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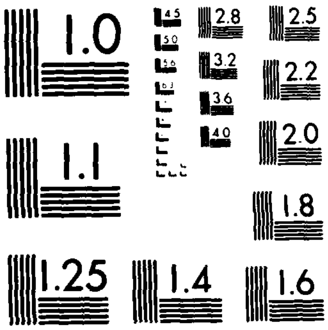


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## ARTIFICIAL INTELLIGENCE THEORY AND RECONFIGURABLE CONTROL SYSTEMS

Robert F. Stengel

June 30, 1984

Department of
Mechanical and
Aerospace Engineering



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Interim Technical Report

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Department of Mechanical and Aerospace Engineering
Princeton, NJ 08544

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## ABSTRACT

A program for the analytic and experimental investigation of reconfigurable control systems is described. Its principal objectives are to extend the theory of artificial intelligence and to develop practical methods of applying artificial intelligence heuristics, statistical hypothesis testing, and modern control theory to the reconfiguration of control systems following sensor failures, actuator failures, power supply or transmission failures, or unforeseen changes in dynamic characteristics. Objectives include the definition of typical failure modes and effects; formulation and investigation of algorithms for detection, identification, estimation, and control; numerical simulation of failure and reconfiguration; and experimentation using a microprocessor-based reconfigurable control system.

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# 1. INTRODUCTION

## 1.1 STATEMENT OF THE PROBLEM

Performance, reliability, and survivability are characteristics that should be possessed by control systems of all types, especially those used in helicopters, tilt-rotor vehicles, and conventional aircraft. The ability to complete the mission is essential to a military aircraft's deployment, and while the increasing use of digital systems will do much to achieve these goals, increased reliance is being placed upon these systems to perform flight critical and flight crucial functions. The penalties for system failure are severe, so it is desirable to design such systems from the beginning for **fault tolerance**.

As is well known, fault-tolerant systems must either be "robust" or "reconfigurable", if not both. In the first instance, changes in the system's overall input-output characteristics are reduced by feedback control, and judicious choice of the feedback gains minimizes the system's sensitivity to parameter variations, measurement errors, and disturbance inputs. The **degree of failure** that can be accomodated by a fixed control structure is necessarily more restricted than that of a variable control structure. In the second case, the system must provide

- Fault Detection
- Fault Identification
- Control Reconfiguration

to maintain acceptable (if not satisfactory) performance. A system that is fault tolerant through an ability to reconfigure is, in some sense, adaptive and redundant. It is adaptive because the control structure that is best for the nominal configuration may have to be adjusted for off-nominal operation, as results from loss or degradation of sensors, actuators, and power supplies, damage to signal and power transmission channels, or unexpected alteration of the aircraft's structural and aerodynamic configuration. Its redundancy can be implemented with hardware or software. Hardware redundancy implies parallel measurements; software ("analytic") redundancy implies flexible state estimation and control laws. In both cases, redundancy improves reliability only if the system can adjust to minimize or eliminate the effects of the failure, either implicitly or explicitly. Voting or averaging schemes overpower the failed unit implicitly, while those that identify and remove the failed unit solve the problem through explicit knowledge of cause and effect, applying **artificial intelligence** to reconfigure the system.

Intelligence -- "the general mental ability involved in calculating, reasoning, perceiving relationships and analogies, learning quickly, storing and retrieving information, using language fluently, classifying, generalizing, and adjusting to new situations", according to **The New Columbia Encyclopedia** -- certainly would appear to have its place in reconfiguring a control system following failure, although some elements of the definition seem more appropriate for the study of linguistics than engineering. Nevertheless, the formalism of linguistics -- including the identification of rules of inference and the hierarchical relationship between morphemes (sounds), words, syntax (structure), and semantics (meaning) -- may have parallels that can be exploited in the control problem. There are numerous instances in which human pilots have applied their own intelligence to revise control strategies, having perceived system damage or failure. To the extent that symbols and perceptions reflect knowledge and its interpretation, there is an analogy to detection, identification, and estimation. "Artificial" intelligence (perhaps better called "machine" intelligence) seeks to quantify the heuristic processes of human intelligence, so the theory forms a natural bridge to fault detection and identification in highly criti l control systems.

Of course, fault detection and identification are only parts of the solution to the problem. Having attained knowledge, it is necessary to **act** on that knowledge, to supplement mind with muscle, so to speak. In that regard, the chosen schema for control must have sound foundations in the physics of the problem, and there must be sufficient control "power" to effect the solution. Furthermore, it is necessary to **demonstrate** the process end-to-end, due to the flight critical/crucial nature of control.

## 1.2 BACKGROUND

Research in artificial intelligence (AI) and fault-tolerant control is relatively new, as the computational tools, sensors, and actuators that make these concepts useful did not exist a few decades ago. Possible relationships between artificial intelligence, control theory, and a third field -- operations research -- are sketched in a Venn diagram (Fig. 1) taken from {1}. There it is suggested not only that these are overlapping areas of concern but that the coupling of these concepts is essential to the effective use of any one of them. In the context of reconfigurable control, the operations research function can be subsumed in the control design function, which necessarily requires physical modeling for the development of estimator/controller gains and structures.

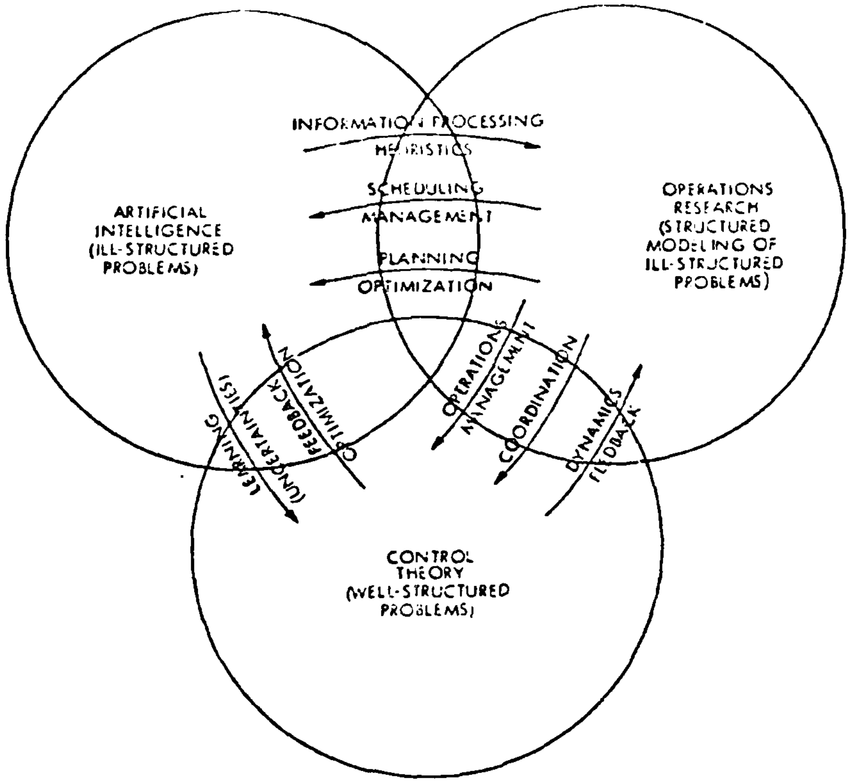


Figure 1. Venn Diagram of Interdisciplinary Issues and Expertise. (from {1})

In spite of the natural affinity between intelligence and control, it appears that little, if any, attention has been directed to applying artificial intelligence to fault tolerant control, so independent paths must be charted in any literature search. The principal exception to this finding is in the area of learning control (also called self-organizing or intelligent control) {2-7}, which does have a number of similarities to reconfigurable control, and which might be distinguished from adaptive (or self-tuning) control by the implied breadth of possibilities for altering the control structure. The main distinction to be drawn between learning and reconfigurable control is that the former places emphasis on "determining how to do things right", while the latter emphasizes "deciding what to do when things go wrong"! There is a difference in the time scale, dimensionality, and precision of on "determining how to do things right", while the latte·· emphasizes "deciding what to do when things go wrong"! There is a difference in the time scale, dimensionality, and precision of objectives that should have a major effect on feasible control structures. Nevertheless, developments in learning and adaptive control may prove helpful in the present project.

For the most part, current writings on artificial intelligence deal with natural language processing, expert consulting systems, theorem proving, combinatorial and scheduling problems, perception problems, automatic programming, robotics, and data-base retrieval {1}. They elaborate on reduction of heuristic-symbolic problem statements to algorithmic-numeric models, on search algorithms, and on learning and training {8-14}. Some of the concepts that are pertinent to the reconfigurable control problem are the following:

- Hierarchical representation, interpretation, and goal structure
- Tree search with refinement (pruning and reordering)
- Hypothesis testing, pattern recognition, and template matching
- Rules of inference, default reasoning, and problem-solving paradigms
- Propositional (or predicate) calculus
- Knowledge-based systems and corresponding symbol structures
- Adaptation and strategies for resolution

Reference to human intelligence characteristics {15-17} is an underlying factor in many of these treatments, and the characterization of heuristic symbols and systems as "fuzzy sets" and "fuzzy automata" have their parallels in stochastic optimal

Although hierarchical representations will have utility in reconfigurable control, not all such structures and theories apply to the problem. Conventional **large-scale systems theory**, though related, really addresses different issues. Typically, a complex system is decomposed into essentially decoupled subsystems, and decentralized control algorithms are developed {19}. It is assumed that the loosely coupled controllers then operate in parallel. Although the reconfigurable flight control system may present a wealth of control-structural hypotheses, it is not necessarily "large scale" in the same sense: at any given time, the objective is to identify and execute the best single control strategy for the entire system.*

Not surprisingly, the literature on fault-tolerant control is more directly applicable to the problem at hand. As mentioned previously, the notions of robustness {20-22}, parallel redundancy {23-30}, and analytic redundancy {30-34} have been investigated, and self-tuning regulators {35-39} should be added to this list. There is not room here to address these accomplishments in detail. Instead, we might ponder what remains to be done as an introduction to the current program. It should be added that improved **computer** reliability is a separate issue that is not addressed here.

There appear to be seven areas of fault-tolerant control needing additional analytic and experimental research:

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* The "best single control strategy" may admit the usual decoupling of longitudinal and lateral-directional flight control under many circumstances.

- Aerodynamic and structural alterations due to damage or failure
- Actuator failure
- Power supply and transmission failure
- Multiple component failure
- Intermittent failure and random bias shift
- Multi-microprocessing for real-time, on-board analytic redundancy
- Operation in heavy turbulence

In addition, continued development and demonstration of sensor failure detection and identification is warranted.

The problems associated with power supply and transmission failure are more critical than the loss of a single actuator, as several control effectors performing different functions may be lost at once. Nevertheless, such failures are relatively common in non-combat service, and battle damage can induce catastrophic loss of control in otherwise flyable aircraft. The related issue of generic multiple failures should be studied. Concurrent multiple failures often are ground-ruled out in the planning stage, yet these are the type most likely to cause trouble. (Many single-point failures are not catastrophic, allowing the pilot to continue the mission or return to base within a reduced flight envelope.) Intermittent sensor failures and random bias shifts should not cause instruments to be taken off line for the duration of the flight. If such units "heal" or if their new biases are identified, they should be returned to active status, and logic must be developed for this purpose. Fault detection and identification of all control system elements could be affected adversely by heavy turbulence, so algorithms that withstand this environment are required.

## 1.3 PROGRAM OF RESEARCH

The research program begins with a failure-modes-and-analysis based upon helicopter and aircraft characteristi jected for the 1990s. It will continue with the defini AI-based multiprocessor algorithms for reconfigurable cont with the design of experiments for such systems. These c will be explored in all-digital and hybrid simulation. A processor reconfigurable control system will be construc programmed for testing in hybrid simulation. The work to ducted can be summarized as follows:

### Preliminary Development

- Specification of baseline dynamic characteristics
- Failure modes and effects analysis
- Review of applicable artificial intelligence theory
- Initial selection of fault detection and identif (FDI) approach
- Initial selection of reconfigurable control approach
- Development of all-digital numerical simulation
- Specification of hybrid simulation experiments
- Hardware specification, assembly, and checkout

### Detail Development

- Algorithm research, development, and refinement
- System coding:
  - Primary estimation and control
  - Executive program and I/O interfaces
  - Experimental logic
  - Sensor FDI

- Actuator FDI
- Power supply and transmission FDI
- Aerodynamic and structural FDI
- Multiple and intermittent FDI

**Experimentation**

- All-digital simulation experiments
- Hybrid simulation experiments:
  - Reconfigured estimation and control
  - Sensor FDI
  - Actuator FDI
  - Power supply and transmission FDI
  - Aerodynamic and structural FDI
  - Control reconfiguration with sensor failures
  - Control reconfiguration with actuator failures
  - Control reconfiguration with power supply and transmission failures
  - Control reconfiguration with aircraft and structural failures
  - Control reconfiguration with multiple failures
  - Control reconfiguration with intermittent failures
  - Control reconfiguration in turbulence

## 2. TECHNICAL DISCUSSION

This section introduces technological foundations of the project. Expert systems, production systems, and an example are discussed first (Sections 2.1), in order that the functions to be implemented and evaluated can be viewed in proper perspective. Similarly, failure modeling for computational and flight experiments (Section 2.2) provides insights on the reconfigurable control system's operation. The overall system operation is discussed in Section 2.3, and a basic methodology for fault detection and identification incorporating artificial intelligence concepts appears in Section 2.4.

An overview of the baseline aircraft-control configuration is shown in Fig. 2. The **primary estimation and control logic** has a conventional structure, as might be found in an LQG or classical controller-observer implementation. The same sensors that provide information for this logic drive the **failure detection, identification, and reconfiguration logic**. The pilot can request specific tests or restart the logic, as required. This feature is necessary for detecting failures in the pilot's cockpit controls, and it provides a means of augmenting the system's artificial intelligence with the human kind.

It is most appropriate to identify the subject area as **knowledge engineering**, which Feigenbaum defines as "bringing the principles and tools of AI research to bear on difficult applications problems requiring experts' knowledge for their solution"{40}. Specific technical issues of control are important in the definition of "intelligent agents" of the expert and/or production systems, but it is anticipated that AI formalisms will have synergistic effects in control system design.

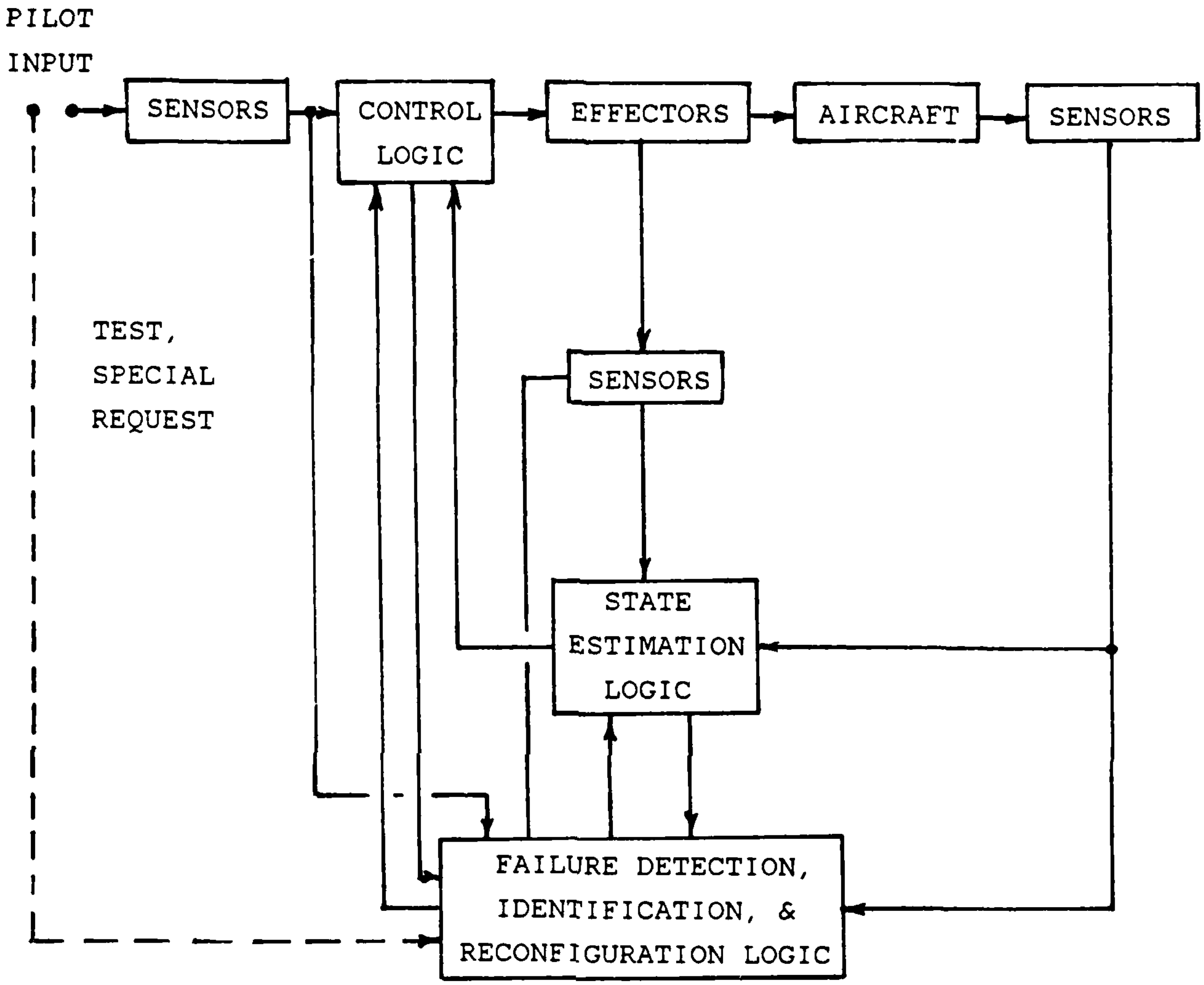


Figure 2. Overview of the Baseline Control Configuration

## 2.1 BASIC CONCEPTS IN ARTIFICIAL INTELLIGENCE

**Expert Systems** - Expert systems are knowledge-based problem-solving programs that attempt to use heuristics and facts as experts use them. The tasks and requirements of such systems can be identified as in {41}:

| Task | Requirements |
|---|---|
| Interpretation | Correct, consistent, complete analysis of data |
| Diagnosis | Fault finding |
| Monitoring | Recognition of alarm conditions |
| Prediction | Reasoning about time, forecasting the future |
| Planning | Defining and achieving goals within constraints and priorities |
| Design | Same as "Planning" |

All of these are important in the context of reconfigurable control systems, but there is a need to go beyond the stated requirements because interpretation, diagnosis, monitoring, prediction, and planning must be used to redesign (or reconfigure) the control system in "real time", i.e., with negligible delay. The common issues of large solution spaces, tentative reasoning, time-varying systems, and "errorful" data must be addressed using probabilistic or pseudo-probabilistic models of the controlled system and its failed states.

The expert system offers an improved formalism for failure detection, identification, and reconfiguration (FDIR) through

- Use of specialized data and solution structures
- Compilation of knowledge
- Transformations of knowledge into efficient axiomatic frames

Whereas previous FDIR algorithms have used a single, generalized representation of failure hypotheses, e.g., a bank of parallel

Kalman filters, an expert system can consider diverse data sources and subproblem abstractions. While some failure indicators may be continuous variables generated by Kalman filters, others may be discrete variables from finite-state models. Each of these indicators can be considered the output of a "production", as defined below. In effect, the expert system can be tuned to accept such information in a balanced way, minimizing the possibility of unnecessary computation.

**Production Systems** - A production system uses procedures (or productions) to generate actions predicated on a data base{11}. Each production has a unique input-output characteristic that produces certain goal conditions from initial conditions. In the cleanest case, each production is independent of every other production; however, in many situations, there is coupling between productions. Consequently, conflicts occur and must be resolved, sometimes requiring logic for back-tracking and reevaluation. A production system can be considered an expert system if its productions capture the heuristics of experts.

For an AI-based reconfigurable control system, the productions are computer programs (or procedures or routines) that model the normal and failed characteristics of the controlled system. Thus, the productions may be realizations of differential, difference, algebraic, or transcendental equations that model the sensors, actuators, power systems, and structure of the controlled system. These, in turn, may incorporate physical modeling and statistical estimation to generate failure metrics, which are processed in response to requests from the executive logic.

**Example of Application** - A qualitative example of the reconfigurable control system implementation can be given for clarification. Consider a generic jet aircraft of modern design. Its control effectors are highly redundant, including

- Elevator
- Rudder
- Ailerons
- Spoilers
- Flaps
- Slats
- Trim Tabs
- Engine Controls
- Thrust Reversers

Several sub-systems, e.g., landing gear and engine bleed air, have control-like effects on aircraft motion when they are deployed or engaged. Each control effector or sub-system will have a **distinctive input signature**, consisting of a unique combination of forces and moments that lead to unique translational and rotational accelerations of the aircraft.

Should an effector fail, there are alternate ways of sensing the failure, and each associated detection algorithm forms the basis of an AI production. Knowing the aircraft's dynamic model, the ensuing motions provide input to a production algorithm that determines which input signature has occurred, in turn indicating which effector has failed. The deflection of the effector itself may be measured, leading to an algebraic (or finite-state) production to determine if the effector responds to control commands. Similar measurements can be made for the effector's power system leading to yet another production. Because each of these indicators is subject to failure, there is uncertainty as to whether or not a failure actually has occurred. A knowledge-based production system then assesses the probability (or pseudo-probability) of a failure, and the expert system decides what adjustments should be made to the control system configuration. For example, if the rudder has failed to its null position, the ailerons and spoilers may be commanded using different control gains or feedback paths. If a left wing slat has failed "down" (while the right slat still is "up"), the ailerons can be commanded to counteract the rolling torque that results. Each failure mode of each effector is modeled by an AI production, and other failure/damage types are treated in like fashion.

## 2.2 FAILURE MODES AND EFFECTS

This section describes the modeling and simulation of failures in an aircraft's flight control system and in the aircraft itself. For purposes of discussion, consider a nonlinear differential equation model of the baseline aircraft (to be simulated),

$$\dot{\underline{x}}(t) = \underline{f}[\underline{x}(t), \underline{u}(t), \underline{w}'(t)], \quad \underline{x}(0), = \underline{x}_0 \tag{2.2-1}$$

where

$$\underline{x} = [V \ \alpha \ \beta \ p \ q \ r \ \theta \ \phi]^T \tag{2.2-2}$$

$$\underline{u} = [\delta_1 \ \ ,,, \ \ \delta_m]^T \tag{2.2-3}$$

The m control effectors represent conventional and unconventional devices, and they may be redundant, i.e., more than enough to assure complete controllability in both structural and qualitiative senses. Equation 2.2-1 can include the effects of closed-loop control, although that is neglected in this brief discussion. The system observation equation is

$$\underline{z}(t) = \underline{h}[\underline{x}(t),\underline{u}(t),\underline{w}'(t),\underline{v}'(t)] \tag{2.3-4}$$

where $\underline{v}'(t)$ represents an error process. At trimmed equilibrium, denoted by $(.)^*$,

$$\underline{0} = \underline{f}[\underline{x}^*,\underline{u}^*,\underline{w}'^*] \tag{2.2-6}$$

Perturbations from the trimmed condition, $\Delta(.)$, can be modeled by linear differential and algebraic equations:

$$\Delta\dot{\underline{x}}(t) = F\Delta\underline{x}(t) + G\Delta\underline{u}(t) + L\Delta\underline{w}(t), \quad \Delta\underline{x}(0) = \Delta\underline{x}_0 \tag{2.2-6}$$

$$\Delta\underline{z}(t) = C\Delta\underline{x}(t) + D\Delta\underline{u}(t) + E\Delta\underline{v}(t) \tag{2.2-7}$$

$$\underline{0} = F\Delta\underline{x}^* + G\Delta\underline{u}^* + L\Delta\underline{w}^* \tag{2.2-8a}$$

or

$$\Delta \underline{x}^* = -F^{-1}(G\Delta \underline{u}^* + L\Delta \underline{w}^*) \tag{2.2-8b}$$

The model can be expanded to include actuator, sensor, and computation dynamics.

The types of failures to be considered are the following:

- Sensor failures
- Actuator failures
- Power supply and transmission failures
- Aerodynamic and structural damage or failures

The device and system failure modes include,

- Null failure
- Hardover failure
- Runaway failure
- Random process failure
- Random bias failure
- Intermittent failure

while aircraft damage or failure can be modeled as a discrete change in dynamic (F,G) characteristics.

It is apparent that all of these failure types and modes can be modeled by modifications to eq. 2.2-6 to 2.2-8. Null failures of the sensors zero the appropriate columns of (C,D,E), while null actuator failures zero the columns of G. The latter affects both dynamic response and trim equilibrium. **Hardover, runaway, and random failures** in sensors and actuators are modeled by $\Delta \underline{v}$ and $\Delta \underline{w}$, respectively. Power supply and transmission failures interrupt the operation of sensor and actuator groups; therefore, a number of matrix columns will be zeroed in this instance. **Intermittent failures** simply require the above effects to be switched on and off.

When the baseline configuration includes closed-loop control, i.e., use of the measurements (eq. 2.2-7), the simulation is more complex but still well-defined. The structure of the baseline control law must be simulated, with the failures injected accordingly.

## 2.3 PRIMARY CONTROL OPERATION AND RECONFIGURATION

The baseline configuration will be assumed to have a primary digital estimation and control system whose gains and parameters will be modified according to flight condition and failure state. For discussion purposes, the primary system will consist of a **full-state estimator** and a **proportional-integral-filter (PIF) control law** {42}.

The eighth-order estimator is either block diagonal or block-diagonally-dominant, reflecting the usual separation into longitudinal and lateral-directional modes, and the number of measurements depends upon the identified failure state of the system. The estimator itself provides analytic redundancy when the operational sensors are fewer than normal. Hardware redundancy management precedes the input of measurements to the estimator, i.e., the functions of analytic and parallel redundancy management are handled separately. Estimator model parameters and gains are chosen for robustness.

The PIF controller is inherently robust. Assuming that the baseline aircraft operates with conventional command modes for up-and-away flight, there would be four pilot inputs (longitudinal and lateral stick, foot pedals, and throttle); hence, there would be up to four integrators for the command variables. (Assuming that pitch rate and roll rate are command variables, only two "extra" integrators would be required {43}). Up to m low-pass filters can be associated with the control surface commands, although it is likely that the number can be reduced to four under most circumstances, reflecting the usual number of independent controls. Block-diagonal dominance applies, and the number of control commands depend on the failure state.

In normal operation, gains would be scheduled with flight condition; therefore, they would be continually varying. Once a failure is detected and identified, the appropriate gains could be selected, but a sudden switch could produce an unacceptably large transient in the system, particularly if control settings are large. As a consequence, the gains should be "faded" from the old values to the new values over a period of time to be determined by a tradeoff of urgency and smoothness {44}.

## 2.4 ARTIFICIAL INTELLIGENCE, FAULT DETECTION, AND IDENTIFICATION

Much of artificial intelligence (AI) relates to learning about unknown systems from observations or other evidence in a manner that emulates human thought processes. Tasks performed almost unconsciously by humans can prove quite demanding for machines. Problems deemed too difficult for individuals often are referred to panels of experts, whose combined knowledge is used to form solutions. The questioning of an individual or a panel of experts is analogous to the retrieval of information from a data base. If **rule-based deduction** is used, the process of finding an answer can be called "intelligent", whether human or artificial {11}. An objective of this research is to use rule-based deduction to detect and identify failures, thereby making reconfiguration possible.

Deduction implies searching a hierarchical tree of possibilities. At each node there must be rules and criteria for continuing along a particular branch. In the context of system failures, the **probabilities of each choice conditioned by the available observations** provide a rational set of criteria, and Bayes's rule provides a reasonable selection process. It also is necessary to develop logic which retains more than one possibility in the search long enough to identify possibly subtle hypotheses and which knows when to stop; hence, there is a need for optimal pruning and stopping rules {45}.

AI heuristics will prove most valuable in formulating FDI hierarchical structure and in identifying faults on an inferential basis. In the first instance, all failure/damage modes and effects must be classified and arranged in levels. For example, the hierarchy for **failure modes** might be

- System
- Function
- Axis
- Device
- Characteristic

while that for **failure effects** might be

- Abnormal motion
- Axis
- Forcing function
- Source

In the second case, rules of inference would process a number of observations in a production system to deduce a failure. For example, combined loss of left aileron, loss of air data from sensors mounted on the left wing, ana rapid roll rate could infer damage to the left wing. To some extent, this sort of reasoning is invoked in operational systems {46}, although formal connections to AI are not identified and the scope of the application does not include aircraft damage.

The familiar concepts of sequential probability ratio, generalized likelihood ratio, and multiple model testing {31,47-55} have potential application to the actual computations, and reference to the general area of fault-tolerant avionics is warranted {56-62}. It is desirable that a minimum number of full-state estimators be used, with each failure state modeled by, at most, a low-order process or "moving window" estimate of the probability density function (also called the likelihood function) or its logarithm. For example, with the Gaussian assumption, the log likelihood function estimate for the $A^{th}$ failure hypothesis based on a moving window of N data points can be expressed as

$$L_A(k) = (1/N) \sum_{i=k-N+1}^{k} \{[\Delta \underline{z}_i - (C\Delta \underline{x}_i + \Delta \underline{u}_i + E\Delta \underline{w}_i)]_A{}^T R_A{}^{-1}[\cdot]$$

where $\Delta \underline{x}$ is the state estimate, $R_A$ is the measurement co
matrix associated with the failure state, and $\underline{c}_A$ is a c
Then the log likelihood ratio of hypotheses A and B is si

$$L_{AB}(k) = L_A(k) - L_B(k)$$

and the decision rule is

- $L_{AB}(k) \leq a$, Accept Hypothesis A
- $a < L_{AB}(k) < b$, Accept previous hypothesis
- $L_{AB}(k) \geq b$, Accept Hypothesis B

The process is made efficient by defining **failure signat**
each hypothesis {31}.

The hierarchical approach suggests that differing
types be processed separately and that a minimal amount o
tation be carried out at any given time. Accordingly, th
separates sensor FDI, which can be associated with the ai
outputs, from actuator/aircraft FDI, which can be associa
control inputs and dynamic response characteristics. In
(unfailed) state, it may be sufficient to carry two hyp

the system is failed or not. On detecting that an unspecified failure has occurred, the logic expands the number of hypotheses to determine which aircraft axes are involved. On determining the axes, the hypotheses associated with unfailed axes are dropped, and more specific hypotheses related to systems and individual components are brought on line.

All FDI results would be broadcast over a data bus so that appropriate adjustments can be made. For example, once a particular sensor is declared failed, this information would be used to reconfigure the primary estimation logic and to modify the actuator/aircraft FDI logic.

## 3. CONCLUSION

A concept and program for applying artificial intelligence theory to improving the fault tolerance of control systems has been described. The concept includes both subjective and objective logic for detecting failures, identifying failed components, and reconfiguring control paths to maintain acceptable performance. The program is directed at realizing the concept through analysis, system design, hardware implementation, and experimental evaluation. Program results will have fundamental application to the formulation of future control structures.

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A program for the analytic and experimental investigation of reconfigurable control systems is described. Its principal objectives are to extend the theory of artificial intelligence and to develop practical methods of applying artificial intelligence heuristics, statistical hypothesis testing, and modern control theory to the reconfiguration of control systems following sensor failures, actuator failures, power supply or transmission failures or unforeseen changes in dynamic characteristics. Objectives

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include the definition of typical failure modes and effects; formulation and investigation of algorithms for detection, identification, estimation, and control; numerical simulation of failure and reconfiguration; and experimentation using a microprocessor-based reconfigurable control system.

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