Artificial Neural Networks Applications: From Aircraft Design Optimization to Orbiting Spacecraft On–Board Environment Monitoring

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National Aeronautics and
Space Administration

Glenn Research Center

August 2002

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Available electronically at http://gltrs.grc.nasa.gov

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Abstract -- *This paper reviews some of the recent applications of artificial neural networks taken from various works performed by the authors over the last four years at the NASA Glenn Research Center. This paper focuses mainly on two areas. 1) Artificial neural networks application in design and optimization of aircraft/engine propulsion systems to shorten the overall design cycle. Out of that specific application, a generic design tool was developed, which can be used for most design optimization process. 2) Artificial neural networks application in monitoring the microgravity quality on-board the International Space Station, using on-board accelerometers for data acquisition. These two different applications are reviewed in this paper to show the broad applicability of artificial intelligence in various disciplines. The intent of this paper is not to give in-depth details of these two applications, but to show the need to combine different artificial intelligence techniques or algorithms in order to design an optimized or versatile system.*

I. INTRODUCTION

Over the last ten years, multidisciplinary design optimization has developed into a field of its own. The primary objective of Multidisciplinary Design Optimization (MDO) is to improve design tools in order to rapidly and efficiently explore high-order design spaces with the aim of increasing significantly system performance and reducing end-product cost substantially by cutting system design cycle time by half. With that in mind, a few years ago the NASA Glenn Propulsion System Analysis Office (PSAO) undertook a review of all its system analysis tools to assess how some of them can be integrated into one unit and at the same time cut drastically the time required to perform the daily aircraft propulsion analysis task by taking advantages of emerging analysis techniques and faster CPUs. The motivation for that review was to minimize the time required to assess technology impact on current and future aircraft / engine design by both analysts and managers. Based on the outcome of that review, the decision was made to develop a simulation-based analysis tool using soft computing techniques. Section II of this paper reviews and discusses the pertinent results obtained using such system.

The second area, though drastically different from the design optimization one, is the field of data acquisition and system monitoring. In this specific case, artificial neural networks were used to monitor the International Space

Station (ISS) microgravity environment quality using on-board accelerometers for data acquisition. The objective of this work was to monitor in near real time the microgravity environment of the station so that Principal Investigators (PI) performing research on the station can know at any moment what the environment is. Artificial neural networks were used to design such a system. The system is used to monitor the operating machinery as well as crew activities. Operating machines and mechanical systems generate vibration. Measurement of these signals (vibration) yields information, which is used for monitoring. For example, data about how a signal varies with time can be used to assess defective and worn parts, design attributes and other problems. Operation of pumps, fans, compressor, generator, engines and most mechanical systems involves periodic motion due to rotation of interacting components. The motion of fans, coils, bearings and shafts generates vibration, which can be related to the machine running speed. Based on that knowledge, a robust monitoring system using artificial neural networks can be developed for use in many fields. Section V of this paper reviews and discusses such a monitoring system for the case of acceleration data acquisition for environment monitoring.

II. NEURAL NETWORKS APPLICATION FOR DESIGN AND OPTIMIZATION

The main objective of this work was to develop a fast optimizing multidisciplinary system design, which could perform both analysis/design and optimization of aircraft and their propulsion systems, such as engine cycle analysis, aircraft sizing, aircraft / engine mission analysis, aircraft noise and emission, engine economics analysis and system weight prediction (Fig. 1). To design such system [1–2], Taguchi techniques, fuzzy logic and neural networks were used. Neural Networks [3–6] were used in this work to provide mappings for fast analysis and design. The use of neural networks was very important in this work because it added both capability and flexibility to analyze the impact of new technologies on engine and aircraft systems and greatly reduces the turnaround time for analysis and design. The result obtained using such approach showed that it yields significant performance improvement in optimizing the design objectives as well as in predicting the system output in

near real time for both single and multiple design objectives even when conflict exists among the design objectives (which is usually the case in design optimization). The use of Neural Networks enables the design analysis tool to simulate a very complex system in near real time (since it is simulation-based instead of being an iterative search) within acceptable accuracy (less than 5% error).

III. DISCUSSION

The optimum solutions obtained using the combined Taguchi Neural Networks and fuzzy logic techniques to maximize thrust, minimize fuel consumption, emission and jet velocity are listed in Tables I- III. As a design constraint, every case starts with the same Mach number and altitude. All other input parameters were free to vary within their pre-specified ranges. The results show that the optimum design solutions can be easily found using the combined techniques; especially in resolving the conflict among design objectives.

To test the generalization of the trained network, 26 unseen cases were used. Each case contains 14 input variables and 4 (out of 11) output variables. Table IV shows the generalization test results in terms of root-mean-square (RMS) error percentage. The error percentages listed in that table are less than 5 %, and are generally acceptable. But, we feel that emission could be further improved by carefully adding more trained input patterns cases. The main reason why emission shows a higher error percentage is because the ratio of the maximum to the minimum input value of the trained patterns is very high, approximately 6.7.

From the result obtained, one can infer that the combination of Taguchi, Fuzzy logic and Neural Networks shows excellent prospect in the MDO field.

IV. DEVELOPMENT OF A GENERIC DESIGN TOOL

The successful result obtained using the neural networks for aircraft and propulsion systems design/analysis and optimization, led to the development of a generic multidisciplinary design optimization tool using the same approach [7]. The objective of the generic design tool was to automate the multidisciplinary system design optimization so that any user can mount his/her application program on top of the generic tool to optimize the design objectives without having to do all the tedious work required in performing MDO. As was the case in the previous work discussed above, neural networks were used to generate the instant input-output mapping. That allows the user to instantly evaluate the optimization performance; to place weights on different objectives or fine-tune the optimum solution. In summary, the use of artificial neural networks helps greatly in accomplishing the following:

1. Greatly reduces turnaround time for technology impact assessment
2. Quick data availability for project advocacy

3. Identification of high payoff investment for less R&D funding
4. Save time, money and resources
5. Keep and increase corporate knowledge
6. Incremental and/or global analysis capability
7. Excellent learning and training tool for new employees

The generic design tool presented here (figs. 2 and 3) combines Taguchi techniques, fuzzy logic and neural networks for system optimization. Figure 2 shows the scheme for the case when the user does not have a database, while fig. 3 shows the scheme when such a database is available to the user. More specifically,

1. Taguchi techniques are used to generate the parameter significance index
2. Fuzzy logic is used to resolve the conflicts among different objectives
3. Neural networks are used to generate instant input-output mapping. Such a capability allows the user to instantly evaluate the optimization performance, particularly in placing the preference weights and fine-tuning the optimum solution.
4. Combination of Taguchi techniques and fuzzy logic proved to be a powerful tool for performing multidisciplinary system optimization

The combination of the three techniques is better than most traditional search-based optimization techniques in three aspects:

1. In seeking the optimum solution, this approach never diverges
2. The optimum solution is obtained in near real time because this approach is simulation-based, which does not rely on an iterative search
3. As a result of Taguchi analysis, the parameter significance index gives the user a good guidance to fine-tune the optimum solution.

This tool is generic in the sense that it can take virtually any type of data set, such as ASCII file or spreadsheet. It is flexible enough to allow the user to easily switch between single and multiple objective optimizations, and between local and global optimizations, at any time. Furthermore, the user can place preference weights on each objective, and also has a chance to fine-tune the optimum solution. Most importantly, the system optimum solution can be obtained in near real time.

V. NEURAL NETWORKS APPLICATION FOR SYSTEM MONITORING

The residual acceleration environment of an orbiting spacecraft in a low earth orbit is a very complex phenomenon. It is subject to quasi-steady acceleration, higher frequency acceleration, and transient disturbances. Many factors [8], such as experiment operation, life-support systems, equipment operation, crew activities, aerodynamic drag, gravity gradient, rotational effects as well as the vehicle structural resonance frequencies (structural modes) contribute

to form the overall reduced gravity environment. Weightlessness is an ideal state, which cannot be achieved in practice because of the various sources of acceleration present in an orbiting spacecraft. As a result, the environment in which experiments are conducted is *not zero* gravity; therefore, experiments can be affected by the residual acceleration because of their dependency on acceleration magnitude, frequency, orientation and duration. Therefore, experimenters must know what the environment was when their experiments were performed in order to analyze and correctly interpret the result of their experimental data. In a terrestrial laboratory, researchers are expected to know and record certain parameters such as pressure, temperature, humidity level and so on in their laboratory prior to, and possibly throughout their experiment. The same holds true in space, except that acceleration effects emerge as an important consideration. In order to aid the researchers assessing the impact of the space environment on their experiments remotely, a monitoring system tool development was developed using artificial neural networks. A brief description of the work is given below.

The main focus of this work [9–11], using soft computing techniques to monitor the microgravity environment on-board the ISS, was to develop an artificial intelligence monitoring system to help Principal Investigator (PI) teams identify the primary vibratory disturbance sources that are active, at any moment of time, on-board the ISS, which might impact the microgravity environment their experiments are exposed to. Such information is made available to PIs via the world wide web (WWW) in near real time, where they can graphically see which event(s) is/are active, such as crew activities, pumps, fans, centrifuges, compressor, crew exercise, etc… in order to decide whether or not to run their experiments based on the magnitude of the acceleration associated with a specific event. This monitoring system detects primarily the vibratory disturbance sources. The system has built-in capability to detect both known and unknown vibratory disturbance sources. A known pattern is defined as the nominal values of the previously measured (learned data set) frequency and acceleration of an existing disturbance source. To design such a complex system, the following artificial neural networks techniques were used: Kohonen's Self-Organizing Feature Map (SOFM) [12], Learning Vector Quantization (LVQ) [13–15], Backpropagation Neural Networks (BPNN) [16]. In addition, Fuzzy logic [17–18] was used to deal with some of the decision making process.

For the acceleration data acquisition, two accelerometers were flown to ISS, April 19, 2001, on the Space Shuttle flight STS-100. One accelerometer, Microgravity Acceleration Measurement System (MAMS), is a low frequency acceleration measurement system, which measures acceleration levels up to 100 Hz. The other, Space Acceleration Measurement System (SAMS), is a high frequency measurement system, which measures acceleration from 0.01 to 300 Hz on the ISS. Both of these accelerometers are tri-axial sensors. Acceleration data are currently being received in real time at our Telescience Center (TSC) at NASA Glenn for the on-board microgravity environment monitoring of the ISS.

In the course of developing the monitoring system many technical challenges were encountered. Chief among them was unknown patterns recognition. SOFM has no ability to do so, nor can LVQ. Unknown patterns recognition was a crucial feature of the monitoring system if it were to succeed at doing what it was supposed to because many of the fundamental frequencies of the events on ISS are not yet known, and since the ISS is being built in increments, they will, without doubt, change to some degrees from increment to increment until assembly complete. Therefore, to overcome that problem we had to come up with a modified approach to pattern classification and recognition. The model we proposed and used throughout this work combines SOFM, BPNN and LVQ, which is referred to as Adaptive Pattern Recognition and Classification (APRC) (Fig. 4). In the proposed model, BPNN is inserted in between SOFM and LVQ to help recognize the unknown patterns, while SOFM and LVQ are used to classify the known patterns. Also, in the proposed model, BPNN is used to keep SOFM in check in order to prevent it from misclassifying patterns since one of the shortcomings of SOFM is the potential for misclassifying patterns that fall on the boundary between two clusters due to the fact that SOFM relies solely on Euclidean distance to assign patterns to respective clusters.

In summary, the proposed APRC model used throughout this work is very innovative in the following aspects:
1. Can recognize unknown patterns
2. Can avoid patterns misclassification
3. Take into account multi-dimensional ranges of neighboring clusters

VI. DISCUSSION

This section presents some preliminary results obtained using the artificial neural networks, which assess the ISS microgravity environment, in order to share with the microgravity scientific community what is currently being seen in terms of disturbances aboard the ISS. It must be pointed out that the ISS microgravity environment characterization is at an early stage, therefore, not too much is known with certainty. The results presented here are, therefore, *VERY* preliminary since we are in the early stage of receiving, processing, analyzing, digesting and comparing the data. There are more questions, at this stage, than answers. With that in mind, let's discuss the content of table 4.

Table 4 shows both acceleration levels and frequencies (after Fourier Transform was performed) for different activities recorded by MAMS-HiRAP aboard the ISS over a 10-day period. The table shows activities, which are present only on the X and Z axes of the MAMS-HiRAP, respectively, and then, activities present only on two axes. This is very important information for experiments, which have

directional and/or frequency sensitivities. It is very important to note that these data are presented in the MAMS-HiRAP on-orbit coordinate systems. The table provides information such as the nature of the disturbance detected (narrow or broadband). In the case of the broadband, the frequency range (low and high end) is provided; also, the median acceleration level is provided along with the lowest and the highest level of acceleration detected for that specific activity over the 10-day period. Finally, a column, which lists some comments, provides some speculations on what that specific activity might be. We have reasons to believe that most of them are correct, but since this is a preliminary look at the data, we will call them "speculation" at this point, until more in-depth analysis is performed. The result obtained, thus far, using actual data showed that the monitoring system correctly detected the disturbance sources activation. The result showed a high success rate in classifying and recognizing the detected events correctly. The total elapsed time from detection of an event on the ISS to pattern classification and recognition and actual display of the events on the world wide web (WWW) for PIs viewing takes approximately 12 seconds for all three axes using a PC with a 500 MHz clock speed.

This monitoring system has demonstrated its capability to automatically detect the vibratory disturbance sources and to correctly classify and recognize them. The Adaptive Pattern Recognition and Classification (APRC) approach presented here has the ability to classify the known patterns, prevent possible misclassification, and also recognize the unknown patterns. Fuzzy logic was used to exploit the tolerance for imprecision, uncertainty and partial truth, along with the experience of the human experts (by means of fuzzy logic rules), to make intelligent decisions as to what vibrating sources are more relevant to a specific sensor.

VII. OVERALL CONCLUSION

In this paper two major applications of artificial neural networks were presented: a non-linear input-output mapping for system optimization, and pattern classification and recognition for system monitoring. In the former, backpropagation networks, a supervised learning algorithm, were used, while in the latter, Kohonen's Self-Organizing Feature Map, unsupervised learning, was used in conjunction with Learning Vector Quantization (supervised learning). It was shown that supervised learning and unsupervised learning compliment each other very well.

Although neural networks alone can provide very accurate input-output mapping, it cannot deal with data imprecision, fuzziness and uncertainty. In contrast, fuzzy logic is well suited for that. Therefore, the combination of these two techniques, known as soft computing techniques, is a powerful tool for design, analysis and systems monitoring, where neural networks provide precision, while fuzzy logic provides intelligence to the system. The works discussed in this paper clearly demonstrated that.

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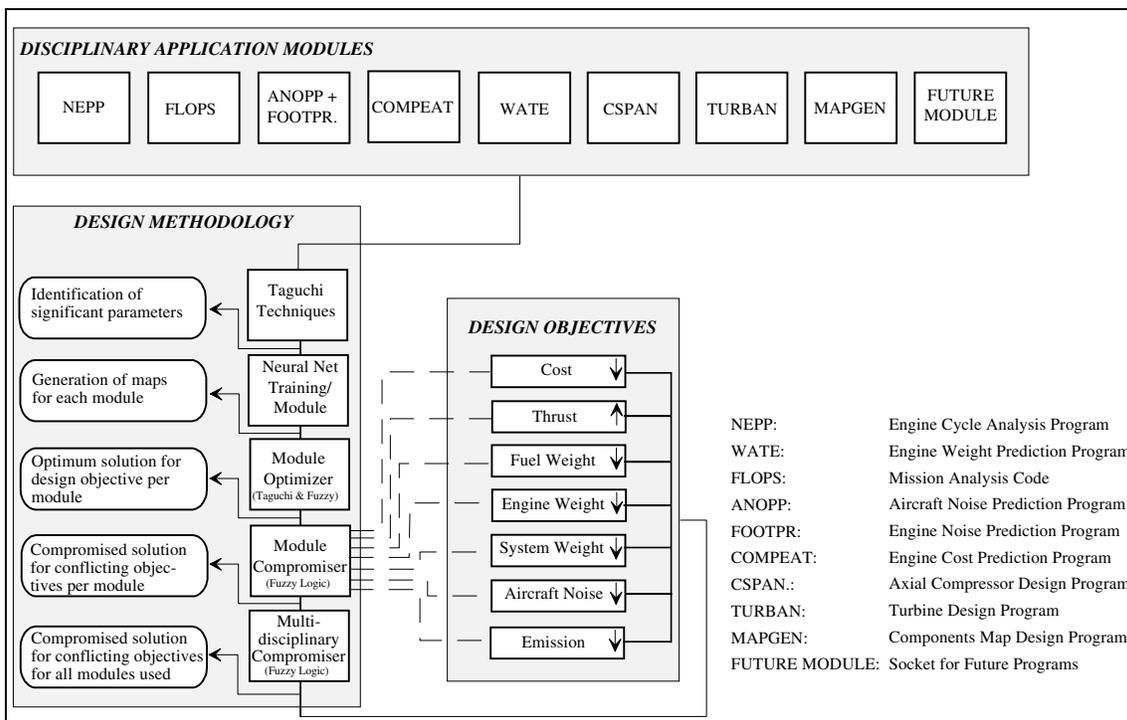
Fig. 1 Multidisciplinary Analysis/Design Structure

Table I Performance Improvement in Optimizing One Design Objective

(1a) Maximizing Thrust

	Thrust	Fuel	Emission	Jet vel.
35,000 ft	**12.57 %**	0.15 %	19.52 %	–7.62 %
Sea level	**6.24 %**	–0.63 %	–10.09 %	–4.93 %

(1b) Minimizing Fuel Consumption

	Thrust	**Fuel**	Emission	Jet vel.
35,000 ft	0.95 %	**14.97 %**	–8.93 %	1.02 %
Sea level	–2.53 %	**9.38 %**	–4.84 %	3.55 %

(1c) Minimizing Emission

	Thrust	**Fuel**	**Emission**	Jet vel.
35,000 ft	–6.40 %	3.44 %	**27.38 %**	4.34 %
Sea level	–4.44 %	0.73 %	**41.60 %**	4.02 %

(1d) Minimizing Jet Velocity

	Thrust	**Fuel**	Emission	**Jet vel.**
35,000 ft	–6.04 %	–4.72 %	13.24 %	**4.33 %**
Sea level	–9.01 %	2.27 %	25.80 %	**8.35 %**

Table II Performance Improvement in Optimizing Three Design Objectives

(2a) Maximizing Thrust, Minimizing Fuel Consumption and Emission

	Thrust	**Fuel**	**Emission**	Jet vel.
35,000 ft	**1.87 %**	**3.57 %**	**5.80 %**	–1.44 %
Sea level	**–0.19 %**	**3.53 %**	**16.91 %**	0.46 %

(2b) Maximizing Thrust, Minimizing Fuel Consumption and Jet Velocity

	Thrust	**Fuel**	Emission	*Jet vel.*
35,000 ft	**1.53 %**	**3.69 %**	0.41 %	**–1.29 %**
Sea level	**–2.57 %**	**5.75 %**	9.16 %	**2.73 %**

(2c) Maximizing Thrust, Minimizing Emission and Jet Velocity

	Thrust	Fuel	**Emission**	*Jet vel.*
35,000 ft	**2.34 %**	1.85 %	**5.08 %**	**–1.89 %**
Sea level	**–2.38 %**	3.72 %	**17.29 %**	**2.33 %**

(2d) Minimizing Fuel Consumption, Emission and Jet Velocity

	Thrust	**Fuel**	**Emission**	*Jet vel.*
35,000 ft	–2.30 %	**8.23 %**	**10.12 %**	**1.76 %**
Sea level	–3.96 %	**6.31 %**	**21.58 %**	**4.00 %**

Table III Performance Improvement in Optimizing Four Design Objectives

	Thrust	Fuel	Emission	Jet vel.
35,000 ft	1.28 %	3.48 %	5.43 %	−1.14 %
Sea level	−1.87 %	4.12 %	15.60 %	1.96 %

Table IV Generalization Test Results

Design Objective / Output	RMS Error
Output 1: Thrust	1.719 %
Output 2: Fuel Consumption	1.617 %
Output 3: Emission	3.727 %
Output 4: Jet Velocity	1.242 %
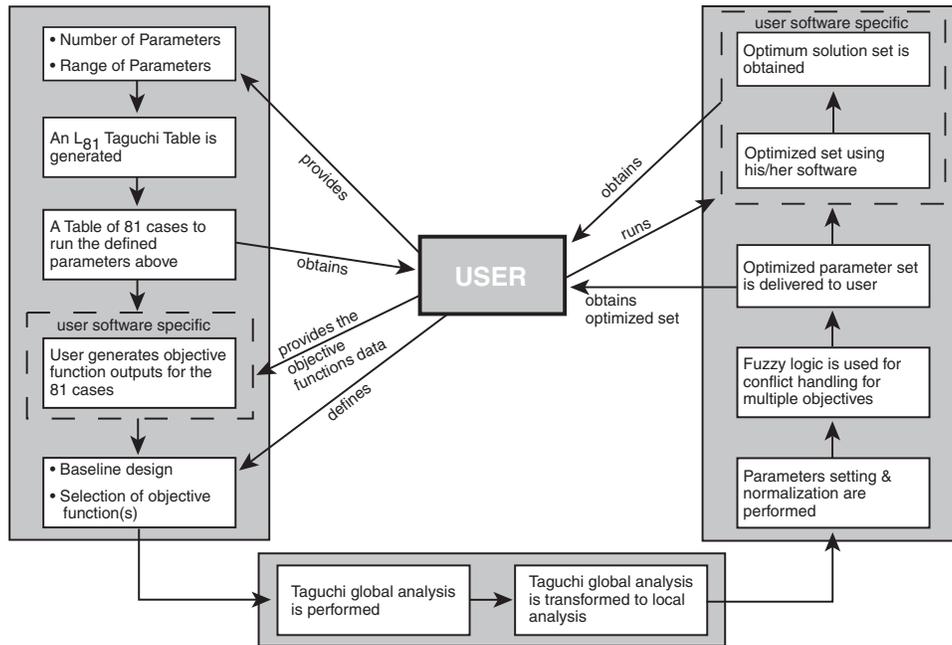
Fig. 2 Generic Single Discipline Optimization with Multiple Objective Functions Architecture I
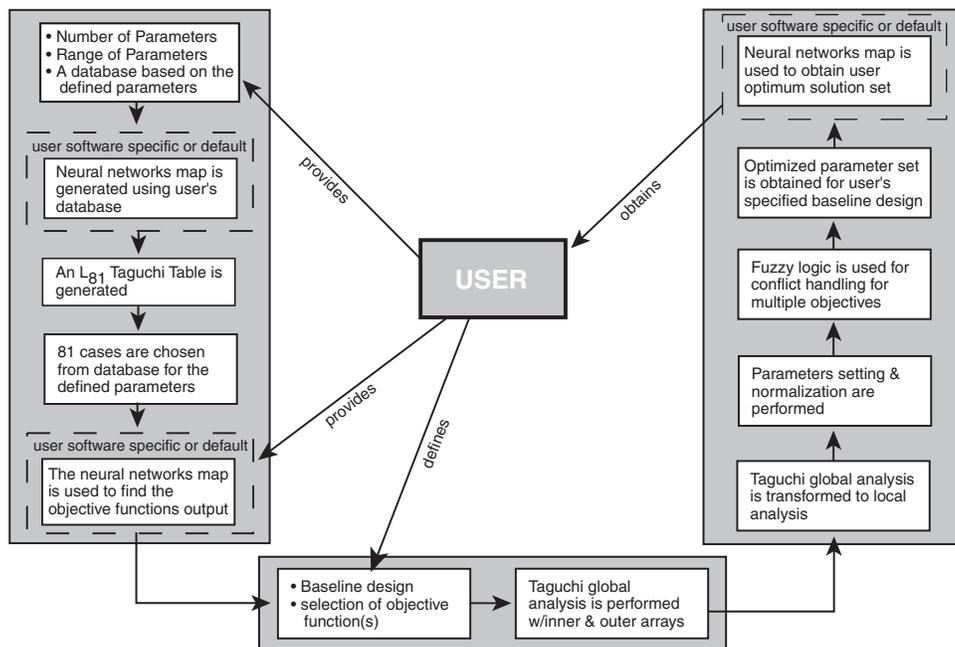
Fig. 3 Generic Single Discipline Optimization with Multiple Objective Functions Architecture II
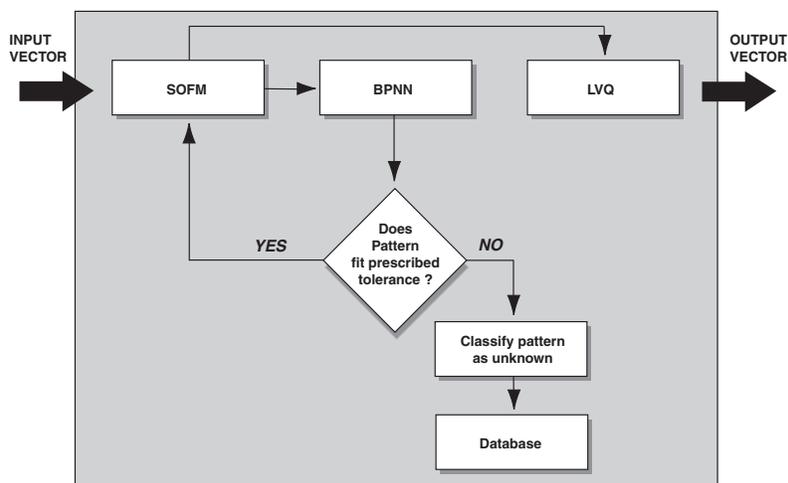

Fig. 4 Adaptive Pattern Recognition and Classification (APRC)

Table V Frequencies and Accelerations Identification of the Neural Networks System for ISS Increment-2 over a 10-day period

MAMS-HiRAP: X-axis only

Nominal Frequency (Hz)	Low end (Hz)	High end (Hz)	Band type	Median Level (µg)	Low end (µg)	High end (µg)	Excitation level (µg)	Comment
1.8311			Narrow	27	8.4121	88.892		Structural
3.7842			Narrow	65	6.9859	121.09	188.93	Structural
4.6387			Narrow	50	21.582	111.43		Structural
11.597			Narrow	20	7.1607	48.046		
13.672			Narrow	30	5.0939	69.260		
14.404			Narrow	51	17.729	84.30		
15.137			Narrow	59	16.879	84.536		
15.991			Narrow	28	15.855	72.29	162.14	
16.602			Narrow	30	5.9014	62.211		
18.677	18.818	19.531	Broadband	21	8.8645	37.908		

MAMS-HiRAP: Z-axis only

Nominal Frequency (Hz)	Low end (Hz)	High end (Hz)	Band type	Median Level (µg)	Low end (µg)	High end (µg)	Excitation level (µg)	Comment
5.9814	5.8594	6.2256	Broadband	16	10.398	17.775	185.04	Structural
7.5684			Narrow	8	5.2704	12.047	171.64	Structural

MAMS-HiRAP: X and Z-axes

Nominal Frequency (Hz)	Low end (Hz)	High end (Hz)	Band type	Median Level (µg)	Low end (µg)	High end (µg)	Excitation level (µg)	Comment
0.97656 (x)			Narrow	14.8	4.8229	43.306		Structural
0.97656 (z)			Narrow	33	8.0831	65.824		Structural
39.185 (x)			Narrow	9.0	5.7623	15.071		
39.185 (z)	38.82	41.75	Broadband	5.0	3.2659	10.555		

MAMS-HiRAP: Y and Z-axes

Nominal Frequency (Hz)	Low end (Hz)	High end (Hz)	Band type	Median Level (µg)	Low end (µg)	High end (µg)	Excitation level (µg)	Comment
9.5215 (y)	9.1553	9.887	Broadband	17	3.2905	54.391		
9.5215 (z)	9.2773	9.644	Broadband	30	4.6486	87.878		
15.625 (y)	15.259	15.99	Broadband	19	7.3364	46.698		
15.625 (z)	15.015	15.99	Broadband	36	8.9874	74.023		
83.984 (y)			Narrow	30	7.5534	34.195		EXPPCS
83.984 (z)			Narrow	25	21.413	34.03		EXPPCS

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1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE August 2002	3. REPORT TYPE AND DATES COVERED Technical Memorandum

4. TITLE AND SUBTITLE

Artificial Neural Networks Applications: From Aircraft Design Optimization to Orbiting Spacecraft On–Board Environment Monitoring

5. FUNDING NUMBERS

WU–400–35–4C–00

6. AUTHOR(S)

Kenol Jules and Paul P. Lin

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–13505

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—2002-211811

11. SUPPLEMENTARY NOTES

Prepared for the 2001 Advanced Study Institute on Neural Networks for Instrumentation, Measurement, and Related Industrial Applications sponsored by the North Atlantic Treaty Organization (NATO), Crema, Italy, October 9–20, 2001. Kenol Jules, NASA Glenn Research Center, and Paul P. Lin, Cleveland State University, Cleveland, Ohio 44115–2425. Responsible person, Kenol Jules, organization code 6727, 216–977–7016.

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Subject Categories: 19 and 35   Distribution: Nonstandard

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13. ABSTRACT (Maximum 200 words)

This paper reviews some of the recent applications of artificial neural networks taken from various works performed by the authors over the last four years at the NASA Glenn Research Center. This paper focuses mainly on two areas. First, artificial neural networks application in design and optimization of aircraft/engine propulsion systems to shorten the overall design cycle. Out of that specific application, a generic design tool was developed, which can be used for most design optimization process. Second, artificial neural networks application in monitoring the microgravity quality on-board the International Space Station, using on-board accelerometers for data acquisition. These two different applications are reviewed in this paper to show the broad applicability of artificial intelligence in various disciplines. The intent of this paper is not to give in-depth details of these two applications, but to show the need to combine different artificial intelligence techniques or algorithms in order to design an optimized or versatile system.

14. SUBJECT TERMS

Multidisciplinary design optimization; Taguchi techniques; Fuzzy logic

15. NUMBER OF PAGES

15

16. PRICE CODE

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