section (PARSEC) is compared with other kinds of parametrization method and is evaluated as appropriate for airfoil description due to its accuracy and intuitiveness.[16]

ANN designers are inspired by the idea that the outcome of data training may largely be dependent on the form the input data takes. On one hand, the form of input data should be excluded with nonmeaningful information so that the training can be guided with some kind of direction. On the other hand, the form itself may hinder the ANN to automatically relate the crucial physical meaning that effectively decides the output data (e.g. aerodynamic performance) during training. For example, the geometric representations are sometimes not effective for neural network training since the hidden semantic meaning of the vectors of input data varies.[37] Data tend to lose its apparent physical meaning in the process of parametrization and normalization. Obviously, the data form has influence on the information where the data are transmitted to the neural network during training. Some knowledge of aerodynamic optimization that is not expressed in data will never be "understood" by the neural network.

The aerodynamic performance of an airfoil is function of its geometrical shape, which implies in many situations (especially when the target aerodynamic performance is not multi-objective) where there may be more than one set of geometrical shape that fits the aerodynamic feature given by designers. Under this circumstance, classification via self-organizing mapping (SOM) can relieve this challenge, applications of which can be seen in Figures 4 and 7, where database of airfoils are classified into several groups according to the similarity of feature data.

Therefore, new forms of geometric representation method are proposed specifically to the network training. Geometry data instead of abstract parameters can be directly input into deep learning network in the form of coordinate of wing profile points, or even in the form of tensors that records the connection of the concerned point with other neighboring points, without the need for complex parametrization.[38] Even at the output, the form can be extended to two-dimensional and three-dimensional pressure distribution over a solid body of aircraft, which can be beneficial for aerodynamic design.[11] For example, a signed distance function (SDF) sampled on a Cartesian grid was proposed as a universal representation for different geometries, which is shown to be effective for convolutional neural networks.[37] SDF not only provides local geometry details, but also contains additional information of the global geometry structure. Another solution is data filtering via principal component analysis (PCA), a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into

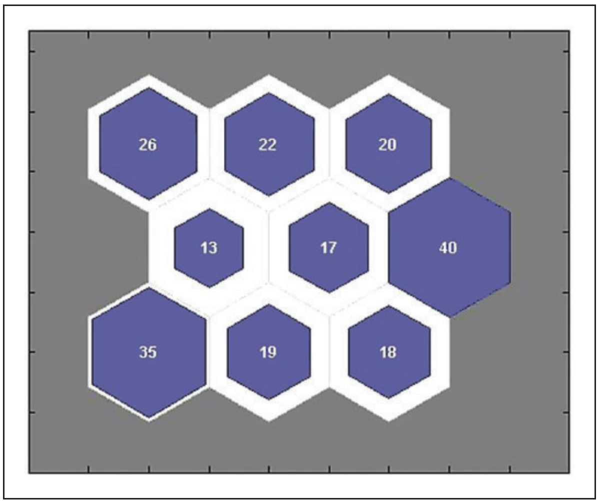

Figure 4. Classification of airfoil database via SOM.

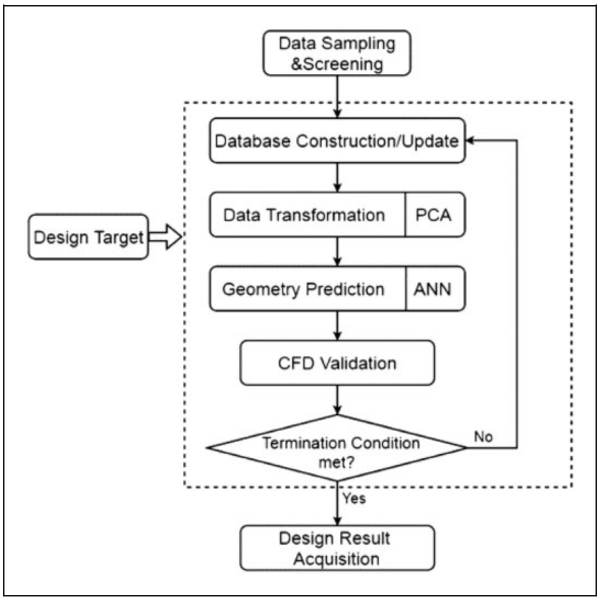

Figure 5. Framework of the PCA–ANN-based inverse design model.

a set of values of linearly uncorrelated variables ''principal components''. PCA reduces the dimensions of the problem with kernel function in interpolating non-linear problems, thus saving computational resources. In the inverse design model of stall lift robustness for high-lift device, PCA is applied to operate on the input data to the network being trained and obtains satisfactory result (Figure 5).[39]

Similarly, there are also studies about the treatment of output data of neural network training. For example, grouped method of data handling (GDMH) neural network can be used in order to transform discrete CFD data into continuous function.[40] The paramount goal of GDMH modeling is to generate a quadratic polynomial function in a feed-forward network whose coefficients are obtained with regression technique. By means of a complex polynomial function, the generic form of relation between the input and output variables can be expressed as Ivakhnenko polynomial.

Utilization of various levels of information. As a matter of fact, the data in the design space can be classified by the information conveyed by data itself.[41] Different levels of information hidden in physics can be extracted via different procedures. For example, multiple design alternatives have to be quickly iterated in preliminary design to make initial decisions without high-fidelity simulations. Similarly, the multilevel surrogate modeling (also termed as variable-resolution model) is proposed to obtain the optimal area in the design space quickly, after which the search for the optimal point location is held in the neighboring region of a smaller area in design space thus saving computational resource. Designers can even directly apply the deep learning approximation model in design space exploration algorithms without training extra lower-dimensional surrogate models.[37] One such application is a multilevel surrogate-based aerofoil shape optimization.[42] As three fundamental parts of ANN, i.e. the form that input data takes, the type, topology and configuration of neural network, and the form the output data takes, the data flow should be complete as well as well-arranged. The progress can also be made at the procedure of surrogate modeling, which can be in new form other than simple data bunching.

Unexploited hidden information in optimization

ANN is used to utilize the resource of accumulated airfoil data so that it can be able to learn from large amount of data, instead of using rule-based programming.[43] There is still room for improvement in making ANN learn in a ''smarter'' way. The hidden information has to be exploited so that the design space contains new perspectives beneficial to optimization. Take drag reduction for example: the flow phenomenon involves many factors that may have impact on the aerodynamic performance, e.g. the position and vibrating frequency of separating in buffets in the boundary layer of transonic airfoil; the peak of pressure value over the surface that indicates shock wave position and the distribution of the pressure that determines the profile drag of an aircraft wing; the location and emerging time of vortex cores; the distribution of boundary layer thickness. A good surrogate model should contain the above information during neural network training, while does not mix all the useful information into a mess.

It is known that different aerodynamic performances of two airfoils are result of their different geometry.[44] In this approach, ANN is expected to correlate the relationship; thereby new airfoil geometry that leads to better aerodynamic performance will be able to be produced. The authors of this paper have done similar research in exploiting airfoil database of geometry and aerodynamic performance from accumulated experiment and CFD calculation results based on ANN.[45] The proposed approach "database self-expansion" is focused on quickly providing new airfoil candidate that has better aerodynamic performance (Figure. 6), which is different from other algorithms e.g. particle swarm optimization, ant colony optimization, etc. The database is classified for data concentration via SOM, as is shown in Figure 7. Conclusively, the comparisons of geometry before and after optimization are shown in Figure 8. The corresponding comparison of aerodynamic performance is shown in Figure 9.

Collaboration with other optimization algorithms. The possibilities of combining the advantages of different optimization algorithms are studied by many researchers. The heuristic algorithm of GA is usually chosen due to its simplicity to implement, their robustness, and flexibility in different situation of various problems. One big disadvantage associated with GA is that they are computationally time-consuming especially in aerodynamic optimization where a CFD solver is used for the fitness function evaluation. This makes the use of ANN an efficient way to reduce the computational time, since ANN decouples the aerodynamic solver from the optimization process where the GA operates simultaneously with ANN.[36] ANN is employed as one of the reliable and fast methods of predicting aerodynamic coefficients to select optimized airfoils[10] as well as a lift-drag ratio optimization for airfoil[46] with GA. Approximated pre-evaluations based on ANN are used in a hybrid optimization procedure with GA to determine airfoil shape in three-dimensional wing design to benefit from the accumulated knowledge thus reducing

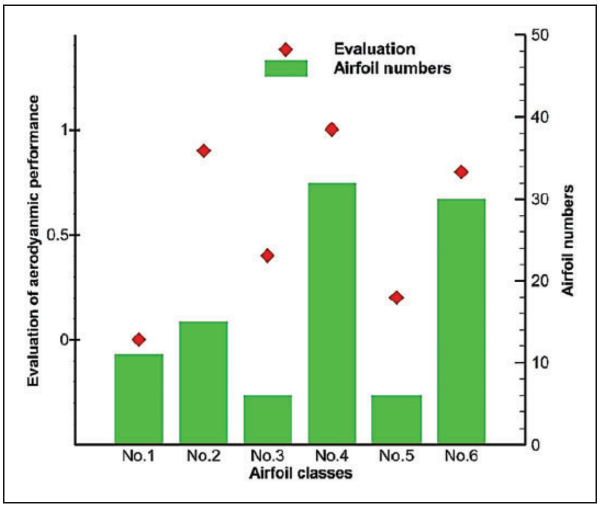

Figure 7. SOM geometry classification situation.

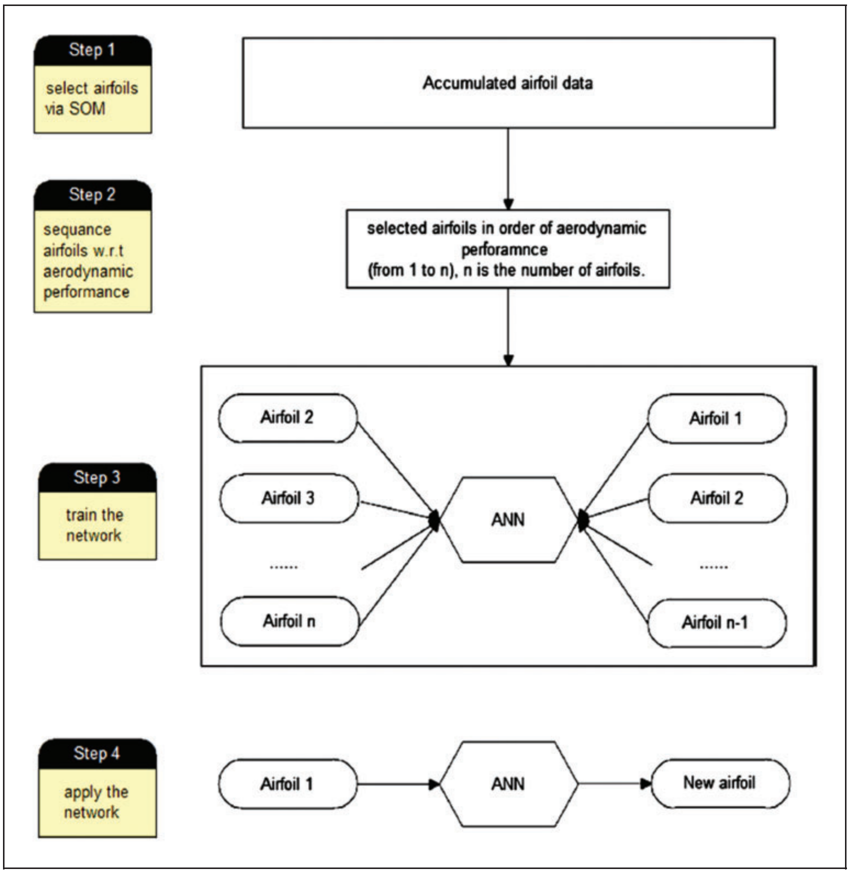

Figure 6. Illustration of database self-expansion flow chart.

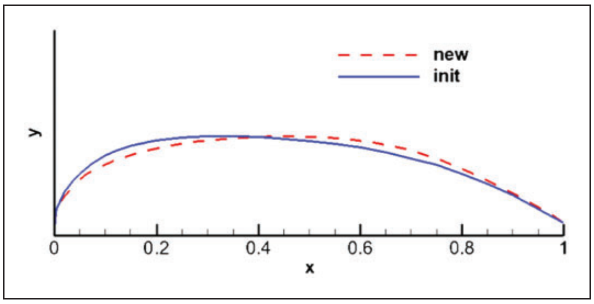

Figure 8. Comparison of initial airfoil and the new airfoil's upper curve by database self-expansion.

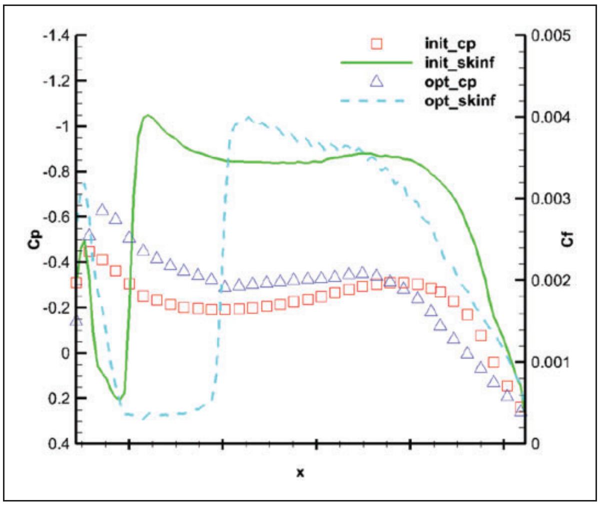

Figure 9. The skin friction coefficient C_f and pressure coefficient C_p distribution at specified position of nacelle surface before and after database self-expansion.

the number of CFD evaluations required at each generation.[47]

There are also other types of combination of optimization algorithms with ANN. A hybrid model that combines state-space model (supported by wind-tunnel experimental data) and ANN is proposed to describe the aircraft unsteady aerodynamic characteristics.[48] Thereby, the separation point model in state-space representation is reserved to describe the time delay of the unsteady aerodynamic responses, while the conventional polynomial model is replaced by ANN to improve accuracy and universality. An architecture combining a variational autoencoder mapping shapes to latent representations and Gaussian process regression is jointly trained to generate improved shapes in the two-dimensional case.[9] A novel algorithm to estimate the optimum value of the fuselage drag coefficient is designed by integrating ANN into the algorithm of simultaneous perturbation stochastic approximation (SPSA).[20]

There are also attempts of using different approaches within the domain of ANN surrogate modeling, although the basic pattern is quite similar to one another. For example, the surrogate models by implementing enhanced neural networks (ENNs) have been conducted in establishing a hybrid optimizer, which is executed to search for the first tentative optimal point.[12] The analysis code is performed on the tentative optimal point to check the difference between the surrogate model ENN and the analysis code.

Deep learning in surrogate modeling. In MLP architecture, the learning capability can be increased by adding hidden layers and/or units in hidden layer. However, the trade-off space between the network size and the learning capability is mainly determined by stereotyped variability due to the underlying assumption of "fully-connected" network structure. In this context, "deep learning" has attracted many studies in recent years, although it is just a sub-concept under ANN. Compared with its conventional MLP counterparts, deep learning is equipped with more training layers and characterized layer (e.g. convolutional layer and pooling layer in the famous LeNet-5).[49] Conventional MLP are compared with the convolutional neural network (CNN) results: the deep learning surrogate modeling exhibits a competitive prediction accuracy with minimal constraints in geometric representation.[50] Deep learning is enabled to learn invariant high-level features when the data have strong spatial and/or temporal correlations. Despite the limitation in application (e.g. progress are mostly seen in the frontier of image recognition) and the requirement of sample data of higher magnitude, deep learning is beneficial in the field of aerodynamic design surrogate model because it no longer needs the a priori treatment to the input data (e.g. the hand-crafting of features by experts), thus human experience can be less relied on and new perspective of design space can be created.

There are an increasing number of applications of deep learning in aerodynamic design, most of which takes different forms than conventional ANN, although the principle of surrogate model is not changed. CNN is able to estimate the velocity field two orders of magnitude faster than GPU-accelerated CFD solver and four orders of magnitude faster than a CPU-based CFD solver at a cost of a low error rate.[37] In a long endurance UAV aerofoil design optimization, repetitively enhanced neural networks (RENN) method is developed and presented for complex and implicit engineering design problems, which constructs an accurate surrogate model and avoids over-fitting during neural networks training from supervised learning data.[12] The optimizer seeks a tentative optimum point, which is then repetitively added into the supervised learning data until tolerance is reached. CNN has been applied to map airfoil shapes to pressure distribution under the framework of classification problem using discretized pressure coefficient.[51] In the testing phase, a new pressure coefficient distribution is given to the CNN model, generating an airfoil shape that is close to the associated airfoil with an average L_2 error of less than 2%. Using conditional generative adversarial networks (cGAN), new data-driven models are trained by deep learning for direct generation of solutions to steady-state heat conduction and incompressible fluid flow purely on observation without knowledge of underlying physical models.[52]

Conclusions

ANN surrogate modeling offers a feasible approach to aerodynamic design in the field of rapid investigation of design space and optimal solution searching. The direct motive of a surrogate model is to establish a data-driven and bottom-up approach used when an outcome of interest cannot be easily obtained. The principle behind surrogate modeling is that data at input and output are related through the pattern of the trained neural network. Introducing the basic principle of ANN as an excellent surrogate modeling method, this paper focuses on its data treatment and configuration setup.

ANN has successfully helped in direct applications of ANN surrogate modeling in aerodynamic design. For example, the numerical search for the optimum shape is of great interest for aircraft and turbomachinery designers. This paper discusses the selection of the type of neural network that may have influence on the optimization effect. It is noted that ANN needs a certain data set to be effectively trained. Treatment to the input and output data for neural network training has also been discussed. In particular, new forms of geometric representation method are proposed specifically to the network training.

ANN not only performs well in surrogate modeling, but also produces potential advantages in optimization. New frontiers of modern ANN surrogate modeling are reviewed in this paper. As for the utilization of various levels of information, the multilevel surrogate modeling is proposed to obtain the optimal area in the design space quickly thus saving computational resource. There has also been attempts of sorting out optimization direction in the accumulated database. Also, there are many types of combination of optimization algorithms with ANN. Lastly, deep learning is beneficial to the field of aerodynamic design surrogate model because it no longer needs the a priori treatment to the input data and thus human experience can be relied less. Meanwhile, new perspective of design space can be created.

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