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A novel learning algorithm to estimate the optimum fuselage drag coefficient

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ABSTRACT

In this study, a novel algorithm to estimate the optimum value of the fuselage drag coefficient is designed by integrating the artificial neural network (ANN) which is an artificial intelligent method into the algorithm of simultaneous perturbation stochastic approximation (SPSA) which is a fast method. SPSA converges to the optimum value for solution very fast. However using SPSA alone requires a function of problem to estimate the optimum solution. On the other hand, ANN is able to estimate the solutions for the problem without need of its any objective function. However ANN needs a certain data set to be effectively trained. Also, the best ANN architecture which accomplish with different data sets of problem may alter. Thus, ANN architecture alone is not adequate for estimating the best result for each different data set. The main target of this study is making SPSA able to be applicable for the problem that has not any objective function by using training capability of ANN. For this purpose, initially, ANN is trained by the data of fuselage drag coefficient obtained by previous experimental results conducted in wind tunnel and varies depending on the geometry of fuselage. Thus, ANN becomes capable to estimate the fuselage drag coefficient for each parameter values of the fuselage shape. Therefore, ANN estimates the fuselage drag coefficient with respect to inputs without the requirement of any experimental computations. Note that ANN does not estimate the optimum value as output but estimates the output regarding to the inputs. The ANN is integrated into the SPSA to fulfill the need of cost function for SPSA. More clearly, the new algorithm evaluates ANN to estimate the fuselage drag coefficient with respect to inputs while evaluates SPSA to estimate the optimum inputs for the optimum fuselage drag coefficient. Through integrating the trained ANN into the SPSA, an effective and novel algorithm estimates the fuselage drag coefficient fast and accurately without defining an objective function is improved.

Keywords: Aerial Vehicle, Fuselage Drag Coefficient, Artificial Neural Network, Simultaneous Perturbation Stochastic Approximation

En uygun gövde sürükleme katsayısı hesabı için yeni bir öğrenme algoritması

ÖZ

Bu çalışmada gövde sürükleme katsayısının en uygun değerini hesaplamak için yapay zeki bir yöntem olan Yapay Sinir Ağları (YSA), hızlı bir yöntem olan Eşzamanlı Dağılım Rassal Yaklaşım (EDRY) algoritması içerisine yerleştirilerek yeni bir algoritma tasarlanmıştır. EDRY en iyi çözüme oldukça hızlı bir şekilde yakınsayabilmektedir. Ancak tek başına EDRY çözümü bulabilmek için problemin bir fonksiyonuna ihtiyaç duymaktadır. YSA ise problemin bir fonksiyonu olmaksızın da çözümü bulabilmektedir. Ancak YSA'nın iyi eğitilebilmesi için belirli bir veri kümesine ihtiyaç vardır. Ayrıca problemin değişen her veri kümesi için en iyi sonucu veren uygun ağ yapısı ve parametreleri de değişebilmektedir. Bu nedenle YSA yalnız başına kullanılarak tek bir ağ yapısı ile her farklı veri kümesi için en iyi sonuca ulaşmak mümkün değildir. Bu çalışmanın temel amacı YSA'nın öğrenme kabiliyetinden faydalanarak

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EDRY’yi bir amaç fonksiyonu olmayan problemler için de kullanılabilir hale getirmektir. Bu amaçla, öncelikle daha önce rüzgâr tünelinde yapılmış deneysel çalışmalar neticesinde elde edilen gövde şekillerine göre gövde sürükleme katsayısının değişimi verileri ile YSA eğitilmiştir. Böylece YSA şekil değerlerine göre gövde sürükleme katsayısını kendisi tahmin edebilecek yeteneğe gelmiştir. YSA artık herhangi bir deneysel hesaplamaya ihtiyaç duymadan giriş değerlerine göre gövde sürükleme katsayısını tahmin edebilmektedir. Fakat burada YSA ile en uygun değer değil, her giriş değeri için bir çıkış değeri bulunmaktadır. EDRY’nin her adımda hesaplamaya ihtiyaç duyduğu maliyet fonksiyonu bu şekilde YSA, EDRY’ye gömülerek giderilmiştir. Yani burada tasarlanan yeni algoritma YSA’yı hangi durumlarda gövde sürükleme katsayısının ne olacağını bulmak için kullanırken EDRY’yi de en iyi katsayının oluşması için en uygun durumların ne olduğunu bulmak için kullanmaktadır. Bu şekilde eğitilen YSA, EDRY’ye gömülerek, gövde sürükleme katsayısını bir bağıntıya ihtiyaç olmaksızın hızlı ve doğru bir şekilde hesaplayan, başarılı ve yeni bir algoritma geliştirilmiştir.

Anahtar kelimeler: Hava Aracı, Gövde Sürükleme Katsayısı, Yapay Sinir Ağları, Eşzamanlı Dağılım Rassal Yaklaşım

1. INTRODUCTION

Drag force is very important for aircraft due to not only directly affects fuel consumption but also indicates the payload of aircraft that includes weather instruments. In order to minimize drag force, various researches are conducted. In most of these researches, the optimum value of the aspects of the fuselage such as the shape of tail and nose are estimated, convenient materials described to reduce the aerial vehicle surface roughness, and aerodynamic shape is optimized [1]. Additionally, in order to reduce the drag forces, placing vortex generators on the surface of aircraft that accelerate the transition into turbulent flow is studied [2]. When designing an aircraft, it is crucial to decide the most appropriate shape of aircraft due to its significant effect of the drag force.

Experimentally, by placing the fuselage in the wind tunnel and using a force measuring system, it is possible to calculate the aerodynamic forces that effect on the fuselage. However it is very expensive to calculate the drag coefficient of each designed fuselage separately by examining them in the wind tunnels. Moreover it is not possible to compute the drag coefficient analytically due to its non-linear complex components. Therefore, stochastic approximation based estimation methods are needed to be implemented to estimate fuselage drag coefficient.

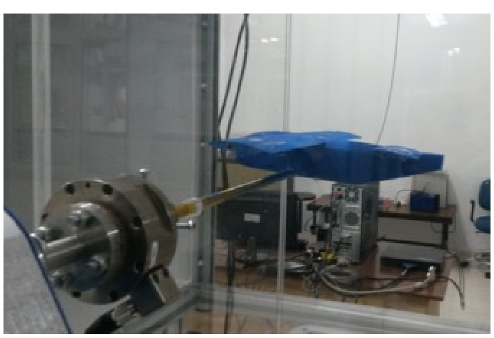

Figure 1. A wind tunnel that provides to calculate the aerodynamic forces

Simultaneous Perturbation Stochastic Approximation (SPSA), one of stochastic approximation algorithm, uses only two observations at each iteration to estimate the solution among random directions for the computation of the gradient. That makes SPSA very attractive and fast optimizer [3]. When compared to computationally expensive algorithms such as fast simulated annealing and genetic algorithms, numerical studies showed that SPSA is more efficient in solving various optimization problems [4]. Also, SPSA is successful in solving constrained optimization problems [5] as seen in this study. In addition, as a stochastic method, SPSA includes an inherent randomness that protects it to stick around a local minimum and provides to converge to the global minimum of the best solution just in a few iterations.

Artificial neural networks [6] are using in solving various engineering problems because of their many advantages such as capability of learning, easily applicable to different problems, capacity for generalization, requirement of less data compared to the traditional estimation techniques, ability to work fast because of parallel structures and flexibility in design. In recent years, ANN is also utilized in solving problems in aeronautics [7], [8].

In previous studies, a few researchers [9], [10] are combined ANN with SPSA, and they used SPSA as a training method of ANN. However, in this paper, SPSA is not applied to train the ANN. On the contrary, ANN is mounted in SPSA algorithm to make SPSA able to estimate the optimum value of fuselage drag coefficient without any equation of objective function. The data of fuselage drag coefficient obtained from experimentally studies are used to train ANN to be capable of estimating the fuselage drag coefficient with respect to new parameter values of fuselage shape. Trained ANN is integrated into the SPSA, and so a novel stochastic algorithm is improved to estimate the optimum fuselage drag coefficient value without any equation of objective function. Also, while it is possible to evaluate only the ANN to estimate the optimum fuselage drag coefficient value, with the novel algorithm in this study, it is aimed to make SPSA able to estimate the optimum fuselage drag coefficient value without using any numerical computation of cost function. Additionally, using a single ANN architecture may not deal with any data set of the problem. On the other hand, valuating only ANN instead of SPSA requires designing new ANNs for our each different experimental data set which is not logical.

2. FUSELAGE DRAG COEFFICIENT OF AN AERIAL VEHICLE

An object located in air flow is influenced by the aerodynamic forces. The forces acting at the vertical axis are defined as weight and lift, and thrust and drag acting at the horizontal axis. Drag force is defined as the resistance against air flow produced by the object in the air. This force is expressed by:

$$D = C_D \frac{\rho}{2} V^2 S \tag{1}$$

where in C_D is the dimensionless drag coefficient, ρ is air density, V is airspeed of the freestream, and S represents straight wing surface. The air flow speed, angle of attack, wing shape, density and compressibility of the air affect the aerodynamic drag force D directly. The components that affecting dimensionless drag coefficient, C_D, are fuselage, wings, and vertical and horizontal control surfaces [11].

It is possible to measure the aerodynamic forces acting on aircraft numerically and experimentally. Numerically, the aerodynamic forces can be calculated as 2D and 3D for different angles of attack and speed values by a numerical analysis program. Experimentally, the aerodynamic forces acting on an air vehicle or wing profile placed in a wind tunnel can be calculated by a force measuring system. In experimental studies [12], [13] carried out to estimate the fuselage drag coefficient C_{Df} was realized at high Reynolds numbers approximately as:

$$C_{Df} = 0.0003\left[3\frac{l_f}{d_f} + 4.5\sqrt{\frac{d_f}{l_f}} + 21\left(\frac{d_f}{l_f}\right)^2\right] \tag{2}$$

where l_f is length of fuselage and d_f is frontal average diameter of fuselage.

3. ARTIFICIAL NEURAL NETWORK INTEGRATED SIMULTANEOUS PERTURBATION STOCHASTIC APPROXIMATION

3.1. Model of Simultaneous Perturbation Stochastic Approximation

In classical SPSA, let $a = 500$ denote the vector includes optimization variables (l_f and d_f data for this paper) and $x_{[k]}$ is the estimate of x at the kth iteration, then

$$x_{[k+1]} = x_{[k]} - a_k g_{[k]} \tag{3}$$

where a_k is a decreasing sequence of positive numbers, and $g_{[k]}$ is the estimate of the objective's gradient at $x_{[k]}$, calculated using a simultaneous perturbation as introduced above. Let $\Delta_{[k]} \in R^p$ be a vector of p mutually independent mean-zero random variables $\left\{\Delta_{[k]1} \;\; \Delta_{[k]2} \ldots \Delta_{[k]p}\right\}$ satisfying given conditions [14], [15]. Then,

$$g_{[k]} = \left[\frac{\Gamma_+ - \Gamma_-}{2d_k\Delta_{[k]1}} \cdots \frac{\Gamma_+ - \Gamma_-}{2d_k\Delta_{[k]p}}\right]^T \tag{4}$$

where Γ_+ and Γ_- are the estimations of the objective evaluated at $x_{[k]} + d_k\Delta_{[k]}$ and $x_{[k]} - d_k\Delta_{[k]}$, respectively. In this study, a novel adaptive SPSA that deal with the constraints which means optimization variables are required to be between lower and upper limits (i.e., $x_{i_{\min}} \le x_i \le x_{i_{\max}}$, ∓ 5 percent for this article) is developed to solve related problems. All the perturbed vector elements, $x_{[k]} + d_k\Delta_{[k]}$ and $x_{[k]} - d_k\Delta_{[k]}$, must also be between the certain lower and upper limits. With these requirements and the guidelines of [3], [16] for the selection of sequences d_k and a_k, d_k is chosen as

$$d_k = \min\left\{d / k^{\Theta}, 0.95\min_i\left\{\min\left\{\eta_{l_i}\right\}, \min\left\{\eta_{u_i}\right\}\right\}\right\} \tag{5}$$

where η_l and η_u are vectors whose components are $(x_{[k]i} - x_{\min_i}) / \Delta_{[k]i}$ for each positive, $\Delta_{[k]i}$ and $(x_{\max_i} - x_{[k]i}) / \Delta_{[k]i}$ for each negative $\Delta_{[k]i}$, respectively. Similarly, a_k is selected as

$$a_k = \min\left\{a / (S+k)^{\lambda}, 0.95\min_i\left\{\min(\mu_{l_i}), \min(\mu_{u_i})\right\}\right\} \tag{6}$$

Where μ_l and μ_u are vectors whose components are $x_{[k]i} - x_{\min_i}) / g_{[k]i}$ for each positive $g_{[k]i}$ and

$(x_{\max_i} - x_{[k]i}) / g_{[k]i}$ for each negative $g_{[k]i}$, respectively.

3.2. Artificial Neural Network Architecture

In this paper, the multi layered perceptron (MLP) is utilized as ANN architectures because of their simple structure [17]. After several trials, the most appropriate network architecture was found as two hidden layers with six and five for first and second hidden layers, respectively. Two inputs are defined. The first one is the length of aerial vehicle fuselage, (l_f), and the second one is frontal average diameter of fuselage, (d_f). ANN estimates the output that is the fuselage drag coefficient while obeying constraints (variance of ∓5 percent) on the inputs. By the evaluation of (2), input and output data sets are conducted for 100 different l_f, d_f and C_{Df} values. Totally, 100 training and testing data are obtained by using (2) which is an approximation of experimental results. Then, the data set is divided as the training: testing ratio that is 80: 20. Because of its fast learning and good convergence capabilities, Levenberg-Marquardt [18], [19] algorithm is underlined to train the MLP. The transfer function is experimentally selected as the linear transfer functions for the input and output layers and the hyperbolic tangent sigmoid functions for the hidden layers to obtain better testing performance. In order to design the most suitable network architecture the number of the neurons for the hidden layers is iterated with combinations of 2–10 neurons in each layer. The iterations are performed to minimize the mean square error function. The best results are the combination of double hidden layers including 6 and 5 neurons, respectively. The epoch number is selected as 300 since any improvement is not seen above this value. After training and testing the ANN, observed results are proposed in Table 1.

Table 1. ANN results after training and testing

Training Algorithm	Neurons in Hidden Layers	Transfer Function for Hidden Layers	Epoch	Training Percentage	Testing Percentage
LM	6-5	Sigmoid	300	92,1	90,2

Although (2) is evaluated to obtain data sets to train the ANN, note that using this equation is not necessary or compulsory. The ANN can be trained by experimental results. Actually, our purpose for using (2) is that it is already defined after experimental measurements. (2) is just used as a preliminary study. Here it is important to note that (2) is just an approximation defined from experiments. The fuselage drag coefficient data is extracted from (2) for the initial design of our novel algorithm. However, after using (2) for this initial design, the algorithm will be capable of and applicable for our experimental data which is conducting in our wind tunnel laboratory. Much bigger data sets conducting at our wind tunnel laboratory will be used in future studies of this algorithm. Also note that, the decided ANN architecture and parameters are compatible for different sized and parameterized fuselage drag coefficient. More clearly, parameters such as number of hidden layers and epoch are selected to be capable of more complex fuselage drag coefficient data sets. Additionally, the values of ANN parameters that not given in this section are selected as their default values.

3.3. Proposed Algorithm

Normally, a classical SPSA algorithm estimates the optimum value of cost function by using the computation of two neighbors of cost function. However, our algorithm estimates the two neighbors via ANN regardless of computation. Thus, our algorithm does not need any equation of cost function. All part of this algorithm is established by operating MATLAB.

The following novel algorithm is generated by using the ANN integrated SPSA that is improved by handling with inequality constraints on the design parameters.
The main purpose of this algorithm is to estimate the optimum fuselage drag coefficient with respect to the length of aerial vehicle fuselage and frontal average diameter of fuselage. The other parameters of SPSA such as d, a, λ, Θ, S are chosen using guidelines provided in [3], [16].
Step 1. Train ANN.

Step 2. Set initial values d, a, λ, Θ, S and $k=1$ and $x = x_{[k]}$.

Step 3. Estimate the objective value by using trained ANN within the constrains for $x_{[k]}$ input parameter

Step 4. Perturb $x_{[k]}$ to $x_{[k]} + d_k \Delta_{[k]}$ and $x_{[k]} - d_k \Delta_{[k]}$, and estimate new objective values for these perturbed values by using ANN to obtain Γ_+ and Γ_-, respectively. Then, compute the approximate gradient, $g_{[k]}$, using (4) with d_k given by (5).

Step 5. Compute a_k given by (6). If $\left\| a_k g_{[k]} \right\| < \delta x$ (where δx is the minimum allowed variation of x) or $k+1$ is greater than the maximum number of iterations allowed, exit, else calculate the next estimate of $x_{[k+1]}$ using (3), set $k = k+1$, and return to step 2.

Step 6. Show estimation results.

Although the SPSA is a fast converging optimization method, it has not the ability of converging to the optimum fuselage drag coefficient value without the neighbor values of the optimum. Therefore, the cost functions are supposed to be computed for SPSA. However, in this article, regardless of computing the cost functions for each evaluation, ANN is applied to estimate them for SPSA. This means that ANN estimates the new fuselage drag coefficients from given length and diameter of fuselage for SPSA estimating the optimum fuselage drag coefficient with respect to the optimum length and diameter of fuselage.

4. RESULTS

Using SPSA parameters, $S = 5$, $\lambda = 0.602$, $a = 500$, $d = 20$ and $\Theta = 0.101$, as depicted in Figure 2, the optimum value of fuselage drag coefficient, C_{Df}, is achieved by very fast convergence and accuracy of the algorithm which means the proposed ANN integrated SPSA algorithm is capable for estimating the fuselage drag coefficient effectively and properly.

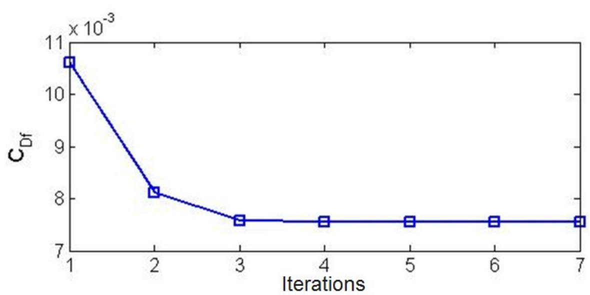

Figure 2. Optimization of fuselage drag coefficient by proposed algorithm.

Although the optimum value of fuselage drag coefficient is estimated using only two variables (l_f and d_f) in this paper, it is seen that the proposed algorithm has the capacity of solving optimization problems such as drag estimation using various variables at the same time due to its two-stepped evolutionary structure. The algorithm is very effective in decreasing the value of the objective function in the first several iterations. Also it is very fast as it is not computing objective function at the each step. After training ANN one time, the cost function can be estimated by ANN for each step.

5. CONCLUSIONS

In this article, a novel ANN integrated SPSA algorithm is proposed. The advantage of ANN which is an artificial intelligent technique and SPSA that has fast convergence capability are combined to estimate fuselage drag coefficient which takes a significant part in aerial vehicle design. Initially, the data set for training and testing ANN is obtained using the results of previous experimental studies in wind tunnels. ANN is trained using the data includes experimental results of fuselage drag coefficient with respect to fuselage shape in order to learn to estimate the new fuselage drag coefficients from given length and diameter of fuselage. Finally, trained ANN is integrated into classical SPSA to generate adaptive SPSA which is able to estimate the objective by two observations for approximations of each component. With ANN, it is possible to use experimental results instead of defining any equations by them.

Although the proposed algorithm is evaluated to estimate the optimum values of fuselage drag coefficient using only two design parameter, trials are proven that our algorithm is capable of estimating the objective using various design parameters at same time as well as solving optimization problems that include various variables, accurately and fast. Using ANN provides the algorithm to work without an equation of cost function. Thus, it is decided to implement this algorithm to solve more complex optimization problems in further studies.

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