

Integrated Aeropropulsion Control System Design*

C-F. Lin
American GNC Corporation
9131 Mason Ave.
Chatsworth, CA 91311

Jic Huang
American GNC Corporation
9131 Mason Ave.
Chatsworth, CA 91311

Francis X. Hurley
Mobility 11'ethnology
U.S. Army Research Office
Research Triangle Park, NC 27709

F.Y. Hadaegh
Jet Propulsion laboratory
California Institute of Technology
Pasadena, CA 91109

Abstract: An integrated intelligent control approach is proposed to design a high performance control system for aeropropulsion systems based on advanced sensor processing, nonlinear control and neural fuzzy control integration. Our approach features the following innovations:

- The complexity and uncertainty issues are addressed via the distributed parallel processing, learning, and online re-optimization properties of neural networks;
- The nonlinear dynamics and the severe coupling can be naturally incorporated into the design framework.
- The knowledge base and decision making logic furnished by fuzzy systems leads to a human intelligence enhanced control scheme.

In addition, fault tolerance, health monitoring and reconfigurable control strategies will be accommodated by this approach to ensure stability, graceful degradation and reoptimization in the case of failures, malfunctions and damage.

1 Introduction

Over the past two decades, modern control theory and technologies have made significant advancements. New design techniques ranging from robust control (H_∞ , μ -synthesis), nonlinear control (inversion based control, nonlinear servomechanism, analytic gain scheduling), to intelligent control (fuzzy logic, neural networks) have successfully demonstrated their effectiveness in the digital "flight-by-wire" aircraft control system, "drive-by-wire" automobiles, bank-to-turn missile systems, high performance robotics, and spacecraft. Nevertheless, relatively less important progress has been made in jet engine control system design. Despite the fact that today's microprocessor techniques enable almost any sophisticated controllers to be implemented in real time, "the control modes used in today's high-performance engines haven't changed significantly since the days of the hydromechanical control systems" [1]. Indeed, with some exceptions) the main jet engine control design techniques have been the linear quadratic regulator (LQR) synthesis and its variations [1], [8], [7].

Studies and demonstrations do indicate that the technology base for significant turbine engine control advancement may be in hand. An early manifestation was the Highly Integrated Digital Engine Control (HIDEC) project of the National Aeronautics and Space Administration (NASA) initiated in the mid 1980s [10]. In HIDEC, trim point displacements from the stall line were automatically lessened when the F-15 aircraft was in steady, low-risk flight conditions. ("Stall line" may represent a variety of fluid mechanical phenomena, including both surge and rotating or deep stall, and both compressor and fan rotating machinery). HIDEC's schedules were precomputed, and limits were not interrelated and readjusted. The program was of interest not only to the aeropropulsion community but also to the unmanned air vehicle community, in part because both onboard and offboard (telemetered) data processing were experimented with. Propulsion efficiency improvements of the order of 10 % were achieved.

It has been estimated that an additional 10 % in fuel savings could be available through more fully intelligent engine control systems. This would translate to great cost savings for the United States Army, which operates large fleets of both air and land vehicles powered by turboshaft engines. Further, intelligent control is clearly synergistic with diagnostics/safety and engine life goals.

In this spirit, the Engineering Sciences Directorate of the United States Army Research Office (ARO) has initiated an Intelligent Turbine Engines thrust. A 1994 Workshop [3] with diverse participation assessed the current state of technology as well as possibilities for advancement past the automatic optimization of fuel flow plus air flow geometry gross variables (such as nozzle exit area, inlet and/or bypass configurations, and vane angles), itself a challenging objective. Numerous other candidate parameters for inclusion in encompassing, general algorithms were suggested. Other aspects were considered as well. For one example, some variables might be appropriately eliminated even in a powerful processing environment because their sensor errors are comparable with their contributions to overall optimization. For another, some issues might manifestly call for separate processor loops, such as control of hot spots or of local vibrations or of tip clearance, or restart actions. For another, some phenomena might be very amenable to purely aeromechanical control, such as automatic suppression of rotating stall through a high pressure air valve reminiscent of a stub

*Research supported under Contract No. DAAH04-94-C-0051, United States Army Research Office

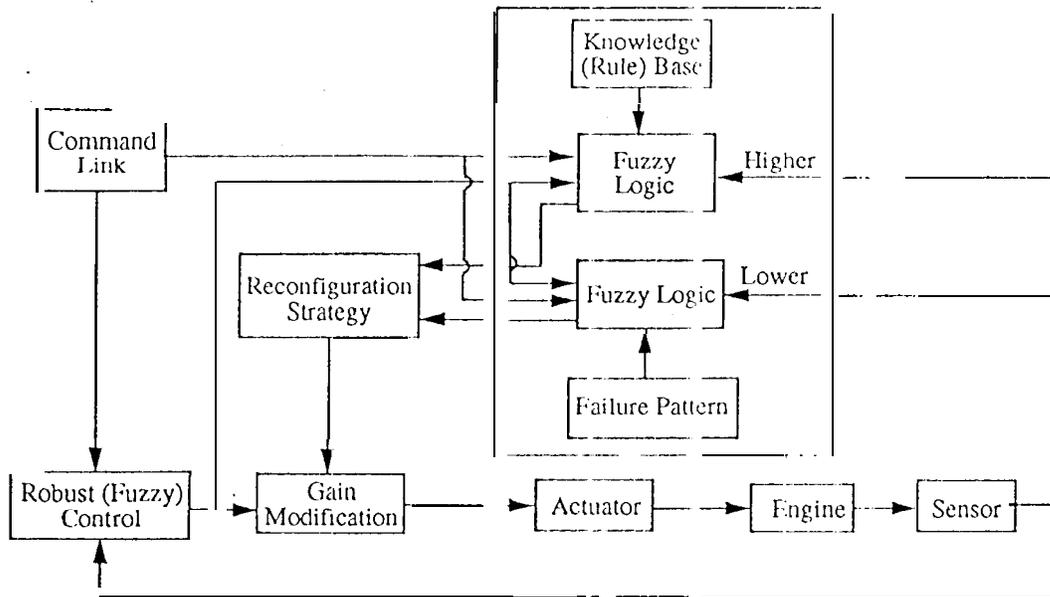


Figure 1: Integrated Robust, Intelligent Engine Control

abreather.

To complement the aforementioned thrust, the Research and Technology Integration Directorate of AR() is funding a Small Business Technology Transfer (SBTT) project on aeropropulsion control featuring a collaboration of American GNC Corporation and the Jet Propulsion Laboratory of the California Institute of Technology. SBTT is a program which aims to meld expertise of the industry and academic spheres, and to move noteworthy research results toward commercial application. Aspects of this particular project include fuzzy logic analysis tools and the neural network approach to processing. It should therefore be able to accommodate many variables, difficult nonlinearities and couplings, uncertainty, and repeated reoptimization, and should be compatible with human thought patterns and with diagnostic/prognostic goals. This paper has been prepared to afford a summary of preliminary results of the investigation.

2 Integrated Approach to Jet Engine Control System Design

The basic mode of control of each type of engine can be divided into a large number of individual modes of control to meet the requirements of the different operating regimes. It is convenient to classify them by their basic objectives as follows [12]:

1. Physical limiting control modes which are required to protect the engine from damage or malfunctions which could result in the loss of power.
2. Thrust control modes which provide the desired performance at all expected operating conditions.
3. Transient control modes which provide the necessary starting and power change capability.

Advanced propulsion control system design should address the following four problems [11], [6], [13], [5], [2].

- significantly reduce control system weight through the application of advanced, lightweight materials and through systems integration;
- increase engine system performance through the development of advanced engine control approaches;
- maintain or enhance the basic control system reliability and tolerance to environmental effects.
- accommodate failure; health monitoring, and reconfiguration.

Due to the highly complicated nature of the jet engine control system design problem, a single control approach has its limit to achieve the above multiple objectives. We have adopted an integrated approach to engine control system design as shown in Figure 1. The heart of this scheme is a robust controller which is aimed to achieve an optimized balance between the engine's performance with respect to a given mission segment and robustness against environmental effects (temperature, vibration, EMI, EMP, etc.). Issues such as sensor/actuator models, sensor/actuator placement, system validation, uncertainty model, model/controlled reduction, and digitization effects can also be addressed in the robust control design. The robust controller can be designed using a variety of modern linear control techniques such as H_∞ , H_2 , and robust eigenstructure assignment, etc., or nonlinear control techniques such as analytic gain scheduling and inversion based control.

The objective of health monitoring is to maintain a regular operation in the presence of damages and failures and, in the case that the regular operation is not possible, to achieve a graceful degradation. The health monitoring objective is

achieved through the distributed parallel processing and learning capabilities of the fuzzy neural networks. The monitoring system can detect sensor anomaly or actuator malfunction, and, accordingly, redirect the feedback control path or adjust the control gain.

The health monitoring and reconfigurable control system can be realized using either neural networks or fuzzy neural networks. Two sets of failures may be encountered in the control system. Predictable failures are handled by calling upon prestored action. Unpredictable failures are accommodated using an on-board inference mechanism. A two-level arrangement of fuzzy decision making logic is thus used. In the lower level, a set of predictable failure patterns is stored in the associated knowledge base. Once a failure is detected, the failure pattern is correlated with the prestored knowledge base. When a match is confirmed, the rule with the highest possibility (membership function) is triggered, the failure is declared, and the corresponding control action which could be a gain adjustment, feedback control path modification, or sensor/actuator shutdown is taken. This layer is running at a higher sampling rate since the fault patterns stored in this layer are typically hard faults such as total actuator failure, structure break, or sensor breakdown. A timely action is normally required. The fuzzy reconfiguration control also has the advantage that the detection, isolation, and action can be implemented using homogeneous reasoning logic. That is, the detection, isolation, and reconfiguration actions take place in one-shot.

3 Robust Non-linear Aero-Propulsion Control System

A turbine engine system can be described by a set of nonlinear state equations as follows: The engine is modeled as [8]

$$\begin{aligned}\dot{x} &= f(x, u, ALT, MN) \\ y &= h(x, u, ALT, MN)\end{aligned}$$

where u, x, y are the input, state, and output vectors, respectively, and (ALT, MN) are scheduling variables. Engine inputs include fuel flows and variable geometries associated with various engine components (for example, combustor fuel flow and variable compressor inlet guide vanes). Engine outputs include component temperatures and pressures as well as the angular velocities of the rotating components (rotor speeds). The scheduling variables of the engine are determined by the aircraft altitude and Mach number.

The control performance requirement can be described by specifying engine thrust performance in response to a pilot command r . The control law translates the pilot command r into the appropriate engine input vector u . A great challenge to the engine control system design is to eliminate the performance degradation caused by the nonlinear nature of the engine dynamics. The previous approach to overcome this difficulty is to resort to gain scheduling techniques. Though gain scheduling has long been an effective design tool for engine control and flight control, it also suffers some serious drawbacks including

- it is computationally expensive due to the necessity of designing many linear controllers;

- it lacks a solid theoretic foundation except for some loose guidelines such as that the scheduling variable should change slowly and it should capture the plant's nonlinearities;
- it fails to furnish a systematic mechanism to schedule gains for the coupled multi-input, multi-output systems.

We have studied two modern nonlinear control approaches, namely, *inversion based control* and analytic gain *scheduling* to overcome the drawbacks of the conventional gain scheduling approach. They will be briefly described below:

3.1 Analytic Gain Scheduling Approach

The analytical gain scheduling method is an analytical formulation of the conventional gain scheduling technique [9], [4]. The analytical gain scheduling technique involves the following steps. First, parameterize a set of equilibrium points of the plant. Second, derive a family of Jacobian linearized systems that are smoothly parameterized by the system's equilibrium points. Third, on the basis of the parametrized linear systems, design a family of parameterized linear controllers to satisfy the given specifications regardless of the equilibrium point. Finally, synthesize a single nonlinear controller in such a way that its Jacobian linearization around the set of equilibrium points is equal to the family of the linear controllers. Clearly, the resulting closed-loop system has the property that its Jacobian linearization around any equilibrium point is a qualified design. While this approach retains the advantages of the conventional gain scheduling technique in that it can bring the wealth of linear control methods, performance measures, design intuition, and computation tools to bear on control design for very general, multivariable nonlinear systems, it needs to synthesize only one controller.

The design consists of the following steps:

Step 1: Find the engine's equilibrium manifold defined by

$$\begin{aligned}f(x(ALT, MN, r), u(ALT, MN, r), ALT, MN) &= 0 \\ h(x(ALT, MN, r), u(ALT, MN, r), ALT, MN) &= r\end{aligned}$$

Along this manifold, we can define a parametrized linear model as follows

$$\begin{aligned}\dot{x} &= A(ALT, MN, r)x + B(ALT, MN, r)u \\ y &= C(ALT, MN, r)x + D(ALT, MN, r)u\end{aligned}$$

where

$$\begin{aligned}A(ALT, MN, r) &= \frac{\partial f}{\partial x}(x(ALT, MN, r), u(ALT, MN, r), ALT, MN)\end{aligned}$$

and so forth. The transfer function of the parametrized linear system is given by

$$H(s, ALT, MN, r) = \frac{C(ALT, MN, r)(sI - A(ALT, MN, r))^{-1}B(ALT, MN, r) + D(ALT, MN, r)}{1}$$

Step 2: Design a parameterized control law. The parameterized control laws can be synthesized in either state space domain or frequency domain. In terms of the frequency domain, the objective of the analytic gain scheduling approach can be

described as follows. Given a desirable closed-loop transfer matrix $H_c(s)$ independent of the scheduling variables ALT, MN , and r , find a nonlinear control law of the form

$$\begin{aligned}\dot{z} &= g(z, r, ALT, MN) \\ u &= g(z, r, ALT, MN)\end{aligned}$$

such that the transfer function of the closed-loop system is given by the desirable transfer function $H_d(s)$. More precisely, write the linearization of the control law as

$$\begin{aligned}\dot{z} &= G_1(ALT, MN, r)z + G_2(ALT, MN, r)r \\ u &= K_1(ALT, MN, r)z + K_2(ALT, MN, r)r\end{aligned}$$

Let the transfer function of the closed-loop system from the command r to the output y be $H_c(s, ALT, MN, r)$. Then the design requirement is given by

$$H_c(s, ALT, MN, r) = H_d(s)$$

Step 3: Integration of the parametrized control law. This step generates a single nonlinear control law by integrating the parameterized control law along the manifold. The details are found in [2].

3.2 Inversion Based Control

A natural idea for handling the nonlinear dynamics is to design the control system on the basis of the more accurate nonlinear model, thus leading to a realistic way to account for the nonlinearity. One of such strategies is the well-known inversion based control which includes the well known input-output feedback linearization and sliding mode control. To date, inversion based control has become a most widely used nonlinear design technique and its application to a variety of fixed-wing aircraft and rotorcraft guidance and control problems has been reported. Basically, inversion based control is able to achieve the following:

- cancellation of the nonlinearities between the input-output channels,
- decoupling of the interactions among different input output pairs.

As a result, it is able to transform a multi-input, multi-output nonlinear design problem to a single-input, single-output linear design problem. In the following, we focus on the input-output feedback linearization approach. We consider the system described by

$$\begin{aligned}\dot{x}(t) &= f(x(t)) + g(x(t))u(t) \\ y(t) &= h(x(t))\end{aligned}\quad (1)$$

where $z(t)$ is the n -dimensional plant state, u is m -dimensional plant input, y is m -dimensional plant output, and $f: R^n \rightarrow R^n$, $g: R^n \rightarrow R^n \times R^m$, and $h: R^n \rightarrow R^m$ are smooth functions. The input-output feedback linearization controller for system (2.1) can be designed by the following steps.

1. Performing input-output feedback linearization. System (2.1) is said to be input-output feedback linearizable if there exist constants ρ_1, \dots, ρ_m and input-output mapping of the form

$$\begin{bmatrix} y_1^{(\rho_1)}(t) \\ y_2^{(\rho_2)}(t) \\ \vdots \\ y_m^{(\rho_m)}(t) \end{bmatrix} = B(x(t)) + A(x(t)) \begin{bmatrix} u_1(t) \\ u_2(t) \\ \vdots \\ u_m(t) \end{bmatrix}\quad (2)$$

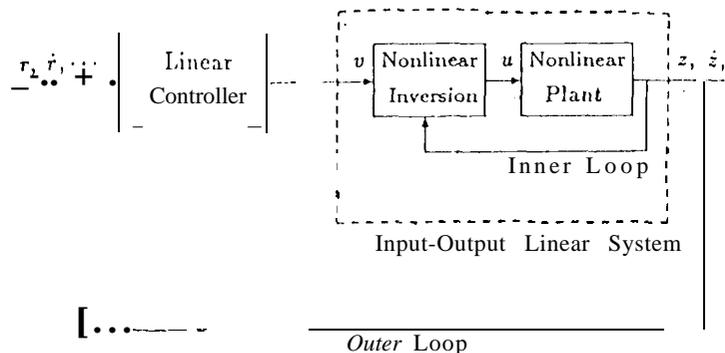


Figure 2: Input-output Feedback Linearization

where $u_i, y_i, i=1, \dots, m$ are components of u and $y, B: R^n \rightarrow R^m$ and $A: R^n \rightarrow R^m \times R^m$ are smooth with $A(z)$ invertible. For if this is the case, the following feedback control

$$u(t) = A^{-1}(x(t))(-B(x(t)) + v(t))\quad (3)$$

where $v(t) = [v_1(t), \dots, v_m(t)]^T \in R^m$, yields

$$y_i^{(\rho_i)}(t) = v_i(t), i = 1, \dots, m\quad (4)$$

which clearly exhibits a decoupled linear input-output structure. The integers ρ_1, \dots, ρ_m are called *relative degree* of (2.1).

2. *Outer loop* design. The purpose of outer loop design is to achieve desired performance on the basis of the decoupled and linearized plant dynamics. For example, suppose we require each component of the output $y_i(t)$ asymptotically tracks a scalar reference input $r_i(t)$, then applying the following control law

$$\begin{aligned}v_i(t) &= r_i^{(\rho_i)}(t) - (k_{i(\rho_i-1)} e_i^{(\rho_i-1)}(t) + \\ &\dots + k_{i1} e_i^{(1)}(t) + k_{i0} e_i(t)), i = 1, \dots, m\end{aligned}\quad (5)$$

where $e = y_i(t) - r_i(t)$ gives

$$\begin{aligned}e_i^{(\rho_i)}(t) + k_{i(\rho_i-1)} e_i^{(\rho_i-1)}(t) + \\ \dots + k_{i1} e_i^{(1)}(t) + k_{i0} e_i(t) = 0\end{aligned}\quad (6)$$

Thus $e_i(t)$ will asymptotically go to zero provided the parameters k_{ij} are such that (6) is stable. Note that due to the particular simple structure of the input-output relation rendered by the inversion control law, a variety of linear control techniques such as LQG/LTR, H_∞ , etc, can be utilized to optimally design parameters k_{ij} . The above described control strategy can be best demonstrated in the block diagram shown in Figure 2.

4 Intelligent Engine Control System

Fault tolerant operation is of extreme importance for jet engine systems. Commonly, failures in jet system can be classified as

- Sensor failures.
- Actuator breakdowns.

Therefore, the objective of a health monitoring and reconfigurable control system is to permit graceful degradation in system performance in the presence of failure conditions mentioned above. Presently, there is a great demand in improving system

survivability, maintainability, reliability, availability, and life-cycle cost effectiveness through failure detection, isolation, and accommodation schemes.

A health monitoring and reconfigurable control system essentially performs fault detection and isolation (FDI) to detect, identify, and assess failures and reconfiguration control to achieve reoptimization and graceful degradation of system performance.

For a successful and reliable fault detection scheme, the primary requirements are:

1. low false alarm/dismissal rates,
2. robustness against disturbances and maneuvers,
3. minimal time delay in fault detection/ isolation.

In isolation, the characteristics associated with the fault components such as location, extent, and consequence of the malfunctions need to be determined. To an extensive isolation system, the mechanism for similar force/moment generation is also provided. After fault detection and isolation, reconfigurable control actions can be invoked to accommodate the faulty conditions. Accommodations for the failures can be made by either a redistribution of remaining control, an invocation of a backup control, or an on-line redesign.

After the detection and isolation of failures, reconfigurations are needed to accommodate the failures. Various approaches to reconfiguration can be used. One of them is to change the parameters to existing control laws. The advantage of this approach is the low computational load on the reconfiguration processor. The pilot may perceive little change in vehicle response when the jet control system switches from nominal (undamaged) to reconfigured control law. Robust control laws can be derived from (1) conventional frequency domain approach (pole and zero distribution), (2) H^∞ , H^2 , or frequency-dependent shaping, (3) intelligent control methods such as fuzzy logic and neural networks.

Previous detection and reconfigurable control concepts include hardware redundancy, analytic redundancy, hypothesis test, etc. These concepts have been applied to aircraft flight control, jet engine, industrial plant, and many other systems with certain success. However, it is noted that the above methods suffer from certain potential limitations such as their incapability of accounting for the modeling errors and tremendous computational complexity. As a result, the design requirements in jet engine reconfigurable control may not be completely fulfilled.

Fuzzy logic and neural networks can be used to avoid the above limitations. Since the 1980s, artificial neural networks (ANNs) have been developed as a powerful, intelligent design paradigm in pattern recognition, data association, and control. Fuzzy logic and neural networks are two of the potential tools for intelligent control design paradigm that can mimic the intelligence level of human beings due to their special features as follows:

- Learning and adapting property through a prescribed training algorithm.
- Massively parallel structure and distributed processing of information.
- Data association capability.

- Simulating human thinking by incorporating the imprecision inherent in all physical systems.
- Converting the linguistic control strategy, based on expert knowledge, into an automatic control strategy.

As a result, fuzzy logic and neural networks can significantly enhance the design of the failure detection, accommodation and reconfigurable control. Figure 3 shows a neural-fuzzy based engine health monitoring system. The sensor failures may cause the closed-loop system performance degradation or unstable. The purpose of the neural-fuzzy detector is to detect this kind of failure with certain confidence. This neural-fuzzy detection/isolation system has n outputs to indicate the health status of these sensors. During operation, the neural-fuzzy network receives the input/output measurements from the closed-loop engine system (with the feedback linearization controller in place). Figure 4 shows a multiple model approach to reconfigurable engine control where a neural fuzzy fault detection and isolation is employed. Due to the universal approximation theorem, neural network can be trained to learn complicated dynamics associated with an engine system. On the other hand, the knowledge base furnished by fuzzy logic system provides an approximate reasoning and heuristic on the cause and action taken with respect to failures. As a result, intelligent failure detection, isolation and reconfigurable control can be implemented in the presence of parameter drifts, and unknown disturbances.

The advantages/benefits from this neural fuzzy FDI scheme are in the follows:

- The training time of the neural network is much more desirable than that of the feedforward multi-layer ANN.
- This FDI scheme is shown to exhibit robust and rapid characteristics in health monitoring for the engine system.
- Precision, no false alarm/dismissal rates of this FDI scheme can provide vital information in management of reconfigurable control in the engine system
- Generalization and associative ability of this FDI scheme show great potential in accounting for unanticipated failures in the engine system.

5 Conclusion

This paper summarizes the preliminary results of our investigation on an integrated approach to aeropropulsion control system design. This approach takes advantage of newly emerged techniques in advanced sensor processing, robust control, nonlinear control, fuzzy-neural based intelligent control and aims to furnish a systematic engine control system design that can meet the ever stringent mission requirements of the future jet engine systems.

6 Acknowledgement

This work was partially performed at the Jet Propulsion Laboratory, California Institute of Technology under contract with the National Aeronautics and Space Administration.

References

- [1] Adibhatla and Shrider. Propulsion issues in design of integrated flight and propulsion control systems – lessons learned from a SIOVL design study. In *Proceedings of AIAA Guidance, Navigation, and Control Conference*, pages 583-590, 1994. “
- [2] C. F. Lin (cd). *Advanced Control System Design*. Englewood Cliffs, New Jersey: Prentice-Hall, 1994.
- [3] D.M. Mann (cd). *Proceedings of intelligent turbine engines for army applications workshop*. Cambridge MA, 1994.
- [4] J. Huang and W. J. Rugh. On a nonlinear multivariable servomechanism problem. *Automatica*, 26(6):963-972, 1990.
- [5] C. F. Lin. *Modern Navigation, Guidance, and Control Processing*. Englewood Cliffs, New Jersey: Prentice-Hall, 1991.
- [6] C.F. Lorenzo and W.C. Merrill. Unintelligent control system for rocket engines: need, vision, and issues. *IEEE Control Systems Magazine*, (1):42-46, 1995.
- [7] W. Merrill, B. Lehtinen, and J. Zeller. Identification of multivariable high-performance turbofan engine dynamics from closed-loop data. *AIAA Journal of Guidance, Control and Dynamics*, 7(6):677-685, 1984.
- [8] W. Merrill, B. Lehtinen, and J. Zeller. The role of modern control theory in the design of controls for aircraft turbine engines. *AIAA Journal of Guidance, Control and Dynamics*, 7(6): 652-660, 1984.
- [9] W.J. Rugh. Analytical framework for gain scheduling. *IEEE Control Systems Magazine*, 11:79-84, 1 1991.
- [10] W.J. Scott. Hidec test show potential for thrust fuel improvements through propulsion, flight control link. *Aviation Week and Space Technology*, 6 April 1987.
- [11] C.A. Skira and M. Agnello. Control systems for the next century's fighter engines. *Journal of Engineering for Gas Turbines and Power*, 114(10):749-754, 1992.
- [12] A.J. Sobey and A.M. Suggs. *Control of Aircraft and Missile Powerplant*. John Wiley, New York, 1963.
- [13] H.A. Thompson. *Parallel Processing for Jet Engine Control* Springer-Verlag, 1992

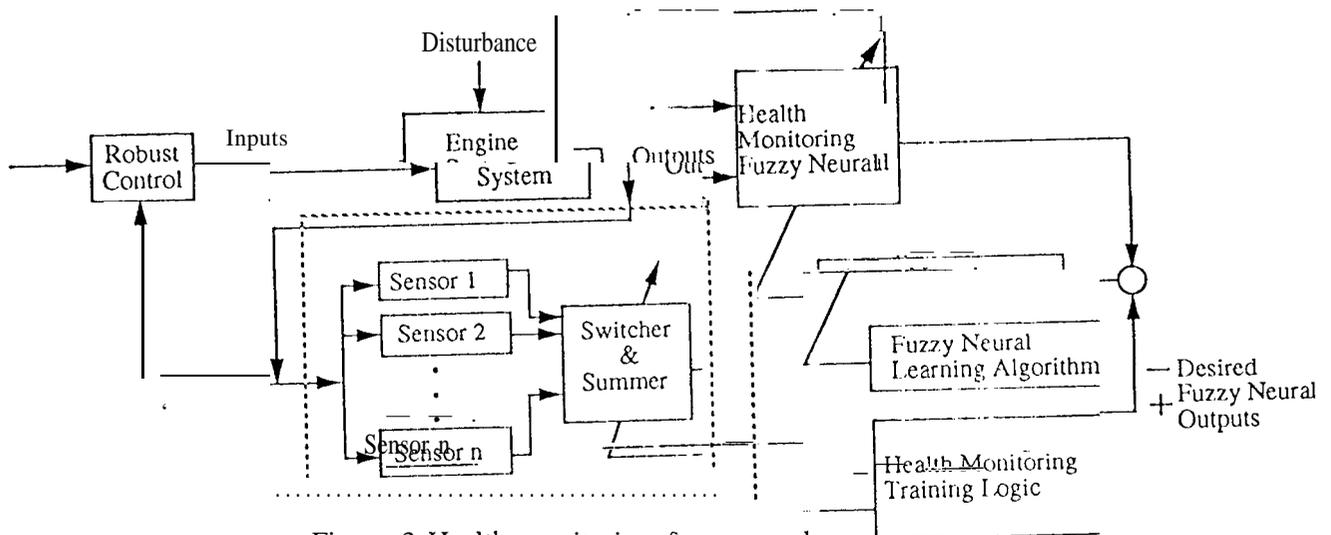


Figure 3 Health monitoring fuzzy neural network

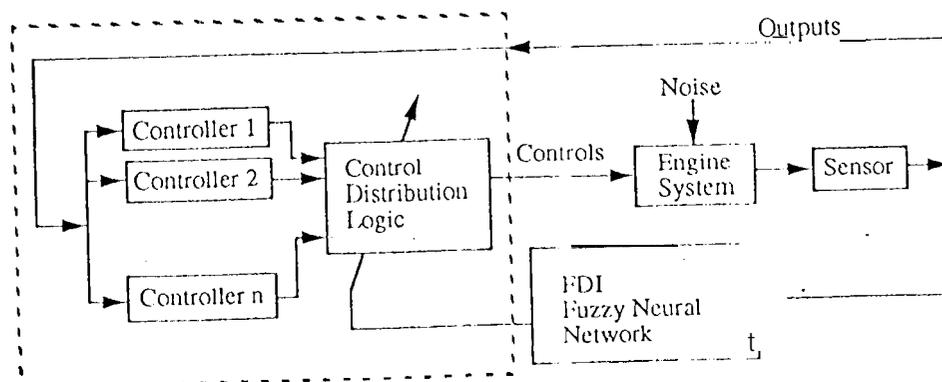


Figure 4 Neural FDI Reconfigurable Control