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Subsonic Aircraft Design Optimization with Neural Network and Regression Approximators

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I. Introduction

OPTIMIZATION methods can be applied to solve real-life industrial problems because the design tool has matured.[1] This is demonstrated through the optimum airframe-engine synthesis for a subsonic aircraft under specified constraints to minimize the gross takeoff weight. Difficulty encountered in the aircraft analyzer is alleviated through two approximation techniques[2]: neural network and regression methods. Convergence deficiency in the nonlinear programming algorithm was overcome through a four-optimizer cascade strategy.[3] The insight gained from using the approximations and the cascade strategy is discussed in the three subsequent sections: aircraft analysis, its design optimization, and conclusion.

II. Aircraft Analysis

The subsonic aircraft is to carry 208 passengers and fly at a cruise speed of 0.8 Mach over a range of 2500 n miles. It is powered by two high-bypass-ratio engines with a nominal thrust of 48925 lbf. The airframe engine design is cast as an optimization problem to minimize the gross takeoff weight. It has nine design variables DV : DV_1, wing aspect ratio (EAR); DV_2, engine thrust (ETHRUST); DV_3, wing area, (ESW); DV_4, quarter-chord sweep angle (ESWEEP); DV_5, thickness-to-chord ratio (ETCA); DV_6, turbine inlet temperature (EETIT); DV_7, overall pressure ratio (EEOPR); DV_8, bypass ratio (EEBPR); and DV_9, fan pressure ratio (EEFPR). It has six constraints g: g_1, landing approach velocity (VAPP); g_2, takeoff field length (FAROF); g_3, landing field length (FARLD); g_4, missed approach gradient thrust (AMFOR); g_5, second-segment climb thrust (SSFOR); and g_6, compressor discharge temperature (CDT). There are four airframe variables—wing aspect ratio DV_1, wing area DV_3, sweep angle DV_4, and thickness-to-chord ratio DV_5—and five engine parameters—engine thrust DV_2, turbine inlet temperature DV_6, overall pressure ratio DV_7, bypass ratio DV_8, and fan pressure ratio DV_9. Constraints are imposed on the landing velocity g_1 not to exceed 125 kn; field lengths for takeoff g_2 and landing g_3 are not to exceed 6000 ft. Missed approach gradient thrust g_4 and second-segment climb thrust g_5 are required to be greater than 5000 lbf. Compressor discharge temp erature g_6 should not exceed 1460°R.

A. Aircraft Analyzer FLOPS

The flight optimization FLOPS[4] code calculates the performance parameters for the subsonic aircraft. The code synthesizes eight disciplines: weight estimation, aerodynamic analysis,[5] engine cycle analysis,[6] propulsion data interpolation, mission performance, airfield length requirements for takeoff and landing, noise footprint calculations,[7] and cost estimation.[8] The FLOPS code became unstable at several design points that resided in the vicinity of the optimum design. The difficulty encountered is illustrated by generating FLOPS solution for a set of design points that are generated by a pseudorandom perturbation about the optimum solution within prescribed upper and lower bounds. The spread of the design space is about 10% of the base solution on either side. The data set referred to as "small-model" contained 1200 design points. Calculation of the aircraft response by the FLOPS code was attempted for the data in the small model. The aircraft weight saturated at a quarter million pound-force for 204 out of 1200 design points. For other design points, the code aborted, or turbine entry temperature reached a million degrees, or a zero thrust condition was encountered. The rate of success of the FLOPS code was about 80%, and it did not change much for two other models referred to as "standard-model" and the "large-model" that contain 2400 and 4800 points, respectively. The FLOPS code, in other words, was unstable at some design points.

B. Approximators

Two competing approximation techniques: neural-network (NN) and regression (Reg) methods are investigated to overcome the deficiency in the analysis of the subsonic aircraft. The regression method uses a set of basis functions and provides both function and gradient approximations. The basis functions can be selected from a full cubic polynomial, a quadratic polynomial, a linear polynomial in reciprocal variables, a quadratic polynomial in reciprocal variables, and combinations thereof. The regression coefficients are determined by using the least-squares solver (DGELS) routine of the Lapack library.[9] The gradient matrix of the regression function with respect to the design variables is obtained in closed form. The neural-network approximator, Cometnet,[10] is a general-purpose object-oriented library. The neural-network capability also provides both the function value and its gradient. Cometnet permits approximations by using different types of kernels, which include linear, reciprocal, and polynomial, as well as Cauchy and Gaussian radial functions. A singular-value-decomposition algorithm for computing the weight factors in the approximating function is used to train the network. A clustering algorithm is used to select suitable parameters for defining the radial functions. The clustering algorithm, in conjunction with an optimizer, seeks optimal values for the parameters over a range for the threshold parameter τ within its domain $(0 < \tau < 1)$. The mean-square error during training is reduced by increasing the threshold, which corresponds to an increase in the number of basis functions.

Six analysis models, referred to as NN-Small, NN-Standard, NN-Large, Reg-Small, Reg-Standard, and Reg-Large are trained. The number of I/O pairs used to train and to validate the models are

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Table 1 Time in CPU seconds in a SGI octane workstation

	Regression method			Neural-network technique		
Optimization parameters	Small	Standard	Large	Small	Standard	Large
Training in seconds	0.2	0.4	0.8	59.1	136	538.8
Reanalysis (FLOPS = 3.1s), ms	——	——	0.08	——	——	2.4
Reanalysis with closed-form gradient, ms	——	——	0.14	——	——	13.5
Design optimization, s	1.6	1.7	1.6	300.9	199.2	166.7
(FLOPS solution time = 2031 s, %)	(0.78)	(0.84)	(0.78)	(15)	(9.8)	(8.2)

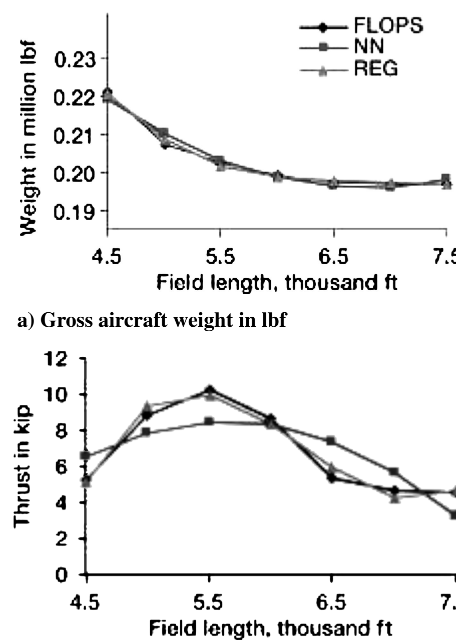
Table 2 Percent absolute error in weight over certain design variable ranges

	Regression		Neural network	
Variable, range, and model	Mean	Standard deviation	Mean	Standard deviation
Thrust (28,000 to 35,000 lbf)				
Small	0.90	0.15	1.05	0.69
Standard	1.22	0.28	0.92	0.61
Large	1.50	0.16	1.01	0.66
Turbine inlet temperature (2900 to 3100°R)				
Small	0.73	0.26	2.08	1.19
Standard	0.81	0.31	2.09	1.21
Large	1.10	0.34	2.11	1.21
Wing area (1800 to 2200 ft^2)				
Small	1.16	0.22	1.30	1.05
Standard	1.10	0.11	1.12	0.96
Large	1.44	0.07	1.16	0.91

(900, 91) for the small models, (1800, 143) for the standard models, and (3600, 280) for the large models. Each model has nine free variables. Aircraft weight and the six constraints are approximated individually. For a balanced comparison of the neural-network and the regression models, the same basis/kernel function is used for the approximators. It contained a full quadratic polynomial along with a linear reciprocal expression in the design variables. Each approximator has 64 unknown coefficients. The redundancy (ratio of I/O pair to number of coefficients) for the small, standard, and large models is (14, 28, 56), respectively. The values of the unknown coefficients in NN and regression method are not the same because they are generated following different training procedures. The central processing unit (CPU) time for training and reanalysis on an SGI octane workstation with the irix 6.5.19-m operating system and a 300-MHZ processor is given in Table 1. The regression method required a fraction of a CPU second for training. The neural-network training required between (1 to 9) min. For a single analysis cycle, the FLOPS code required about 3 CPU seconds. This was reduced to milliseconds by the approximators.

To access the performance of the approximators, a solution was calculated for a randomly selected design point $(DV_1, \ldots, DV_9) =$ (8.9579, 31607.7515, 2177.9724, 18.5423, 0.0874, 2982.4585, 37.2243, 5.8297, 1.8295). The three regression models predicted the aircraft weight within 2% error. It was reduced to less than 1% by the neural-network technique. For the compressor discharge temperature, the error in regression and neural-network methods averaged (0.1 and 2%), respectively. The average error in the field length constraints ranged between (1 to 3)% for both approximators. The error in approach velocity was similar to field length constraints. The performance of the approximators for the three models is further assessed by calculating the mean error and standard deviation in the aircraft weight for 101 design points for three variables: engine thrust (in the range 28 to 35 kip), wing area (1800 to 2200 ft^2), and turbine inlet temperature (2900 to 3100°R), as shown in Table 2. Both NN and Reg approximators produced about 1% mean error for all three variables, except for a 2% error for the turbine inlet temperature by the neural-network technique. The standard deviation in error by the regression method was less than 3/10 of 1%. This was increased to about 1% by the neural-network technique. The error was comparable for the small, standard, and the large models.

Sensitivity of the design was examined for the aircraft to land and takeoff on shorter and longer runways in the range of 4500 and 7500 ft from the 6000-ft nominal value. Other parameters are retained at their nominal value. Optimum aircraft weight vs the field length obtained by the three methods (FLOPS, NN, and Reg) is shown in Fig. 1a. The second-segment climb thrust is given in Fig. 1b.



a) Gross aircraft weight in lbf

b) Second-segment climb thrust

Fig. 1 Subsonic aircraft sensitivity analysis with respect to field lengths for the small model.

The approximators exhibited less than 1% error in the aircraft weight, and it is a monotonic function of the field length. Aircraft weight is increased for shorter field length, and it is decreased for longer length, as expected. The neural-network and regression method exhibited (0.34 and 0.61)% error, respectively. For the second-segment climb thrust constraint, the regression method closely follows the constraint while NN took an average path.

III. Aircraft Design Optimization

Design optimization of the subsonic aircraft is obtained via the CometBoards[11] test bed of NASA Glenn Research Center. FLOPS analyzer, regression, and neural-network models are softcoupled into CometBoards. Softcoupling allows integration of a new analysis code into the test bed without any change to the source code. The optimum solution of the subsonic aircraft can be obtained using any one of the three analysis methods: the FLOPS code, neural-network, and regression method based analyzers.

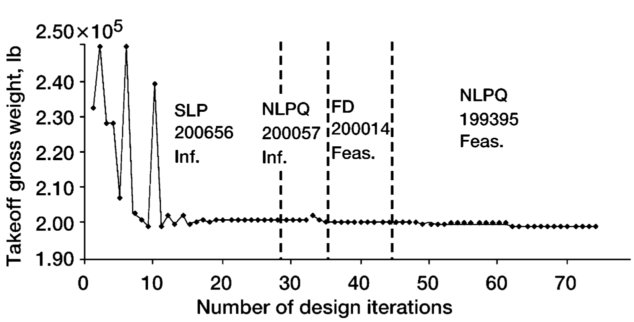
The design space of the subsonic aircraft optimization problem is distorted because both variables and constraints vary over a wide range. For example, an engine thrust design variable measured in kilo pound-force is immensely different than the bypass ratio, which is a small dimensionless number. Likewise, a landing velocity constraint in knots and a field length limitation in thousands of feet differ both in magnitude and in units of measure. In CometBoards the effect of distortion is reduced by scaling the merit function, design variables, and constraints such that their normalized magnitudes are around unity. A four-optimizer cascade algorithm (SLP -NLPQ-FD-NLPQ) consisting of sequential linear programming (SLP), sequential quadratic programming (NLPQ), method of feasible directions (FD) and NLPQ was used.

The optimum solutions calculated using the three analyzers (FLOPS, NN, and Reg) are given in Table 3. The convergence of aircraft weight vs iteration is shown in Figs. 2a and 2b for the FLOPS analyzer and the large-regression model. CPU time to optimum solution by the three analysis methods is given in Table 1.

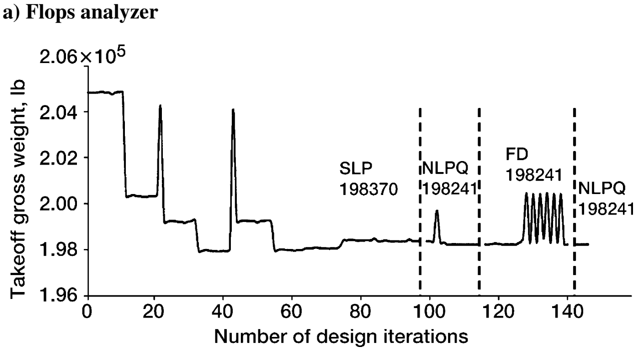
The deviation in the aircraft weight is about 1% between the three analyzers. The error in the engine thrust was about $\frac{1}{2}$%. The takeoff field length constraint calculated by the approximators exhibited a 3% error. However, the error reduced to 1% for the landing field length. Overall, the optimum solutions calculated using the FLOPS analyzer and large-regression and neural-network models are found to be in good agreement (see Table 3). The (SLP -NLPQ-FD-NLPQ) cascade algorithm converged to 199–395 lbf for the optimum takeoff gross weight when the FLOPS analyzer was used. The first SLP cascade algorithm produced an infeasible solution, whereas the final NLPQ method produced feasible optimum solution. Optimization with the approximator required double the number of design iterations (140) than it did with the FLOPS code (70) (see Figs. 2a and 2b). The time to solution was in favor of the approximator: 1.6 CPU seconds for the regression method, against 2031s with the FLOPS code. The average solution time for the small, standard, and large neural-network model was 222 s (see Table 1). The convergence pattern contained more oscillations when regression method was used (see Fig. 2).

Table 3 Optimum solution with original and approximate analyzers

Variables and constraints	FLOPS	Regression	Neural network
Aircraft weight	199395.3	201219.6	199904.7
	Design variables		
Wing aspect ratio	8.8	8.8	8.2
Engine thrust	32346.6	32181.1	32402.9
Wing area	1851.3	1834.7	1830.0
Quarter-chord sweep angle	20.2	17.0	16.0
Thickness-to-chord ratio	0.1	0.1	0.1
Turbine inlet temperature	3100.0	3094.5	2950.0
Overall pressure ratio	40.5	38.0	38.0
Bypass pressure ratio	6.1	5.1	5.0
Fan pressure ratio	1.8	1.8	1.9
	Constraints		
Landing approach velocity	120.7	121.8	121.5
Takeoff field length	5998.3	6172.5	6162.6
Landing field length	5562.8	5618.9	5606.4
Missed approach gradient thrust	5000	4572	3719
Second-segment climb thrust	9619	9241	8409
Compressor discharge temperature	1428.3	1403.6	1402.4.8



a) Flops analyzer



b) Large-regression-model analyzer

Fig. 2 Convergence history for the subsonic aircraft.

IV. Conclusions

The subsonic airliner design is a difficult optimization problem because of a distorted design space and an unstable analysis tool. The limitations were overcome through a cascade algorithm along with neural-network and regression method. The optimum solution was obtained for the real-world industrial problem. The optimum aircraft weight calculated by the flight-optimization system analyzer and the regression-method approximation matched well. The deviation in the design variables between the two analyzers was not significant. The overall performance of neural-network and regression method was comparable. The neural network followed a mean path, whereas the regression method closely followed the aircraft analyzer. For a single analysis cycle the aircraft-analyzer time measured in seconds is reduced to milliseconds by the approximators. The training, validation, and solution required a small fraction of the aircraft analysis and design time. For design optimization the central processing unit time with the aircraft analyzer measured in hours, reduced to minutes by the neural network, and seconds by the regression method.

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