NASA/TM—2004-213059 AIAA–2004–4606

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August 2004

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Prepared for the
10th Multidisciplinary Analysis and Optimization Conference
cosponsored by the American Institute of Aeronautics and Astronautics
and the International Society for Structural and Multidisciplinary Optimization
Albany, New York, August 30–September 1, 2004

National Aeronautics and
Space Administration

Glenn Research Center

August 2004

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This work was sponsored by the Low Emissions Alternative Power Project of the Vehicle Systems Program at the NASA Glenn Research Center.

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The Flight-Optimization-System (FLOPS) code encountered difficulty in analyzing a subsonic aircraft. The limitation made the design optimization problematic. The deficiencies have been alleviated through use of neural network and regression approximations. The insight gained from using the approximators is discussed in this paper. The FLOPS code is reviewed. Analysis models are developed and validated for each approximator. The regression method appears to hug the data points, while the neural network approximation follows a mean path. For an analysis cycle, the approximate model required milliseconds of central processing unit (CPU) time versus seconds by the FLOPS code. Performance of the approximators was satisfactory for aircraft analysis. A design optimization capability has been created by coupling the derived analyzers to the optimization test bed CometBoards. The approximators were efficient reanalysis tools in the aircraft design optimization. Instability encountered in the FLOPS analyzer was eliminated. The convergence characteristics were improved for the design optimization. The CPU time required to calculate the optimum solution, measured in hours with the FLOPS code was reduced to minutes with the neural network approximation and to seconds with the regression method. Generation of the approximators required the manipulation of a very large quantity of data. Design sensitivity with respect to the bounds of aircraft constraints is easily generated.

Nomenclature

n	number of design variable, number of basis functions
Obj	merit function
R	number of kernel functions
w	weight factor
x	design variables
y	functional approximation
∇y	gradient matrix
β	regression coefficients
φ	kernel function
τ	threshold parameter

Subscripts/Superscripts

i,j,k	regression indices
k	k^{th} merit function
ℓ	l^{th} design variable, lower bound
ri	i^{th} basis function for the r^{th} kernel

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Acronyms

CometBoards	comparative evaluation test bed of optimization and analysis routines for the design of structures
CPU	central processing unit
DV	design variable
FD	method of feasible directions
FLOPS	Flight Optimization System
IFM	Integrated Force Method
I/O	input/output pairs
NEPP	NASA Engine Performance Program
NLPQ	nonlinear quadratic programming algorithm
NN	neural network
OPR	overall pressure ratio
SLP	sequential linear programming

I. Introduction

The Flight Optimization System (FLOPS[1]) of NASA Langley Research Center is a standard aircraft analyzer. The FLOPS code combines multiple disciplines from aerodynamics and engine cycle analysis to mission performance. The code uses data tables for internal calculations. A brief description of the FLOPS code is given in Appendix 1. For a subsonic aircraft problem the code became unstable for some design points. The analysis limitation propagated into design optimization, and it encountered convergence difficulty. The anomalous design points resided in the vicinity of the optimum solution. These designs cannot be segregated prior to the optimization calculations. The aircraft problem appears to be a good candidate for the application of approximation techniques.

Two competing approximation techniques: neural network (NN) and regression methods are investigated to overcome the deficiency. The regression method uses a set of basis functions and provides both function and gradient information. NN approximation also uses a variety of kernel functions and produces the same two pieces of information. Both methods have been applied successfully for a variety of multidisciplinary applications.[2–4] The approximate methods are developed using a set of high-fidelity training pairs and selected basis functions. The approximate models are validated for use as an alternate reanalysis tool for the subsonic aircraft analysis and design optimization.

Design optimization of the subsonic aircraft is obtained via the CometBoards[5–6] test bed of NASA Glenn Research Center. CometBoards has been successfully used to solve a number of problems: structural design of space station components,[7] the design of nozzle components for air-breathing engines,[2] design of supersonic aircraft,[3] mixed flow turbofan engines,[8] and wave rotor concepts in jet engines.[9] The regression method and neural-network-based aircraft analysis tools have been incorporated into CometBoards. The optimum solution of the subsonic aircraft can be obtained using any one of the three analysis methods: the FLOPS code, NN, and regression method analyzers. The design capability is also used to calculate sensitivity with respect to the bounds on aircraft constraints; for example, the takeoff and landing field lengths.

This paper examines the performance of different analysis methods in design of a subsonic aircraft. Optimal solutions calculated by three different methods are compared. The efficiency in analysis and design is examined by comparing the central processing unit (CPU) time to solution. The paper is organized in 11 sections: the subsonic aircraft design optimization problem, the FLOPS aircraft analyzer, the CometBoards design optimization test bed, justification for use of approximate methods, regression method, NN technique, training approximate analyzers, performance of approximators for analysis and design optimization, design sensitivity analysis, positivity constraints, and conclusions.

II. Subsonic Aircraft Design Optimization Problem

The subsonic aircraft is powered by two high-bypass-ratio engines with a nominal thrust of about 48 925 lbf. The aircraft is to carry 200 passengers and an eight-member crew, fly at a cruise speed of 0.8 Mach over a range of 2500 n mi. The objective of the optimization is to determine the airframe-engine design combination that will meet specified constraints and minimize the gross takeoff weight. A good match between airframe and engine is achieved by combining the airframe variables with engine parameters. Nine active variables, listed in Table 1, were selected. There are four airframe design variables: wing aspect ratio DV_1, wing area DV_3, sweep angle DV_4, and thickness to chord ratio DV_5. The five engine design parameters are engine thrust DV_2, the turbine inlet temperature DV_6, the overall pressure ratio DV_7, the bypass ratio DV_8, and the fan pressure ratio DV_9. Constraints are as follows: the

Table 1. Design variables and constraints of the subsonic aircraft

Design variables	Constraints
DV_1. Wing aspect ratio, (EAR)	g_1. Landing approach velocity, (VAPP)
DV_2. Engine thrust, (ETHRUST)	g_2. Takeoff field length, (FAROF)
DV_3. Wing area, (ESW)	g_3. Landing field length, (FARLD)
DV_4. Quarter chord sweep angle, (ESWEEP)	g_4. Missed approach gradient thrust, (AMFOR)
DV_5. Thickness to chord ratio, (ETCA)	g_5. Second segment climb thrust, (SSFOR)
DV_6. Turbine inlet temperature, (EETIT)	g_6. Compressor discharge temperature, (CDT)
DV_7. Overall pressure ratio, (EEOPR)	g_7. Excess fuel capacity, (EXFUE)
DV_8. Bypass ratio, (EEBPR)	
DV_9. Fan pressure ratio, (EEFPR)	
Variables not used but can be considered include	Constraints not used but can be considered include
DV_a. Taper ratio of wing, (ETR)	g_a. Range of aircraft, (RANGE)
DV_b. Cruise Mach number, (EVCMN)	g_b. Specific thrust, (ST)
DV_c. Cruise altitude, (ECH)	g_c. Specific fuel consumption, (SFC)
DV_d. Engine throttle ratio, (EETTR)	g_d. Compressor discharge pressure, (CDP)

landing velocity g_1 is not to exceed 125 knots. 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 positive. Compressor discharge temperature g_6 should not exceed 1460 °R. Excess fuel g_7 should be positive. Constraints g_1, g_2, g_3, and g_6 restrict the landing approach velocity, takeoff field length, landing field length, and compressor discharge pressure, respectively, to not exceed their upper bounds. The g_4, g_5, and g_7 constraints, scaled with respect to 101 000, 100 000, and 5 000 lbf, respectively, restrict the variables to be positive. These are referred to as the positivity constraints.

The FLOPS code has a provision to use a composite merit function that can be expressed as

$$Obj = \sum_{k=1}^{7} w_k \beta_k \tag{1}$$

Here, Obj represents the merit function, w_k represents the kth weight factor, and the parameter β_k can be selected from the following list:

(1) Gross takeoff weight of the aircraft
(2) Mission fuel
(3) The product of the Mach number and the ratio of lift-to-drag
(4) Range
(5) Cost
(6) Specific fuel consumption
(7) NO_x emissions

For the subsonic problem, the gross takeoff weight is selected as the merit function by setting w_1 = 1.0, and the other weight factors to zero. The objective of the optimization study is to determine the optimum gross takeoff weight of the aircraft for the nine design variables and the seven behavior constraints listed in Table 1. Optimum solution is also calculated for the aircraft to operate on shorter and longer runways in the 4500 to 7500 ft range. This exercise is referred to as sensitivity analysis.

III. FLOPS: An Aircraft Analyzer

The FLOPS code calculates the performance parameters for subsonic and supersonic aircraft generating the constraints and merit function required for design optimization. The code synthesizes eight disciplines: weight estimation, aerodynamic analysis,[10,11] engine cycle analysis,[12–14] propulsion data interpolation, mission performance, airfield length requirements for takeoff and landing, noise footprint calculations,[15] and cost estimation.[16–21] The FORTRAN code has 11 modules with over 42 000 statements. The subsonic aircraft problem required several input/output (I/O) files. A brief description of the code is given in Appendix 1. Numerical data tables (or table lookups) used in the code can abruptly interrupt the calculations. Approximate methods can alleviate such limitations of the FLOPS code.

IV. CometBoards: A Design Optimization Test Bed

The research to compare different optimization algorithms and alternate analysis methods for structural design applications has grown into a multidisciplinary design test bed that is still referred to by its original acronym, CometBoards, which stands for comparative evaluation test bed of optimization and analysis routines for the design of structures. The modular organization of CometBoards, shown in Fig. 1, allows innovative methods (or computer codes) to be tested quickly through its soft coupling feature. Optimizers and analyzers are two important modules of CometBoards. The optimizer module includes a number of algorithms:

The fully utilized design[22]
Optimality criteria methods[22]
The method of feasible directions[23]
The modified method of feasible directions [24]
Three different sequential quadratic programming techniques[25–27]
The Sequential Unconstrained Minimizations Technique[28]
Sequential linear programming[23]
A reduced gradient method[29]

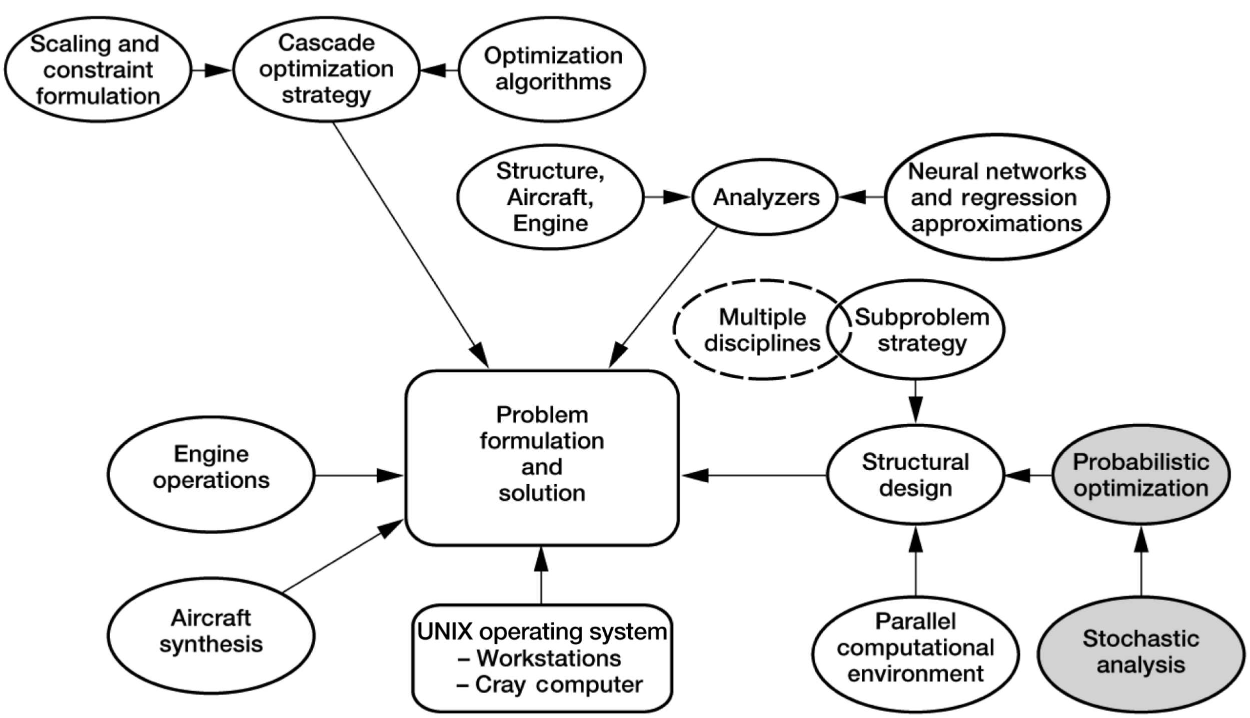


Figure 1. Organization of CometBoards.

Likewise, the analyzer module includes

COSMIC/NASTRAN[30]
The nonlinear analyzer MHOST[31]
The U.S. Air Force ANALYZE/DANALYZE code[32]
IFM/ANALYZERS [33]
The aircraft flight optimization analysis code FLOPS [1]
The NASA Engine Performance Program NEPP [34]

Some of the other unique features of CometBoards are

A multiple optimizer cascade strategy [8]
Design variable and constraint formulations
A global scaling strategy
Analysis and sensitivity approximations through regression and NNs
Substructure optimization on sequential as well as parallel computational platforms[35]

CometBoards has provisions to accommodate up to 10 different disciplines, each of which can have a maximum of 5 subproblems. The test bed can optimize a large system, which can be defined in as many as 50 different subproblems. Alternatively, a component of a large system can be optimized. The design test bed has been successfully used to solve a number of multidisciplinary problems. The CometBoards test bed has over 50 numerical examples. It is written in FORTRAN 77, except for the NN code Cometnet,[36] which is written in the C++ language. The C++ code is integrated into the CometBoards FORTRAN code through soft-coupling. Soft-coupling is achieved by first generating an executable file from the Cometnet C++ source code; then Cometnet is invoked from CometBoards through a system call. Information is exchanged between the two programs through data files. CometBoards is available on UNIX-based SGI and Sun workstations. CometBoards is continuously being improved to increase its reliability and robustness for optimization at system as well as at component levels. Stochastic calculations are being implemented into CometBoards. This paper emphasizes the approximation module of CometBoards, which includes regression method and NN approximations for the design optimization of the subsonic aircraft.

V. Justification for Use of Approximate Methods

The difficulty encountered in the FLOPS code is illustrated by generating its response for a set of design points that lie in the vicinity of the optimum solution. The FLOPS code is run for three sets of analysis data that are created by a pseudo-random perturbation about a base design within prescribed upper and lower bounds as shown in Table 2. The design space spread is about 10 percent of the base design on each side. The first set of data is referred to as “small-model,” and it contains 1200 design points. The “standard-model” and the “large-model” contain 2400 and 4800 points, respectively. Each set of the nine design variables and the seven response variables (associated with design constraints) constitutes one I/O pair (which is also used to train the approximate methods). The success rate of the FLOPS analyzer is given in Table 3. The rate of success was about 80 percent for each model. For the

Table 2. Base design bounds

Design variables	Lower bound	Initial design	Upper bound
Wing aspect ratio (DV_1)	7.340	8.500	8.810
Engine thrust (DV_2), lb	28000	31500	34200
Wing area (DV_3), ft^2	1830	2000	2200
Quarter chord sweep angle (DV_4), deg	16.0	18.5	21
Thickness to chord ratio (DV_5)	0.088	0.095	0.0997
Turbine inlet temperature* (DV_6), °R	2950	3000	3100
Overall pressure ratio* (DV_7)	38	40	40.50
Bypass ratio* (DV_8)	5	6	6.10
Fan pressure ratio* (DV_9)	1.8	1.85	2

*Redundancy in these design variables may cause instability in the subsonic aircraft calculations.

Table 3. Success rate of the FLOPS analyzer for the subsonic aircraft

I/O Pairs	Small	Standard	Large
Total I/O pairs—FLOPS	1200	2400	4800
Usable I/O	991	1943	3880
Success rate, percent	83	81	81
Bad I/O	209 (17.42%)	457 (19.04%)	920 (19.17%)
Saturated at 250 kip for aircraft weight	204	448	891
Code aborted	3	7	16
Negative million for engine thrust	1	1	6
Zero thrust	1	1	7
Used for training	900	1800	3600
Used for validation	91	143	280

standard model only 1943 usable I/O pairs could be generated out of the 2400 requested design points. The aircraft weight saturated at a quarter million pound-force for 448 design points. The code aborted for seven designs. Turbine entry temperature reached a million degrees for one case and a zero thrust condition was encountered for another case. The 250 000 lbf weight, 10^6 °R temperature, and zero thrust condition are either reference or flagged value of the unsized aircraft. The response for the small and large model was similar with minor deviations.

The design space of an aircraft optimization problem is distorted because both design 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 the design optimization test bed CometBoards the effect of distortion is reduced by scaling the merit function, design variables, and constraints such that their normalized magnitudes are around unity.

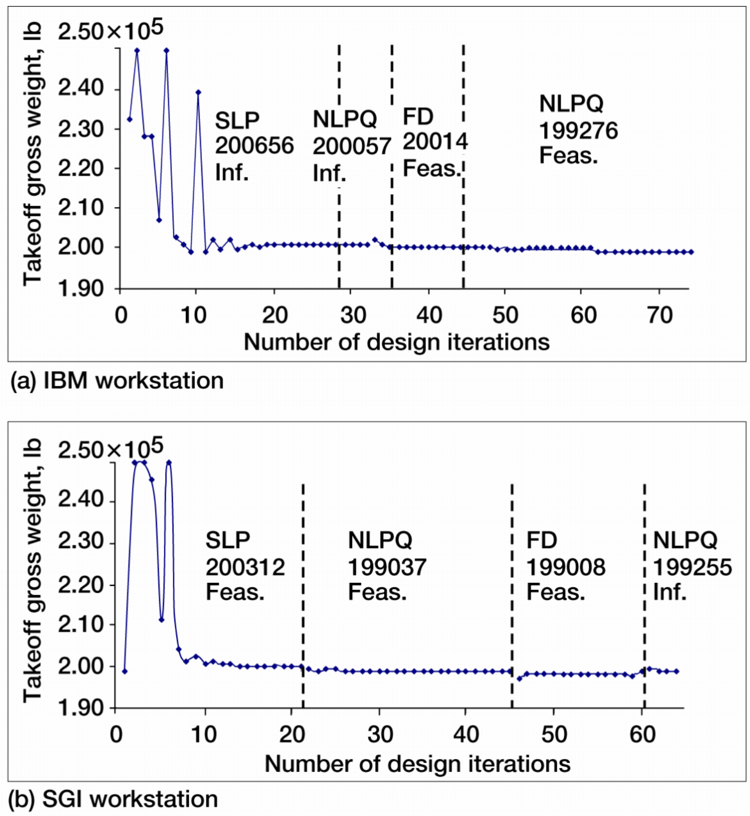


Figure 2. Convergence history for the subsonic aircraft with FLOPS analyzer and a cascade strategy in an IBM and SGI workstations.

Design optimization of the subsonic aircraft was attempted using the combined CometBoards-FLOPS code. None of the one dozen individual optimization algorithms available in the CometBoards test bed could successfully solve the problem. A better solution could be obtained when a cascade strategy was employed. The generation of an optimum solution required manual intervention, restarts, as well as a change of the initial designs and bounds. A four-optimizer cascade was employed to solve the problem: sequential linear programming (SLP), followed by a nonlinear quadratic programming algorithm (NLPQ), then method of feasible directions (FD), and finally NLPQ.

Solutions generated on IBM and SGI workstations are depicted in Fig. 2. The cascade algorithm converged to 199 276 lbf for the aircraft weight. The same cascade algorithm encountered difficulty on an SGI workstation when it was initiated from a different initial design. Likewise a slightly different cascade exhibited a contrary move. The problem was solved on the SGI workstation with the original cascade algorithm when the design bounds were

Table 4. Summary of optimum design solutions with positivity constraints

	Success 1 IBM workstation	Success 2 SGI workstation	Percent variation
Aircraft weight, lb	199275.578	199254.844	0.010
Design variables:			
Wing aspect ratio (DV_1)	8.547	8.63	–0.96
Engine thrust (DV_2), lb	31589.572	31595.923	–0.020
Wing area (DV_3), ft^2	1897.735	1879.461	0.972
Quarter chord sweep angle (DV_4), deg	15.650	16.411	–4.637
Thickness to chord ratio (DV_5)	0.093	0.093	0.0
Turbine inlet temperature (DV_6), °R	3060	3100	–1.290
Overall pressure ratio (DV_7)	40	40.188	–0.469
Bypass ratio (DV_8)	5.936	5.896	0.678
Fan pressure ratio (DV_9)	1.824	1.80	1.333
Constraints:			
Landing approach velocity (g_1), kn	119.25	119.72	–0.392
Takeoff field length (g_2), ft	6000	6042.66	–0.706
Landing field length (g_3), ft	5490	5514.84	–0.450
Missed approach gradient thrust (g_4), lb	3737	3905.67	–4.318
Second segment climb thrust (g_5), lb	8300	8548.0	–2.901
Compressor discharge temperature (g_6), °R	1423.50	1429.81	–0.441
Excess fuel capacity (g_7), lb	0.2	0.0	-------

changed, see Fig. 2(b). The optimum designs are given in Table 4. A minor deviation is observed in the two solutions. There was only a 0.1-percent change in the aircraft weight. There was a 3-percent deviation in the engine bypass ratio design variable and 1 percent variation in the second segment climb thrust constraint. Such deviation is considered minor because the subsonic airframe engine synthesis is a difficult nonlinear multidisciplinary analysis as well as design problem. The subsonic aircraft problem appears to be a candidate for the use of approximation techniques because the FLOPS analyzer can fail for some design points, the subsonic aircraft optimization process can become tedious, and a significant reduction can be achieved in the CPU time to solution.

VI. Regression Method

The linear regression method and NN technique are used as two competing approximators in CometBoards. The regression method uses several types of basis functions. These functions can be selected from (1) a full cubic polynomial, (2) a quadratic polynomial, (3) a linear polynomial in reciprocal variables, (4) a quadratic polynomial in reciprocal variables, and (5) combinations thereof. Consider, for example, regression analysis of an n-variable model with a combination of a cubic polynomial in design variables and a quadratic polynomial in reciprocal design variables. The regression function has the following explicit form:

$$y(\vec{x}) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \sum_{j=i}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=i}^{n} \sum_{k=j}^{n} \beta_{ijk} x_i x_j x_k + \sum_{i=1}^{n} \vec{\beta}_i \frac{1}{x_1} + \sum_{i=1}^{n} \sum_{j=i}^{n} \vec{\beta}_{ij} \frac{1}{x_i x_j} \tag{2}$$

The regression coefficients $\vec{\beta}$ are determined by using the double precision general matrix linear least squares solver (DGELS) routine of the Lapack library.[37] The gradient matrix of the regression function with respect to the design variables is obtained in closed form. For the example with n variables, the gradient matrix for the regression function has the following form:

$$\nabla y = \begin{Bmatrix} \dfrac{\partial}{\partial x_1} \\ \dfrac{\partial}{\partial x_2} \\ \vdots \\ \dfrac{\partial}{\partial x_n} \end{Bmatrix} y \tag{3}$$

where

$$\frac{\partial y}{\partial x_\ell} = \beta_\ell + \sum_{i=1}^{n} \beta_{i\ell} x_i + \beta_{\ell\ell} x_\ell + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \beta_{ij\ell} x_i x_j + \sum_{i=1}^{n} \beta_{ii\ell} x_i^2 + \sum_{i=1}^{n} \beta_{i\ell\ell} x_i x_\ell + \beta_{\ell\ell\ell} x_\ell^2 - \frac{\beta_\ell}{x_\ell^2} - \frac{1}{x_\ell^2} \sum_{i=1}^{n} \beta_{i\ell} \frac{1}{x_i} - \frac{\beta_{\ell\ell}}{x_\ell^3} \tag{4}$$

and $\beta_{ij} = \beta_{ji}$ for $i > j$, $\beta_{ijk} = \beta_{ikj}$ for $j > k > i$, etc.

Reanalysis and sensitivity calculations given by Eqs. (2) to (4) require trivial computation, once the regression coefficients have been obtained from a single training cycle.

VII. Neural Network Technique

The NN approximator Cometnet is a general-purpose object-oriented library. Cometnet is soft-coupled to the CometBoards test bed. The NN capability provides both the function value and its gradient. Cometnet approximates the function and its gradient with R kernel functions as follows:

$$y(\vec{x}) = \sum_{r=1}^{R} \sum_{i=1}^{n_r} w_{ri} \varphi_{ri}(\vec{x}) \tag{5a}$$

$$\frac{\partial y(\vec{x})}{\partial x_\ell} = \sum_{r=1}^{R} \sum_{i=1}^{n_r} w_{ri} \frac{\partial \varphi_{ri}(\vec{x})}{\partial x_\ell} \tag{5b}$$

where y is the functional approximation, $\vec{x}$ is the vector of independent variables, φ_{ri} represent R kernel functions, n_r represents the number of basis functions in a given kernel, and w_{ri} are the weight factors.

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[38] 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. Over-fitting is avoided with a competing complexity-based regularization algorithm. Training of the merit function and each of the constraint functions can use different basis functions.

VIII. Training Approximate Analyzers

The I/O pairs generated earlier (see Table 3) are used to train three models for the NN and regression methods. The models are referred to as small, standard, and large. The number of I/O pairs used to train and validate the models is (900, 91) for the small model, (1800, 143) for the standard model, and (3600, 280) for the large model. Each method has nine free variables, being the design variables given in Table 1. Aircraft weight and the seven constraints are approximated individually. The basis functions for both approximators contain a full quadratic polynomial in the design variables (DV) along with a linear reciprocal expression in the DV. Each approximator has

Table 5. CPU time in seconds in an SGI octane workstation

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

Table 6. Performance of the approximators during analysis

		Regression method, percent error			Neural network technique, percent error		
Response variables	FLOPS solution	Small	Standard	Large	Small	Standard	Large
Aircraft weight, lb	204 725.75	1.85	1.67	1.60	–0.21	–0.47	–0.66
Approach velocity, kn	112.73	0.91	0.83	0.80	–1.93	–0.09	–2.18
Takeoff field length, ft	5490.55	3.66	3.09	2.91	–1.12	–1.59	–2.03
Landing field length, ft	5173.08	0.94	0.88	0.85	–1.94	–2.11	–2.21
Missed approach thrust, lb	3766.80	–14.48	–12.82	–12.22	–5.76	–3.66	–1.91
Second segment climb, lb	8516.09	–5.29	–4.67	–4.45	–2.68	–1.91	–1.25
Compressor discharge temp, °R	1383.64	–0.07	0.20	0.01	–2.03	–1.84	–2.06
Excess fuel, lb	4237.26	–77.59	–70.03	–66.94	4.77	17.08	24.87

64 unknown coefficients. The redundancy (ratio of I/O pair to number of coefficients) is 14, 28, and 56 for the small, standard, and large models, respectively. The values of the coefficients in NN and regression need not be the same because they are generated following different procedures. The CPU time for training, reanalysis, and design optimization on an SGI octane workstation with the irix 6.5.19m operating system and a 300 MHZ processor is given in Table 5. The regression method required a fraction of a CPU second for training. The NN training required between 1 and 9 minutes. For a single analysis cycle, the FLOPS code required about 3 CPU seconds. This was reduced to milliseconds by the approximators. Gradient calculation is inexpensive by the approximators. For optimization the CPU time to solution by FLOPS was 34 minutes. This was reduced to less than two seconds by the regression method, while the NN average time was about 4 minutes. For analysis and design calculations the approximate methods are found to be efficient.

IX. Performance of Approximators for Analysis and Design Optimization

Solutions obtained by different approximation models for a randomly selected design point (DV_1, … , DV_9 = 8.9579, 31607.7515, 2177.9724, 18.5423, 0.0874, 2982.4585, 37.2243, 5.8297, 1.8295) are given in Table 6. The three regression models predicted the aircraft weight with 2 percent error. It was reduced to less than 1 percent for the NN technique. For the compressor discharge temperature, the error in regression and NN methods averaged 0.1 and 2 percent, respectively. The average error in the field length constraints ranged between 1 and 3 percent for both approximators. However the error was positive for the regression method, while it was negative for the NN. The error in approach velocity was similar to field length constraints. The error was higher for the positivity constraints g_4, g_5, and g_7. The solution fidelity was about the same for the small, standard, and the large models.

To further assess the overall performance of the approximators the errors in the aircraft weight is calculated at 101 design points for engine thrust (in the range 28 to 35 kip), wing area (1800 to 2200 ft^2), and turbine inlet temperature (2900 to 3100 °R). The mean errors and the standard deviations for the three models is given in Table 7.

Table 7. Percent absolute error in weight over certain design variable ranges

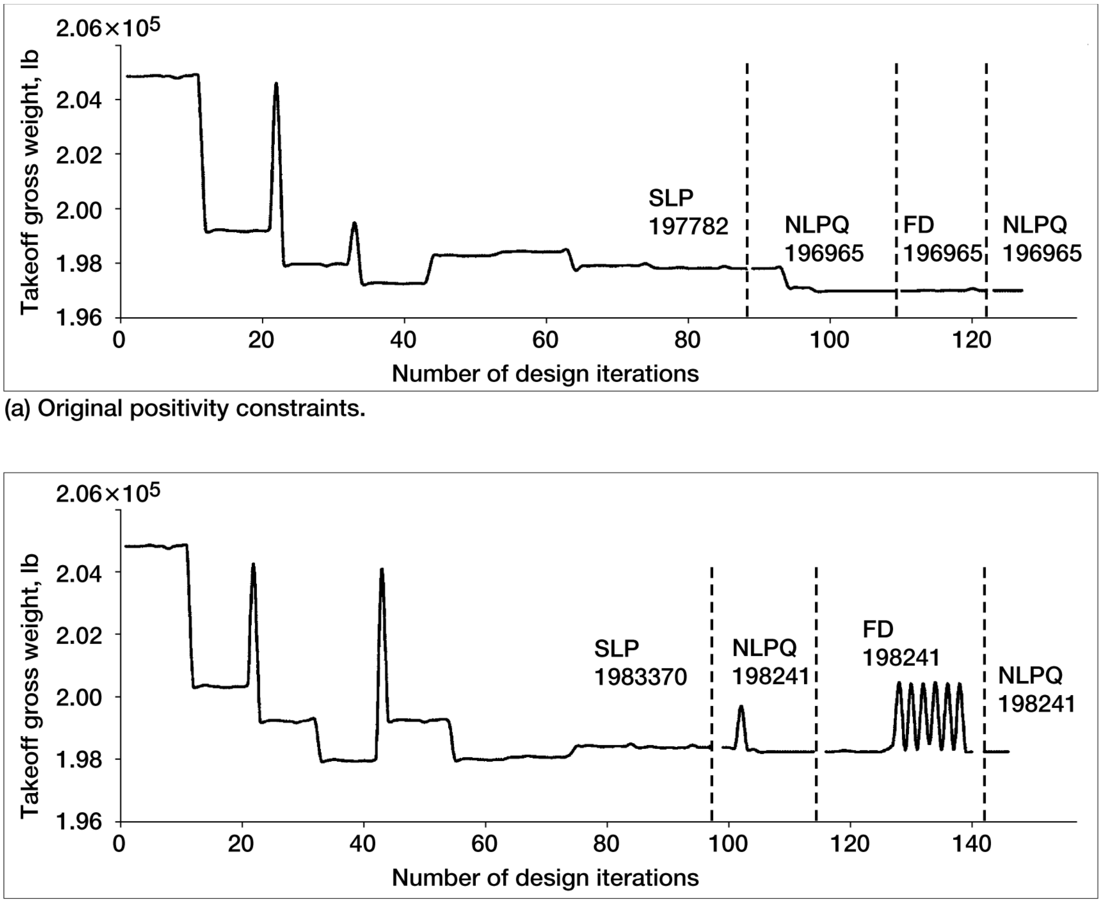
Variable, range, and model	Regression Mean	Regression Standard deviation	Neural network Mean	Neural network Standard deviation
Thrust (28 to 35 kip)				
Small	0.90	0.15	1.05	0.69
Standard	1.22	0.28	0.92	0.61
Large	1.50	0.16	1.01	0.66
Turbine inlet temperature (2900 to 3100 °R)				
Small	0.73	0.26	2.08	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

Table 8. Optimum solution with original and modified positivity constraints

	FLOPS original	Regression original	FLOPS modified	Regression modified
Aircraft weight, lb	199046.9	196965.1	199395.3	198240.8
Design variables:				
Wing aspect ratio (DV_1)	8.6	8.8	8.8	8.8
Engine thrust (DV_2), lb	31408.5	30179.5	32346.6	32181.1
Wing area (DV_3), ft^2	1899.8	1915.0	1851.3	1834.7
Quarter chord sweep angle (DV_4), deg	16.0	16.7	20.2	17.0
Thickness to chord ratio (DV_5)	0.1	0.1	0.1	0.1
Turbine inlet temperature (DV_6), °R	3100	3100.0	3100.0	3094.5
Overall pressure ratio, (DV_7)	40.5	38.0	40.5	38.0
Bypass ratio (DV_8)	6.1	5.0	6.1	5.1
Fan pressure ratio (DV_9)	1.8	1.8	1.8	1.8
Constraints:				
Landing approach velocity (g_1), kn	119.0	117.9	120.7	120.9
Takeoff field length, (g_2), ft	6000	6000.0	5998.3	6000.0
Landing field length (g_3), ft	5479.4	5425.8	5562.8	5573.7
Missed approach gradient thrust (g_4), lb	3746.1	3136.1	5000	5000
Second segment climb thrust (g_5), lb	8385	7721	9619	9594
Compressor discharge temperature (g_6), °R	1429.0	1405.2	1428.3	1405.9
Excess fuel capacity (g_7), lb	0	2553.8	500	500

Both approximators produced about a 1-percent mean error for all three variables, except for a 2-percent error for the turbine inlet temperature by the NN technique. The standard deviation in error with the regression method was less than 0.3 percent. This was increased to about 1 percent with the NN technique. The error was comparable for the small, standard, and large models.

In the aircraft design optimization, the FLOPS analyzer was replaced by the approximate models without any other change. This combined code was run to obtain optimum solution for the aircraft. The combined solution is given in Table 8. CPU time to solution is given in Table 5. A convergence graph that shows the aircraft weight



(a) Original positivity constraints.

(b) Modified positivity constraints.

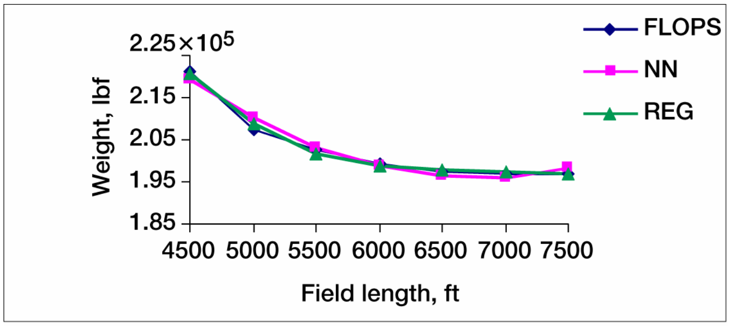
Figure 3. Performance of the large model with Regression method with original and modified positivity constraints.

versus iteration is depicted in Fig. 3 for the large regression model. From a comparison of this graph with Fig. 2(b), which used the FLOPS code, we observe:

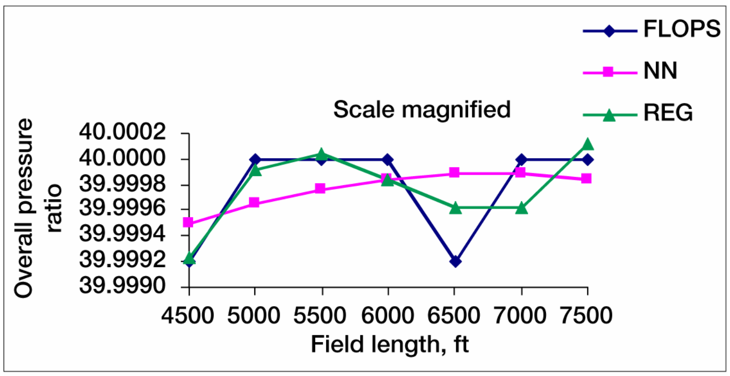
1. Design with the approximator required about double the number of iterations than it did with the FLOPS code. However, the time to solution was in favor of the approximator: 1.6 CPU seconds for the regression method, versus 2031 s for the FLOPS code. The NN used 222 s.
2. The convergence pattern contained oscillations for both the regression method and the FLOPS code. The amplitudes of the oscillations in the first cascade algorithm were considerably smaller for the regression method, see Figs. 2(b) and 3. However, a cascade algorithm was required for the FLOPS code as well as for the regression method.
3. The approximator exhibited 1 percent error in the optimum weight of the aircraft. For field length and approach velocity constraints the error was less than 2 percent. Error was greater for the positivity constraints, which is discussed subsequently.

X. Design Sensitivity Analysis

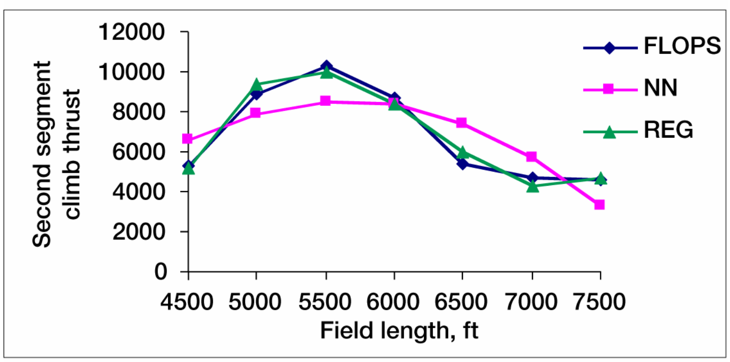
Design sensitivity was examined for the aircraft to land and takeoff on shorter and longer runways ranging from 4500 to 7500 ft in length with 6000 ft as the nominal value. Other parameters are retained at their nominal value. The optimum solutions are depicted in Fig. 4. Optimum aircraft weight versus the field length obtained by the three methods (FLOPS, NN, and regression) is shown in Fig. 4(a). Likewise the overall pressure ratio and second segment climb thrust are given in Figs. 4(b) and (c), respectively. The approximators exhibited less than 1 percent error in the aircraft weight. Aircraft weight is increased for shorter field length and it is decreased for longer length, as expected.



(a) Gross aircraft weight.



(b) Overall pressure ratio.



(c) Second segment climb thrust.

Figure 4. Subsonic aircraft sensitivity analysis with respect to field lengths for the small model.

The NN and regression methods exhibited 0.34 and 0.61 percent error, respectively. Overall pressure ratio (OPR) constraint is graphed in a magnified scale in Fig. 4(b). The approximators hardly exhibit any deviation from the FLOPS solution. Observe however, the discontinuity in the OPR constraint. The regression method has a tendency to hug the data points while NN exhibited a propensity to follow a mean path. The discontinuity will adversely effect the aircraft optimization when the FLOPS code is used. The NN should experience no limitation in design optimization. The performance of the regression method for design optimization is expected to be intermediate between the FLOPS code and NN method. Behavior of the second segment climb thrust constraint is similar to that for OPR. The regression method closely follows the constraint while NN takes an average path.

XI. Positivity Constraints

Three constraints of the problem: g_4 (missed approach gradient thrust), g_5 (second segment climb thrust), and g_7 (excess fuel capacity) restrict the associated parameter to be positive. The parameters were allowed to approach zero. In a modified case the parameters are pushed away from zero, through specified lower bounds: $g^\ell \leq g$, $g_4^\ell = g_5^\ell =$ 5000 lbf and $g_7^\ell =$ 500 lbf. The optimum solutions for four different situations are given in Table 8. From a comparison of the FLOPS-modified case to the base design (second to the last column), we observe

1. Aircraft weight: The modified regression solution (see the last column in Table 8) matched the base solution with a 0.58 percent error. The errors with the original regression and FLOPS solutions were 1.2 and 0.2 percent, respectively.
2. Design variables: The modified regression solution for engine thrust and turbine entry temperature exhibited 0.5 and 0.2 percent error, respectively. The quarter chord sweep angle variable exhibited the most deviation: 16.0 percent for the modified regression versus 21 percent for the original solution.
3. Constraints: There was little error in constraints between the modified regression solution and the base design. Constraints g_4 and g_7 became active for both the FLOPS and regression methods. For the g_5 constraint, the error was 0.3 percent for the modified regression case; between the original FLOPS and original regression cases, it was 13 and 20 percent, respectively.
4. Overall, the modified regression solution exhibited a closer match with the base design.

XII. Conclusions

The cascade optimization strategy solved the subsonic aircraft design optimization problem, even though restarts were required. It is preferable to restrict the behavior parameters from approaching zero values. The optimum aircraft weight calculated by the Flight Optimization System (FLOPS) analyzer and the regression method approximation matched well. The deviation in the design variables between the two analyzers was not significant. Deviation can be significant for some behavior constraints when these constraints approach zero values. Overall, the performances of the neural network and regression method were comparable. The neural network followed a mean path, while the regression method exhibited a tendency to closely follow the FLOPS solution. For a single analysis cycle the FLOPS time measured in seconds is reduced to milliseconds by the approximators. The training, validation, and solution required a small fraction of FLOPS analysis and design time. For design optimization, the central processing unit (CPU) time with the FLOPS analyzer measured in hours was reduced to minutes by the neural network, and seconds by the regression method. Generation of high-fidelity input/output pairs to train the approximators was time consuming.

Appendix
Organization of Flight Optimization System—FLOPS code

The multidisciplinary FLOPS code can be used for preliminary design evaluation of aircraft concepts. The FLOPS FORTRAN code has nine modules: weights, aerodynamics, engines cycle analysis, propulsion data scaling and interpolation, mission performance, takeoff and landing, noise footprint, cost analysis, and program control. The FLOPS manual (Ref. 1) specifies preparation of input data, which follows a namelist format with default values.

The subsonic aircraft has a fuselage with a length of 152.35 ft, width of 16.44 ft, and depth of 17.00 ft. It is to carry 200 passengers with 5 stewardesses and 3 flight crewmembers. It is powered by two wing-mounted engines with a design point net thrust of 48925.0 lbf per engine. It is a separate-flow turbofan engine with two compressor components. The weight of the engine is 9410 lbf. The baseline engine nacelle is 19.75 ft long with an average diameter of 7.81 ft. Wing area is 2272 ft^2, sweep angle is 31.5°, taper ratio is 0.267, and wing thickness-to-chord ratio is 0.109.

Nominal parameters of the engine include a bypass ratio of 5, overall pressure ratio of 29.5, fan pressure ratio of 1.67, compressor discharge temperature of 1460 °R, and maximum dynamic pressure of 800 lbf/ft^2. Fuel capacity is 57 000 lbf, and there are 10 tanks.

The range of the aircraft is 2500 n mi, the maximum cruise altitude is 4000 ft, and the maximum operating Mach number is 0.843. The ramp weight is 250 000 lbf. Maximum allowed takeoff and landing field length is 6000 ft. Maximum allowed approach velocity is 125 n mi. Ground operations include a takeoff time of 0.4 min, taxi in-and-out time of 10 min, and reserve holding time of 0.5 hr.

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

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1. AGENCY USE ONLY (*Leave blank*)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	August 2004	Technical Memorandum

4. TITLE AND SUBTITLE

A Subsonic Aircraft Design Optimization With Neural Network and Regression Approximators

5. FUNDING NUMBERS

WBS–22–708–24–05

6. AUTHOR(S)

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7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

National Aeronautics and Space Administration
John H. Glenn Research Center at Lewis Field
Cleveland, Ohio 44135–3191

8. PERFORMING ORGANIZATION REPORT NUMBER

E–14504

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

National Aeronautics and Space Administration
Washington, DC 20546–0001

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

NASA TM—2004-213059
AIAA–2004–4606

11. SUPPLEMENTARY NOTES

Prepared for the 10th Multidisciplinary Analysis and Optimization Conference cosponsored by the American Institute of Aeronautics and Astronautics and the International Society for Structural and Multidisciplinary Optimization, Albany, New York, August 30–September 1, 2004. Surya N. Patnaik, Ohio Aerospace Institute, Brook Park, Ohio 44142 and NASA Resident Research Associate at Glenn Research Center; and Rula M. Coroneos, James D. Guptill, Dale A. Hopkins, and William J. Haller, NASA Glenn Research Center. Responsible person, Surya N. Patnaik, organization code 5930, 216–433–5916.

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Unclassified - Unlimited
Subject Category: 05 Distribution: Nonstandard

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12b. DISTRIBUTION CODE

13. ABSTRACT ***(Maximum 200 words)***

The Flight-Optimization-System (FLOPS) code encountered difficulty in analyzing a subsonic aircraft. The limitation made the design optimization problematic. The deficiencies have been alleviated through use of neural network and regression approximations. The insight gained from using the approximators is discussed in this paper. The FLOPS code is reviewed. Analysis models are developed and validated for each approximator. The regression method appears to hug the data points, while the neural network approximation follows a mean path. For an analysis cycle, the approximate model required milliseconds of central processing unit (CPU) time versus seconds by the FLOPS code. Performance of the approximators was satisfactory for aircraft analysis. A design optimization capability has been created by coupling the derived analyzers to the optimization test bed CometBoards. The approximators were efficient reanalysis tools in the aircraft design optimization. Instability encountered in the FLOPS analyzer was eliminated. The convergence characteristics were improved for the design optimization. The CPU time required to calculate the optimum solution, measured in hours with the FLOPS code was reduced to minutes with the neural network approximation and to seconds with the regression method. Generation of the approximators required the manipulation of a very large quantity of data. Design sensitivity with respect to the bounds of aircraft constraints is easily generated.

14. SUBJECT TERMS

Subsonic aircraft; Design optimization; Regression method; Neural network; FLOPS; CometBoards

15. NUMBER OF PAGES

16

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	