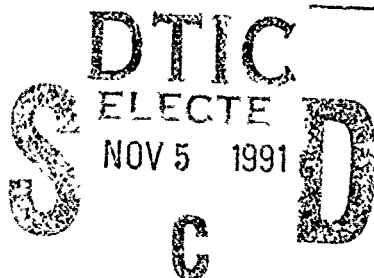Report No. NADC-91080-60

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NEURAL NETWORK AND FUZZY LOGIC TECHNOLOGY FOR NAVAL FLIGHT CONTROL SYSTEMS

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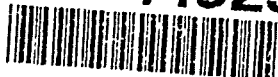Warminster, PA 18974-5000
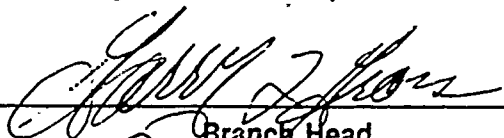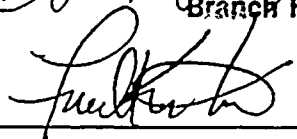
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13. ABSTRACT (Maximum 200 words)

Neural networks and fuzzy logic have the potential to overcome some of the most difficult problems that occur in the design and implementation of modern Flight Control Systems (FCS). Ultimately, this may yield significant gains in performance, robustness, cost survivability and reliability. However, it is still uncertain what neural network and fuzzy logic functions are both technologically feasible and suitable for flight control system implementation. In this report, an ongoing comprehensive program to develop and assess this technology for Naval FCS applications is described. Currently, this program is focused on the development of a neural network FCS design tool, a neural network flight control law emulator, a fuzzy logic automatic carrier landing system and a neural network flight control configuration management system. For each project, some initial results are given. Also, several new and planned projects are discussed. These include learning augmented adaptive control, neural network augmented nonlinear control, optical neurons and neural augmentation of conventional control systems.

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I. Introduction

Modern military aircraft must be capable of performing many diverse missions under an exceptionally wide variety of flight conditions. This need has generated a constant increase in demands for agility, speed, precision, and survivability. As a result, the role of the FCS has expanded well beyond the traditional one of augmenting stability and controllability with very limited authority[1-2]. On current aircraft such as the F/A-18, F-16, and the F-22, the FCS has already taken on the role of a full authority system that largely determines effective vehicle dynamics. In the future, many high performance military aircraft will critically depend upon the capabilities of advanced flight control systems. This is particularly true for aircraft designs that incorporate supermaneuverability, low observability, relaxed aerodynamic stability, reduced structural stiffness, and vertical take-off/landing. Future aircraft will also increase the complexity of the FCS with the need to manage large numbers of control effectors including new forms of control such as thrust vectoring vanes or vortex control. In addition, the FCS will be used to implement complex functions that are possible because of the wealth of information available over common avionics data buses. This will include completely new functions such as impairment detection and control system reconfiguration after hardware failures and battle damage, and integration of numerous subsystems such as propulsion, weapons, and structural control. Yet, even today's flight control systems are burdened by the lack of effective control law design techniques, expensive and lengthy software development cycles, and the limited processing power available on most aircraft. Thus, while there has always been considerable interest in creating better approaches to the design and implementation of flight control systems, there is currently more need for them than ever.

As current research suggests, neural network and fuzzy logic based approaches to control may have substantial benefits in performance, robustness, reliability, and cost. This has been demonstrated for a variety of systems[3-8] including some initial work with

aircraft[9-16]. For this reason, the Naval Air Development Center began a comprehensive program in 1989 to develop and assess neural network technology for Naval FCS applications[16,18,20-21]. Our approach throughout this program has been to avoid the widely used neuro-control "black box" techniques in which the type of system being controlled is considered unimportant. Blindly applying generic neural control techniques to aircraft is unlikely to have any more success than previous applications of generic control theoretic techniques. Flight control systems are in many ways a unique subset of control systems. They require carefully considered and well thought out approaches tailored to their particular characteristics and requirements[16]. Any less may provide an interesting demonstration of the power of neural networks, but is unlikely to see real use on a production aircraft.

The largest obstacle in the transition of neural network based approaches into production aircraft is system validation. System validation is absolutely essential due to the criticality of the FCS, the conservatism of the aircraft community, and the skepticism directed towards neural networks. Yet, to achieve this validation will likely require the formation of new techniques, much in the way techniques have been developed over the past few decades for digital flight control systems. Therefore, the goal of the present phase of our work is not only to prove that neural network based approaches are feasible, but also to develop neural network based approaches that can meet the flight safety requirements for implementation on manned aircraft. To achieve this goal, we have three major in-house efforts, three contracted efforts, and plans for additional contracted and in-house efforts. This report will describe these efforts and give some initial results. It will also attempt to provide some insight into the full scope of the problems and limitations affecting the design and implementation of current military flight control systems.

Aircraft are time-varying non-linear dynamic systems with six degrees of rigid body freedom and numerous aeroelastic modes. These dynamics vary considerably over a large

range of flight conditions and are often altered by configuration changes. Even without these changes, the best aircraft math models are often highly uncertain, and some areas of the flight envelope are never well understood. Among dynamic systems, aircraft hold an interesting distinction of being one of the few systems that may be deliberately designed to have very fast open loop unstable modes for the sake of maneuverability. For example, the X-29 was designed with an instability that has a time to double amplitude of only about an eighth of a second. One result of these fast instabilities, beyond the increasing dependence of the aircraft on the FCS, is to make rate and position saturating non-linearities take on an exceptional amount of importance. This is particularly true since the aircraft environment has one of the richest varieties of substantial magnitude disturbances found in any controlled dynamic system. In addition to the more obvious limits set by control effector saturations, there are other often unanticipated limits. These are generally caused by either the aircraft's structural bending modes or the wide range of air flow characteristics that can occur over individual control surfaces. This can place limits on controller bandwidth and cause loss of effectiveness or even reversal of control inputs in some flight conditions.

In any case, the most notable difference between the FCS and other control systems is the role of the pilot. The pilot is not the classical control operator who chooses set points and lacks substantial effect on the dynamic characteristics of the closed loop system. Instead, the pilot must be treated as a highly adaptive element within the loop. Pilots are even capable of producing poor damping, limit cycles, and instabilities when attempting to control aircraft with marginal closed-loop characteristics. Further, the dynamic response of the system must be tailored toward what the pilot wants (such as mission tailored flying qualities) and not what seems best from basic control criterion.

Given the wide range of factors described above, it is not surprising that no single methodology can incorporate even a substantial number of the important features needed

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to be considered in design. Designs are extremely labor intensive and require costly ad hoc trial and error adjustment during piloted flight simulation. Even then, all major aircraft flight control systems have had deficiencies that were only discovered in flight tests. Also, given the increasingly complex requirements on the FCS, if many factors are not dealt with early in the design process, the result will definitely be aircraft that cannot achieve their full potential. Using neural networks to resolve some of these complex design issues and create designs with better performance for less l or and cost is the goal of our neural flight control law synthesis project[18]. A complete description of this project along with some initial results is given in section II.

With neural control law synthesis, the structure of the FCS, itself, remains conventional. However, conventional flight control systems sometimes perform poorly in situations where human pilots possess techniques that perform well. This often occurs due the pilots ability to intelligently alter control strategies and plan ahead for future events. One example of this type of situation involves automatic carrier landing systems(ACLS)[19]. The ACLS is designed to track glideslope. However, the real problem is not to track glideslope, but to have the proper terminal conditions at the carrier. For this reason, our second in-house project involves creating a new form of automatic carrier landing controller using a hybrid neural network/fuzzy logic approach. This approach will incorporate Naval fighter pilot knowledge, Naval control engineer knowledge, and unsupervised neural network learned airframe knowledge into the controller[20]. One major advantage of this type of controller is that it can be expressed as a set of parallel English rules. This provides a transparency that can ease the validation process and readily adapt to pilot criticisms during flight testing. A full description of this project with some initial results is given in section III.

Current control laws have become exceptionally complex, and often require substantial software development after the completion of FCS simulation. They also require a

considerable amount of software support throughout the life of the aircraft. This is due not only to the complexity of the control law, but also to the high iteration rates required by modern aircraft. Achieving acceptable rates within available throughput often leads to considerable difficulty with problems like delays from subtle multi-tasking errors. Neural networks, however, have the computational efficiency and speed to calculate immensely complex control laws rapidly if they are implemented in specialized hardware. They also can train directly from the software simulator to eliminate significant software development and supports costs. In addition, they may incorporate some hardware robustness benefits such as graceful degradation after damage. Therefore, our third in-house program involves emulating an existing flight control law with a neural network[21]. A description of this project with some initial results is given in section IV.

Another important issue concerns adverse dynamics that can occur during configuration changes. This is an area that is becoming much more important as the FCS becomes "tailored" to individual mission and tactical segments. Also, reconfiguration after battle damage o hardware failures has recently become a much more viable possibility with the completion of flight tests for a prototype system by the Air Force[22]. A contracted effort by Systems Technology, Inc. and STR is attempting to apply neural networks with on-line learning to this problem as described in section V[23].

Finally, section VI will briefly discuss recently begun and planned efforts. The recently begun efforts are learning augmented adaptive control[31] and neural network augmented nonlinear control theory methods. Both these projects center on advanced techniques that use neural networks for several features including on-line learning to overcome the uncertainty associated with the flight control design process. Ultimately, this type of on-line learning may be necessary to avoid trading performance for robustness or performing large amounts of on-line tuning.

The planned efforts are neural network/fuzzy logic augmentation systems and optical neurons. Augmentation systems may provide great benefits, but allow easy validation since

they can be of limited authority and analyzed as a disturbance to a conventional flight controller. Optical neurons may provide an excellent way to implement neural networks. This will be followed, in section VII, with our conclusions.

II. Neural Network Flight Control Law Synthesis

Work in neural control law synthesis is being done under an NADC Independent Exploratory Development(IED) program. The overall objective of this program is to incorporate emerging neural network technology into a feasible concept that will simplify and improve flight control system development. As briefly mentioned in the introduction, the flight control law design process is a very lengthy and complicated one. The engineer begins with an uncertain nonlinear model determined only from wind tunnel testing and computational fluid dynamics. A baseline structure that defines the feedback parameters and compensations for the FCS is then developed based on the aircraft's predicted features, flying qualities requirements, and proposed mission requirements. Next, the engineer linearizes the aircraft model at various points in the flight envelope and applies combinations of classical and modern linear control theories to generate controller gains and filter time constants. The final nonlinear control law is obtained by switching or interpolating between these separate linear controllers as a function of a small number of parameters. Limited parameters are used since additional ones would require excessive memory requirements due to the dimensionality of the associated look up tables. Essentially, the engineer has created a discrete nonlinear mapping of design points in the aircraft envelope into sets of desired control system gains. This drawn-out design technique, however, limits the total number of trim points the engineer can investigate for a given aircraft due to the high amount of labor associated with each design. Also, since it relies heavily on uncertain linear approximation models to represent the aircraft, it often yields unsatisfactory results, particularly when the aircraft is subject to large motions. So far, robust controller design techniques such as H_∞ and μ Synthesis or nonlinear techniques like feedback linearization offer the best chance for solving some of these problems. Still, due to the difficulty of expressing complex aircraft design features in a mathematically tractable form, all current techniques will both neglect some factors and overdesign for others. Piloted handling qualities, in particular, have proven extremely difficult to incorporate in any technique.

Our approach to the design problem is to use neural networks to synthesize the continuous nonlinear functional mapping between aircraft design points and control system gains and time constants. As has been proven, many neural networks are capable of doing this for almost any complex relationship with a large number of inputs and outputs. Therefore, we are not limited to a small number of parameters as the basis for scheduling gains, but can use additional rapidly changing aircraft parameters like angle of attack and sideslip. The neural network may allow us to determine the important relationships between these quantities without significantly complicating the process. Some additional anticipated benefits are the reduced labor and expense required to develop flight control laws, and the increased number of design points used in the flight envelope. Furthermore, the neural network may provide significant insights into how the scheduled points should be distributed throughout the flight envelope. It may point out better interpolation functions to be used between these scheduled points. Also, the designs themselves may be more optimal due to the use of performance indices that are far too complex to be used in any mathematical setting. These indices may also finally allow inclusion of adequate pilot handling qualities criterion.

Our current approach is illustrated in Fig. 1. Here, pilot inputs are supplied to both the augmented aircraft model and a set of desired performance models. The performance models exemplify various desired maneuvering characteristics of the aircraft and depend primarily on the type of aircraft, the current mission requirements, and the level of flying quality sought. Typical maneuvers such as pitch doublets and rolls are performed at each design point in the envelope. When the maneuvers are completed, a cost function is used to "grade" the controller with respect to the performance models. The "grade" is then used to adjust the weights and biases in the neural network and produce new parameters for the controller at each design point. The new parameters enable the augmented aircraft to achieve responses that more closely match those of the ideal performance models. The

process is then repeated until the "grade" falls below a specified tolerance and the proper controller gains have been determined.

This neural network approach has three main advantages over the standard neural control techniques. First, the neural network only designs gains and time constants for a known control law structure. Implementation of the control law, including verification and validation, proceed using established methodologies. Secondly, the speed and efficiency of the training algorithm is not critical to the success of the procedure since it is all done off-line. Finally, it could readily be transitioned into an on-line neural gain scheduler for existing and future flight control hardware. This on-line approach would have great performance benefits due its literally infinite number of scheduled gains. Also, it could easily schedule gains on many parameters including rapidly changing ones. This could also be done as a limited authority neural augmentation system instead of a full gain scheduler. The benefit of an augmentation system being that the neural network outputs can be limited and treated as a disturbance to allow simpler validation.

Current work is centered on a nonlinear F/A-18 longitudinal aircraft model with data for the full maneuvering envelope. The reference performance model being used is based on an actual high performance jet aircraft which has been augmented to meet MIL-F-8785C[24]. The neural network choses six gains and one time constant in the F/A-18 pitch control system. The neural networks being used are standard feedforward sigmoidal networks with adaptive back-propagation learning and the Cerebellar Model Articulation Controller(CMAC) network[25-26]. Initial results with standard feedforward networks have been good. Fig. 2 compares desired and actual angle of attack, pitch rate, and normal acceleration responses to a specific stick input before training for .8M at 40,000 ft. Fig. 3 shows the same responses after neural network training. Similarly, Fig. 4 shows responses before training at .65 M at 20,000 ft. that can be compared with after training responses in Fig. 5. These plots demonstrate that the neural network is able to schedule gains to greatly improve the performance and handling qualities of the aircraft.

III. Fuzzy Logic Automatic Carrier Landing System

Carrier landings are one of the most difficult and unforgiving tasks that are routinely undertaken by jet aircraft[19]. Modern jet aircraft are difficult to handle at low approach speeds and must be brought down onto a small moving target in the presence of large disturbances. Basic feedback techniques have many limitations, particularly in their response to small maneuvers, carrier motion, atmospheric turbulence, and carrier air wake turbulence. The main reason for these problems is that a standard ACLS is only concerned with tracking glideslope, whereas the real goal is to have the correct terminal condition. Human pilots have successful techniques for dealing with these situations, although they do not have the speed, response capabilities, consistency, and precision of automatic systems. Therefore, the goal of this task is to use fuzzy logic and neural network techniques[4,27] to create an automatic system that utilizes human knowledge, automatic control techniques, and knowledge derived directly from the airframe through unsupervised neural network learning techniques. This controller would then be able both to intially incorporate human knowledge, and to be easily changed to reflect pilot criticism during flight testing and simulation.

Originally, in an attempt to be fair to the current ACLS, the fuzzy system is only being given the same inputs that are given to the conventional ACLS. This must be done since additional inputs could improve standard feedback ACLS performance. Several possible strategies that incorporate varying degrees of fuzzy human knowledge, neural network airframe knowledge, and basic ACLS structure knowledge are being tested on a six degree of freedom non-linear simulation of an F/A-18. The model has gust, carrier air wake, and sensor noise models. It also has rate and position saturations on the engine and actuator models.

The initial controller developed was the system of Fig. 6, using only Navy controls engineer knowledge on proper feedback techniques for carrier landing, and Navy fighter

pilot knowledge on carrier approach flying techniques. For the inital approach phase of 8000-4000 ft. to carrier, the fuzzy system has about the same integrated glideslope error as the current system, but decreases the number of aborted approaches or wave-offs, by 48 percent. The reason for this is that the fuzzy system is excellent at making rapid maneuvers with little overshoot, and it does not just track glideslope. For example, if the aircraft is a little high before entering the carrier air wake, the fuzzy system will make no changes and allow the settling effect of the airwake to correct glide slope position. Fig. 7 shows the response of the fuzzy system to a high position and very high sink rate condition. The system is trying to return to a sink rate of about -14.5 ft/sec when it hits the glide slope. Fig. 8 shows the fuzzy system can make the adjustment to sink rate with fast rise time and almost no overshoot. This same situation led to a wave-off by the conventional ACLS. Fig. 9 shows a low condition far from the carrier. In this case, instead of just tracking glide slope, the fuzzy controller waits until intersection. This prevents wasting control power making an unnecessary quick return to glideslope.

The major effort at the moment is on completing the controller for the full approach, and performing extensive analyses on it. After this, neural network derived rules will be added to the system to see if improvements are possible. The new controller will be given additional inputs such as weather condition to see if this yields improvements. Also fuzzy pilot or mission computer supplied inputs will be included such as fuzzy stores information. Instead of having to modify control gains every time a new configuration is created, the pilot could just specify, for example, that there was a medium size store about half way out on the wing. Additionally, fuzzy damage information might be input by the pilot. Even with both the pilot's awareness and the best damage detection techniques available, it is still difficult to determine the extent and type of many failures. Nonetheless, it is easy for the pilot to specify, for example, that the plane is only rolling about half as fast as normal. This input might allow an impaired aircraft to land safely. Following this,

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work on real-time on-line learning will begin. The modularity of this type of network makes learning quick and efficient. Also, since only a few of the fuzzy associations fire at any given time, learning does not change the total network and override much previously learned knowledge.

IV. Neural Network Control Law Emulator

The main benefit of using a neural network to emulate an existing flight control law is its capability of removing large software development and supports costs. The remaining costs would only be those involving redundancy management, built-in-test, and other associated functions of the flight control computer(FCC). Also, its fast and efficient computation would allow much more complex control law structures to be used. The neural FCC could be physically robust depending on the type of network used. This type of graceful degradation may help supply the degree of safety needed for all critical flight control components. There are three primary problems associated with implementing this neural network approach. The first is the validation problem that has been discussed throughout this paper. The second is the need for fast predictible learning times and fast validation to incorporate changes that need to be made to the system during flight tests. Replacing software development time with months of learning time, and repeated Monte Carlo simulation for validation would not be an improvement. The final problem is the FCC's use of dynamic control laws. It is unlikely that a static control law, even a very complex one represented by a feedforward neural network, could ever adequately control an aircraft. Therefore, recurrent networks seem the best possibility. However, feedforward networks are already extremely difficult to validate, and recurrent ones are orders of magnitude more difficult since they need to be validated through time as well as space. Thus, the basic strategy is to use a network with additional outputs that represent intermediate flight control law states and make them inputs after a one time frame delay. This would also allow many quick changes to be made to the network during flight tests without retraining the network since all inputs and internal states are available for digital computer manipulation. In addition, it is also much more transparent to analysis than a more arbitrary feedback system.

To perform this feedforward mapping, a large number of neural techniques were

examined. The majority of these fall in an unexplored area between statistical regression, systems identification, and table look-up schemes. The architectures and learning paradigms which were tested include standard sigmoidal networks with adaptive back-propogation learning, CMAC networks[25-26], radial basis networks[28], and various hybrid approaches[29-30 for example]. Each architecture was tested under a large number of design iterations to determine the best structural parameters and learning methods that could be reasonable achieved. Best results were attained by avoiding the "black box" approach, and modifying neural network structures to take advantage of available knowledge about the flight control law. Three basic features were determined to be very useful for a neural network to best perform this mapping problem. The first was the use of neurons with spatially local receptive fields. This is necessary since most training techniques converge only to small mean errors and require excessive training times to capture local features. These small local errors ultimately leads to arge drift over time due to the feedbacks. The second beneficial feature was the use of vector quantization to position the local neurons. This apportions more neurons in more complex areas of the space if it is done correctly. This is important not only for matching the complex areas of the space, but also for avoiding overgeneralization in simple areas of the space. The final beneficial feature was the use of discontinuites that could be adjusted during training. Without these, the neural network will literally tie itself into knots in an attempt to fit the sharp discontinuities and singularities found in this problem.

The above features were incorporated into a new hybrid architecture which could be trained relatively quickly with a combination of supervised and unsupervised techniques. This architecture, along with the aforementioned ones, was applied to the control system in Fig. 10, which is representative of the type of complexity found in modern flight control laws. This control system includes scheduled gains and biases, limits, integrators, filters, and mode logic switches. For each neural architecture that was tested, a considerable

amount of effort was spent on determining optimal network parameters and training techniques. This was necessary due to the lack of design guidelines for many of the examined networks. The results were that the new hybr' architecture had a significantly smaller error than the other architectures that w... 'est ... the response of this architecture to uncorrelated inputs with a 10ms frame rate ov . 5 sec. is shown in Fig. 11. The reason there is no drift over time is due to the excell... matching of internal variables as shown in Fig. 12. Internal variables are matched well n.. e this network was optimized more for internal variables than outputs. For this sample problem, the network has the accurac, to replace a flight control computer and requires only seventy neurons. Exact accuracy is not called for since a digital flight control computer typically has noisy inputs and sends outputs to actuators with analog loop closures that use 1 and 5 percent resistors and capacitors. The real goal is not to achieve exact duplication of the control law, but to achieve identical closed loop response characteristics of the aircraft. For the future, we are working on improving neural architectures for flight control law emulation, and achieving fast alteration and validation tec..niques. We are also concurrently applying the current architecture with some of the other more successful ones to a full complex flight control system.

V. Neural Network Configuration Management

This program is a contracted effort to Systems Technology, Inc.(STI) and STR.. The objective of this project is to explore the ability of artificial neural networks to identify and compensate for adverse dynamics that can be encountered during configuration changes of high performance aircraft. Configuration changes may occur in response to damage control, mission profile segment transition, and tactical mode change. The neural network will attempt to minimize the likelihood of false reconfigurations and opt ize mission effectiveness following appropriate reconfigurations. The major focus of the initial phase of the project was on an experimental variant of the F/A-18 with stabilator and thrust vectoring damage. The neural techniques used were an adaptive clustering network which was placed parallel to a conventional controller and trained by feedback error learning. On-line learning was greatly enhanced for these networks with an algorithm that added new radial basis function neurons to the network on-line. The results thus far have shown that neural networks can intrinsically identify these failures and compensate for them within several seconds, but additional work will be necessary to judge how well neural networks can perform on the full problem.

VI. Future and Recently Begun Efforts

Our other contracted efforts are from the responses to a Broad Agency Announcement on neural network based approaches to flight control for Naval fighter and attack aircraft. The first effort is learning augmented adaptive control which is being done by Charles Stark Draper Labs[31]. This program will attempt to develop special purpose neural network learning systems that can provide real-time on-line learning within a flight control system architecture. The approach will be applied to the control of a nonlinear six degree of freedom high performance jet aircraft model by designing with a simple model and evaluating how well the controller can adapt to the full model with on-line learning. The possibility of realizing successful on-line learning is greatly enhanced by the use of some innovative spatially local neural networks.

The second effort is to augment nonlinear control methods and is being done be Guided Systems Technology. The objective of this research is to demonstrate a method for design and implementation of high performance jet aircraft control systems that makes use of both neural networks and robust nonlinear control theory. Neural networks will be used to deal with model uncertainty in the design process and perform the mappings required in feedback linearization of the aircraft's dynamics[32]. This will be applied to a full six degree of freedom nonlinear F/A-18 High Alpha Research Vehicle(HARV) simulation.

We also have plans for in-house work in neural network and fuzzy logic augmentation systems(NNFLAS) to conventional flight control systems. The reason for using an augmentation system is that by limiting the authority of the NNFLAS, the neural/fuzzy component may be treated as a disturbance to the conventional system to allow easy validation. The benefits of such a system, however, may be to provide on-line learning through neural networks, and to provide improved handling qualities specifications through complex neural network cost functions and fuzzy logic rules.

Optical neural networks are of considerable interest since they avoid many limitations inherent in silicon neural network implementations and have exceptionally high processing

speeds. Also, for avionics systems, light based computing is of particular interest since it is immune to the high electromagnetic flux environment that may be encountered on aircraft. For these reasons, we are planning work in this area as well.

VII. Conclusions

It is still too soon to judge whether neural networks will prove able to overcome any FCS problems in ways that are suitable for flight testing and eventual routine use. The programs presented here hope to bring neural networks based approaches to such a level. Following successful flight tests, of course, the way would be open for more unconventional and innovative approaches to neuro-control that may ultimately create controllers that are vastly different from current ones. However, at the moment most of our approaches are geared toward creating neuro-control systems that are constrained to behave similarly in function to current systems. Even the carrier landing study and configuration management study are more involved with augmenting existing systems than creating completely unconventional ones. The one area that has sufficient potential to justify much higher risk approaches is that of on-line learning. Even if on-line learning is not suitable for fleet aircraft, just having on-line learning available during flight testing or manned simulation could be incredibly valuable for the development process. For that reason, we are doing work in that area despite the potential problems, since we believe they may be surmountable.

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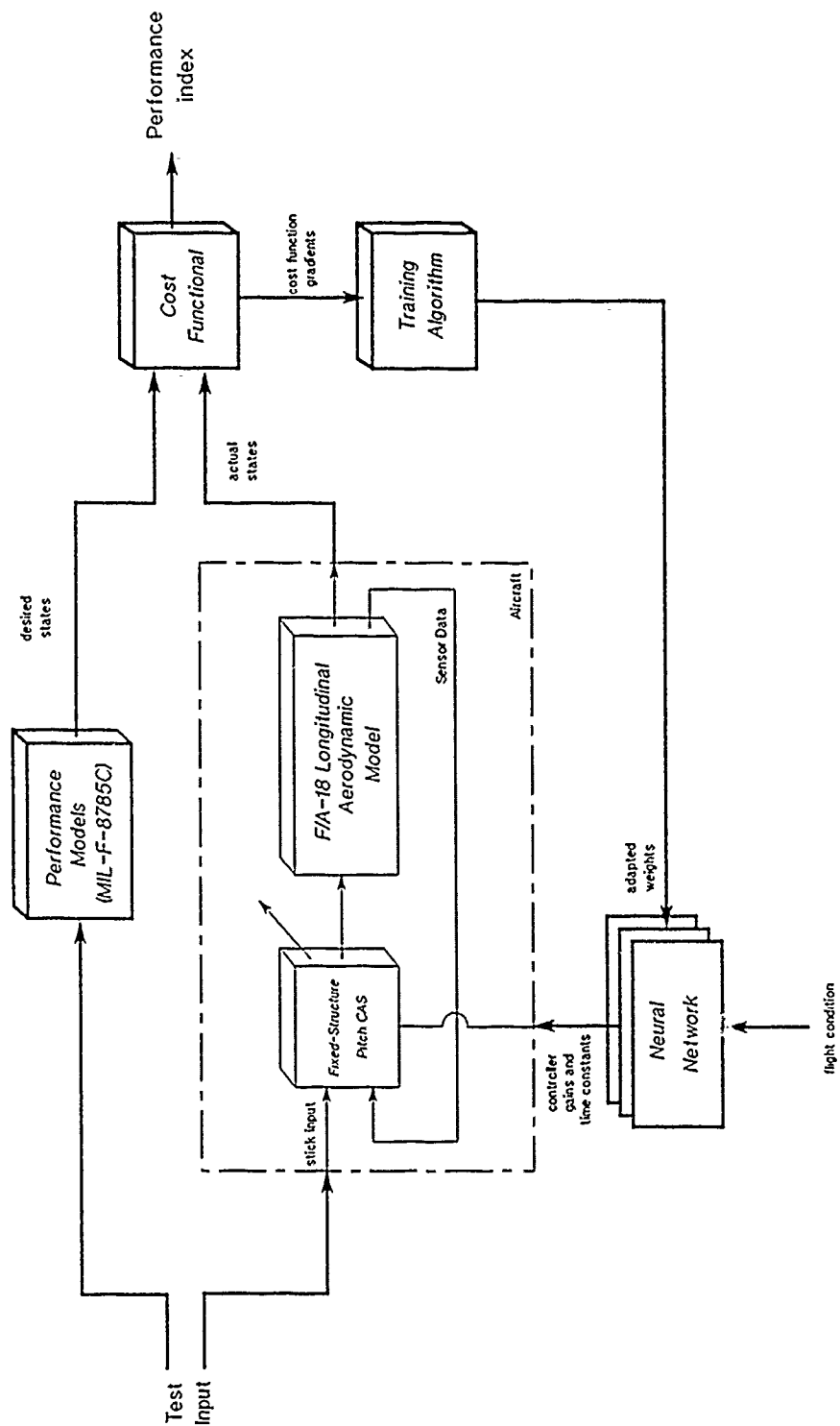
Fig. 1 Control Law Synthesis Method

23
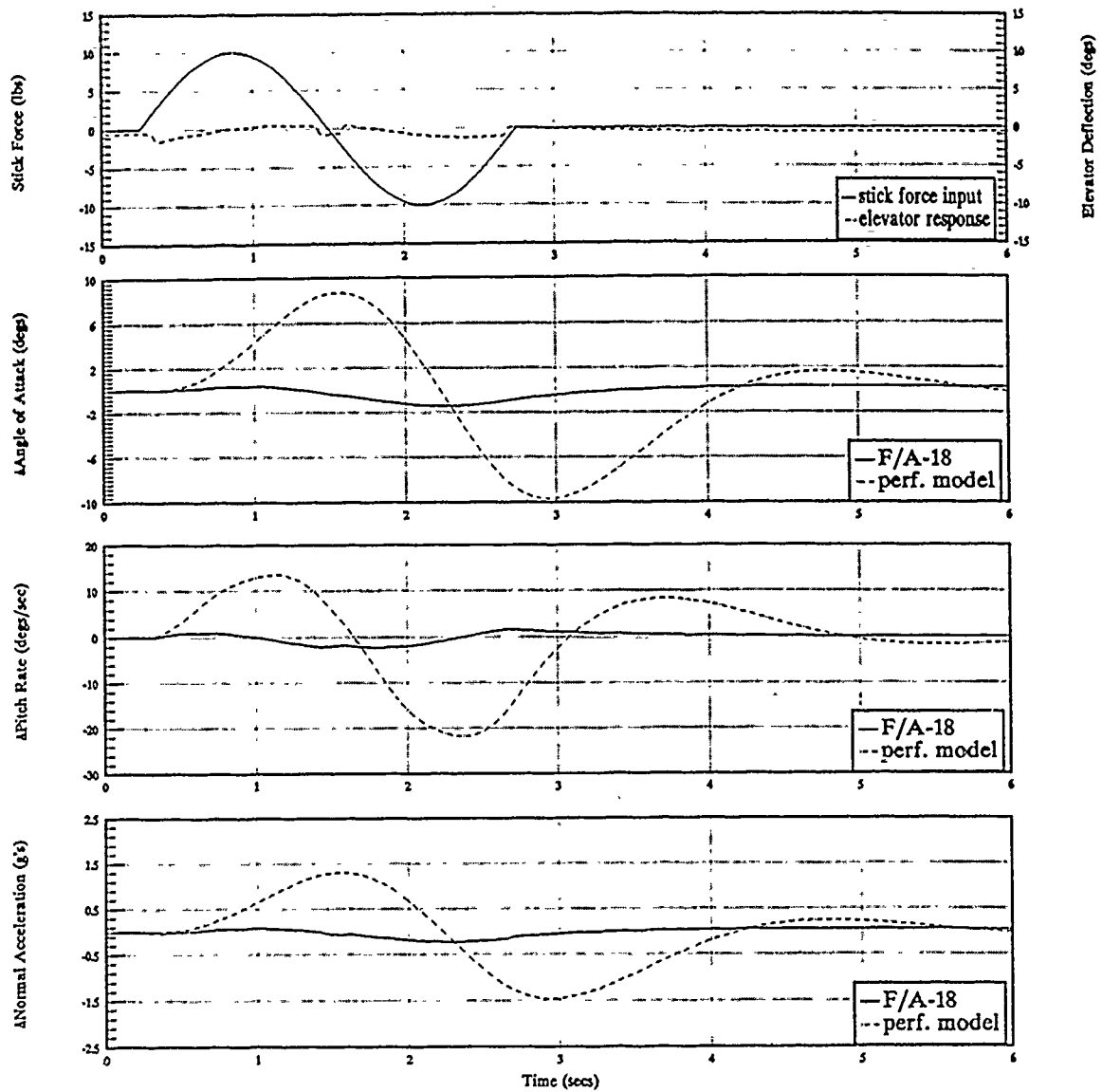
40,000 ft - 200 knots (CAS) - .68M

Fig. 2 F/A-18 Responses Before Training

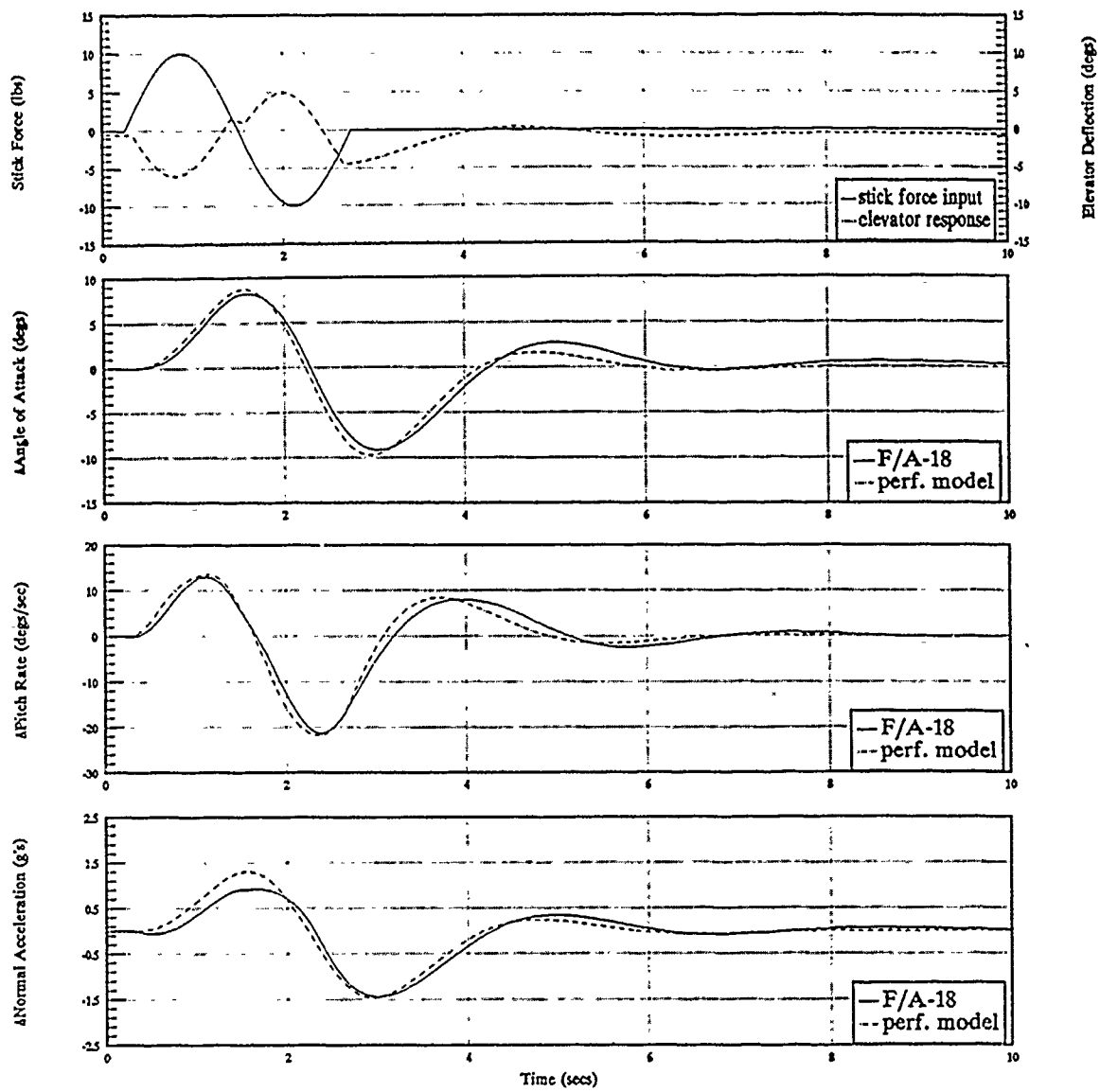# 40,000 ft - 200 knots (CAS) - .68M

Fig. 3 F/A-18 Responses After Training

20,000 ft - 300 knots (CAS) - .65M
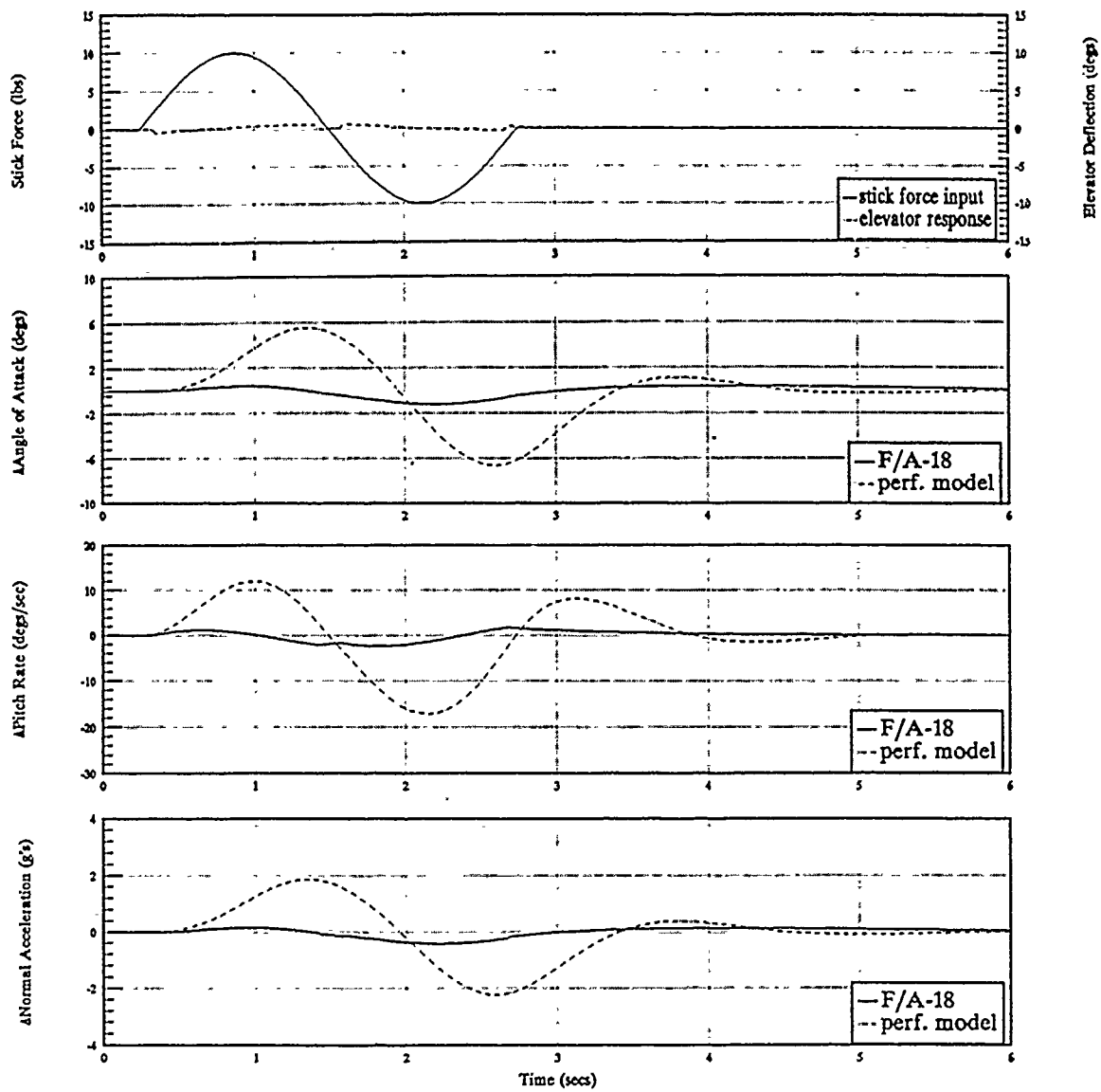
Fig. 4 F/A-18 Responses Before Training

20,000 ft - 300 knots (CAS) - .65M

Fig. 5 F/A-18 Responses After Training

Fig. 6 Fuzzy Logic Carrier Landing System

Fig. 7 Position Response to High Slope and Fast Sink Rate

Fig. 8 Sink Rate Response to High Slope and Fast Sink Rate
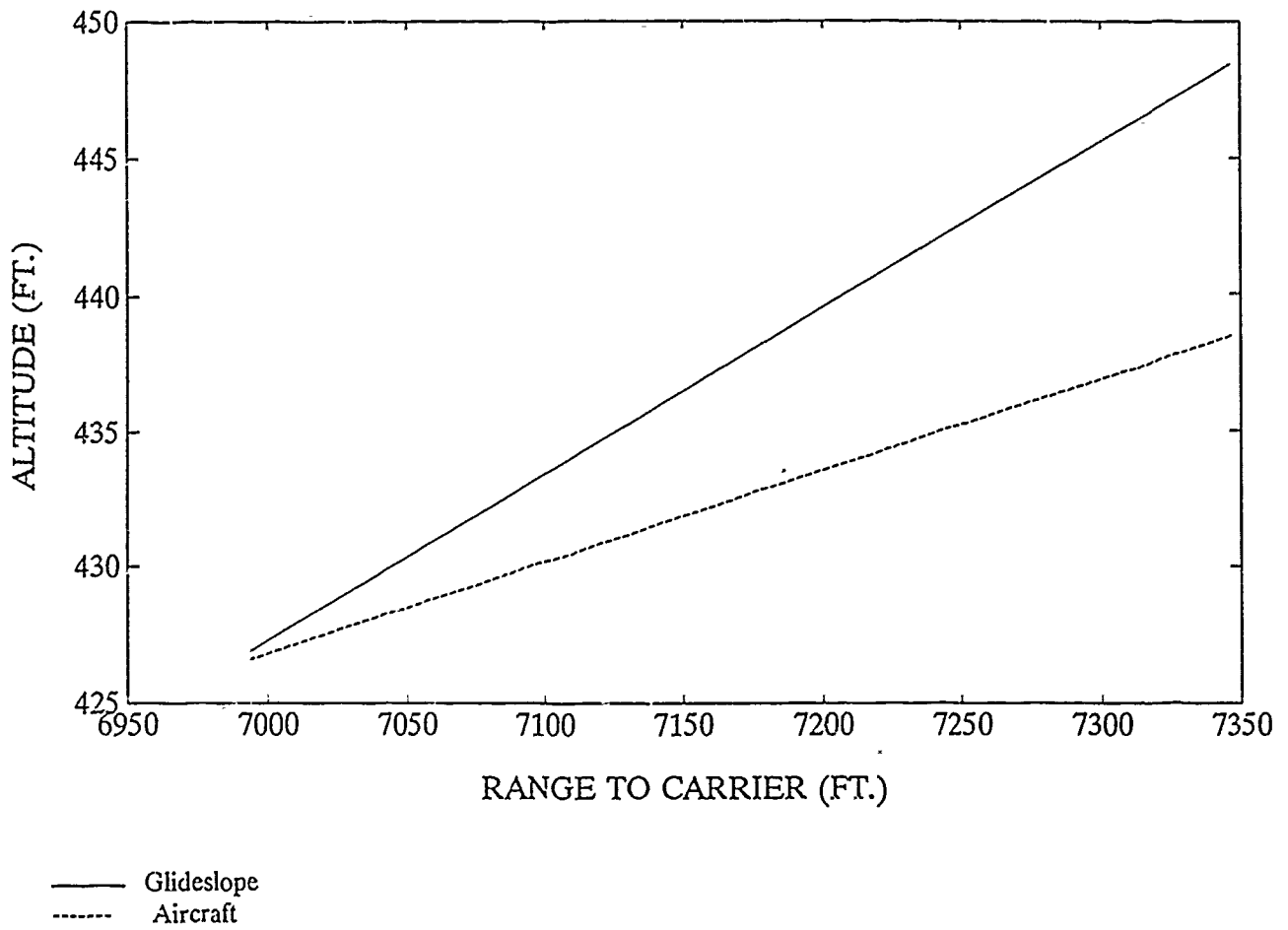
Fig. 9 Response to Slightly Low and Far from Carrier
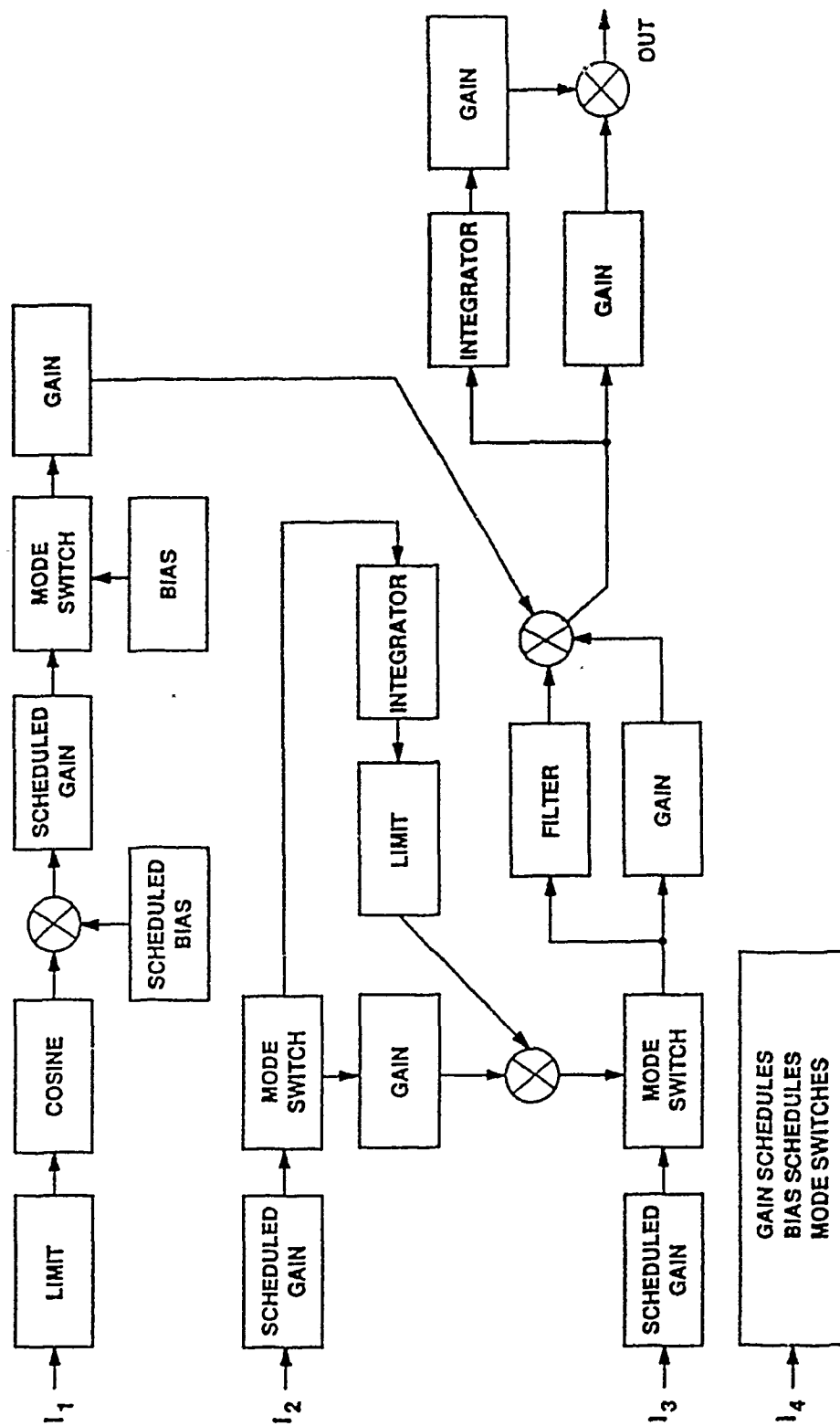
Fig. 10 Representative Control System
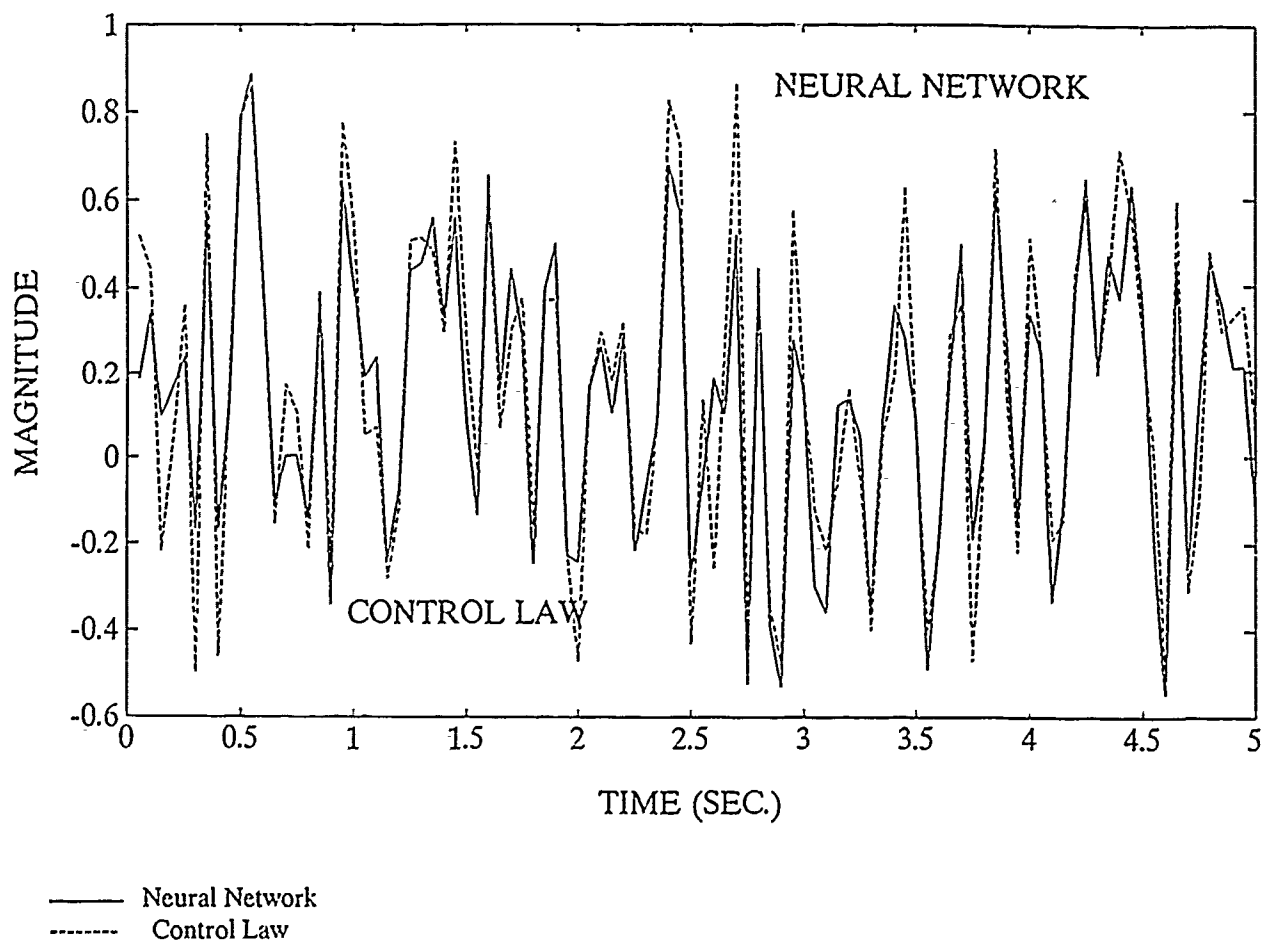
Fig. 11 Emulator Response for Uncorrelated Random Inputs
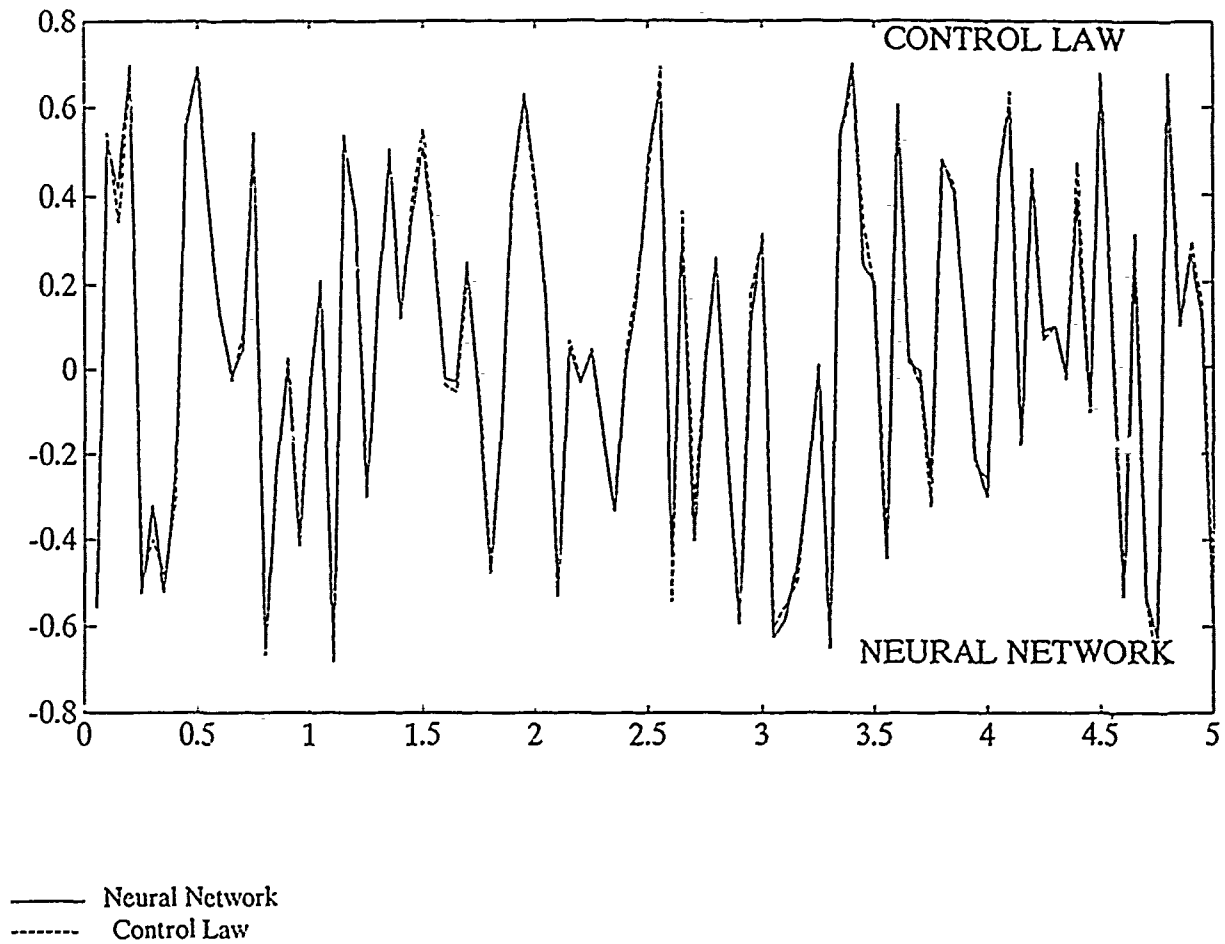
Fig. 12 Emulator Response for Internal Variable

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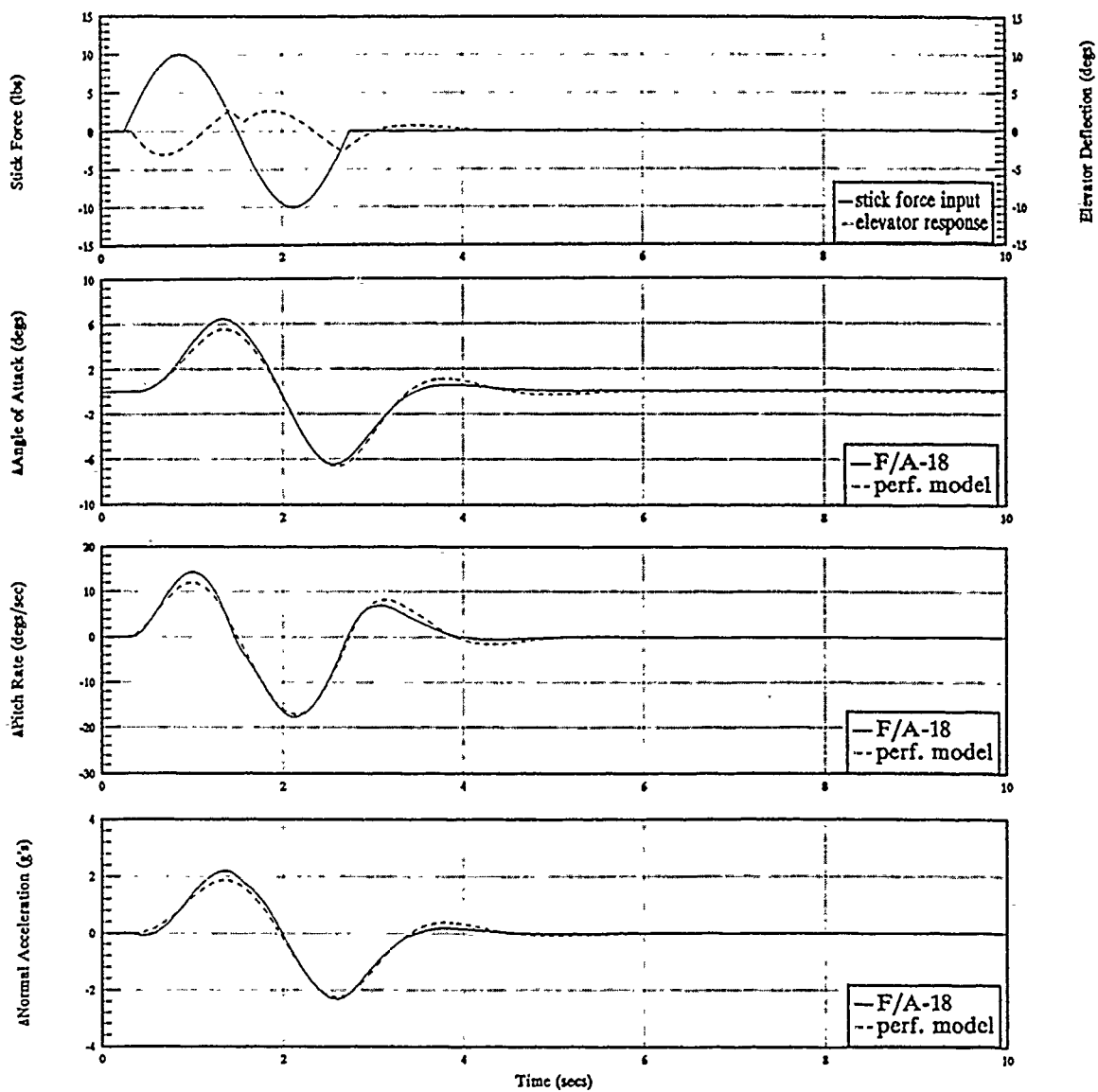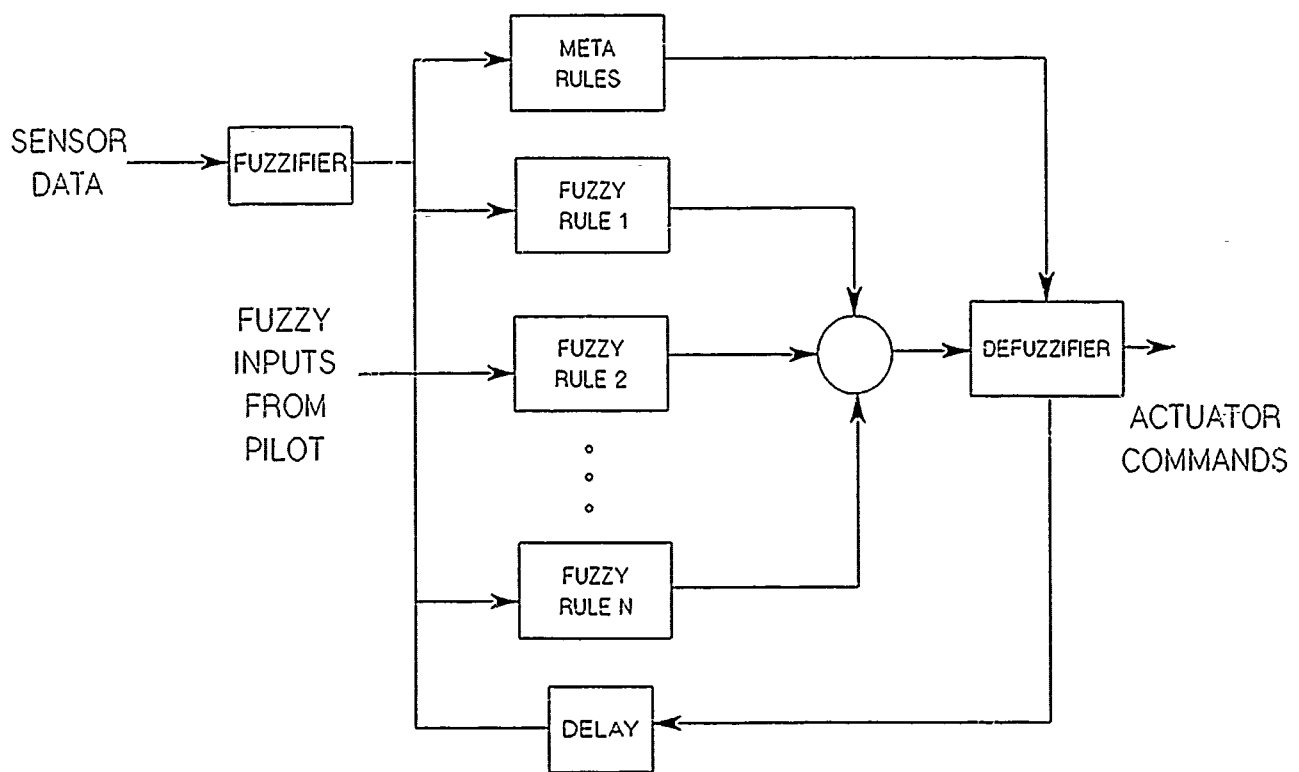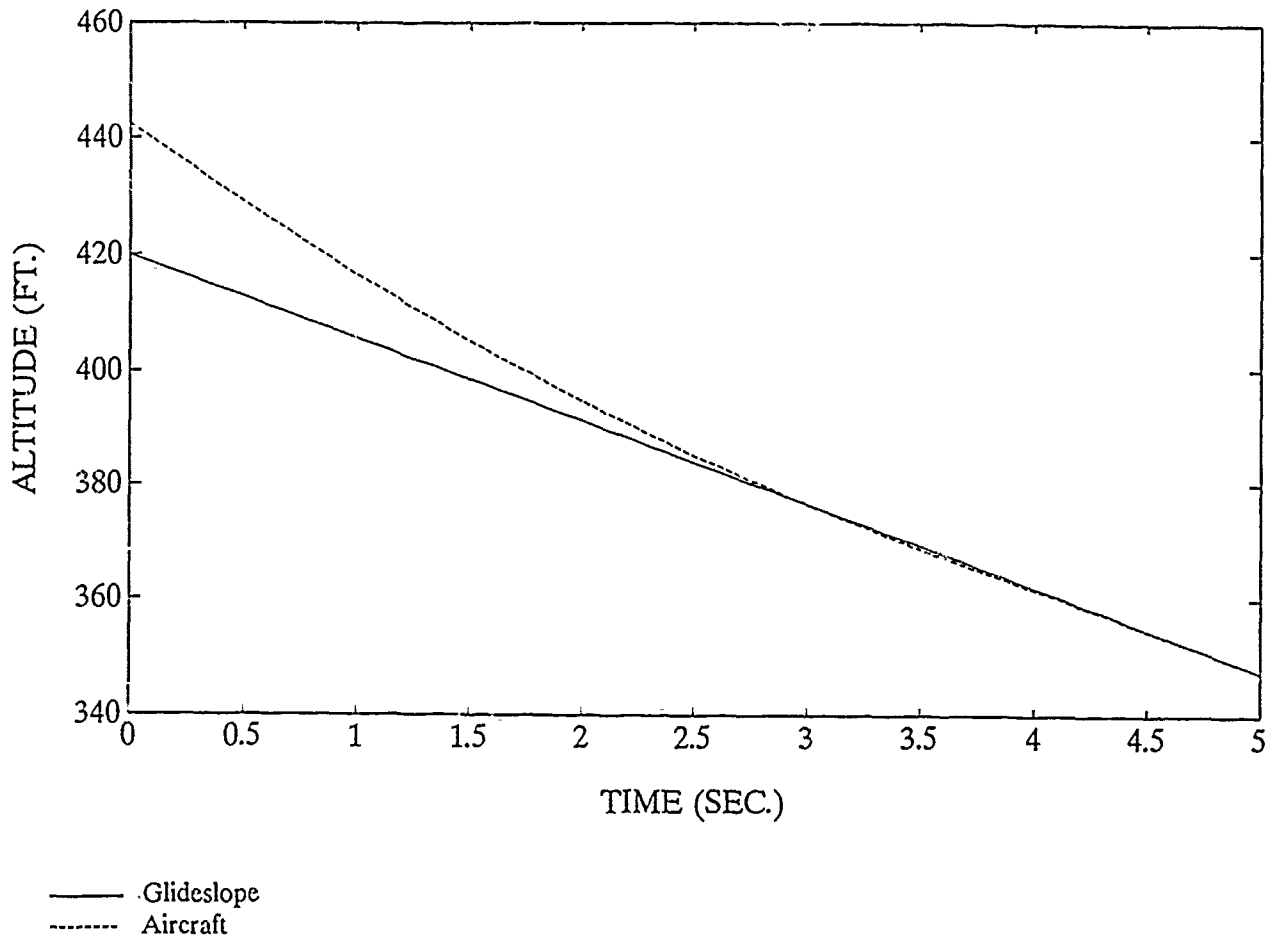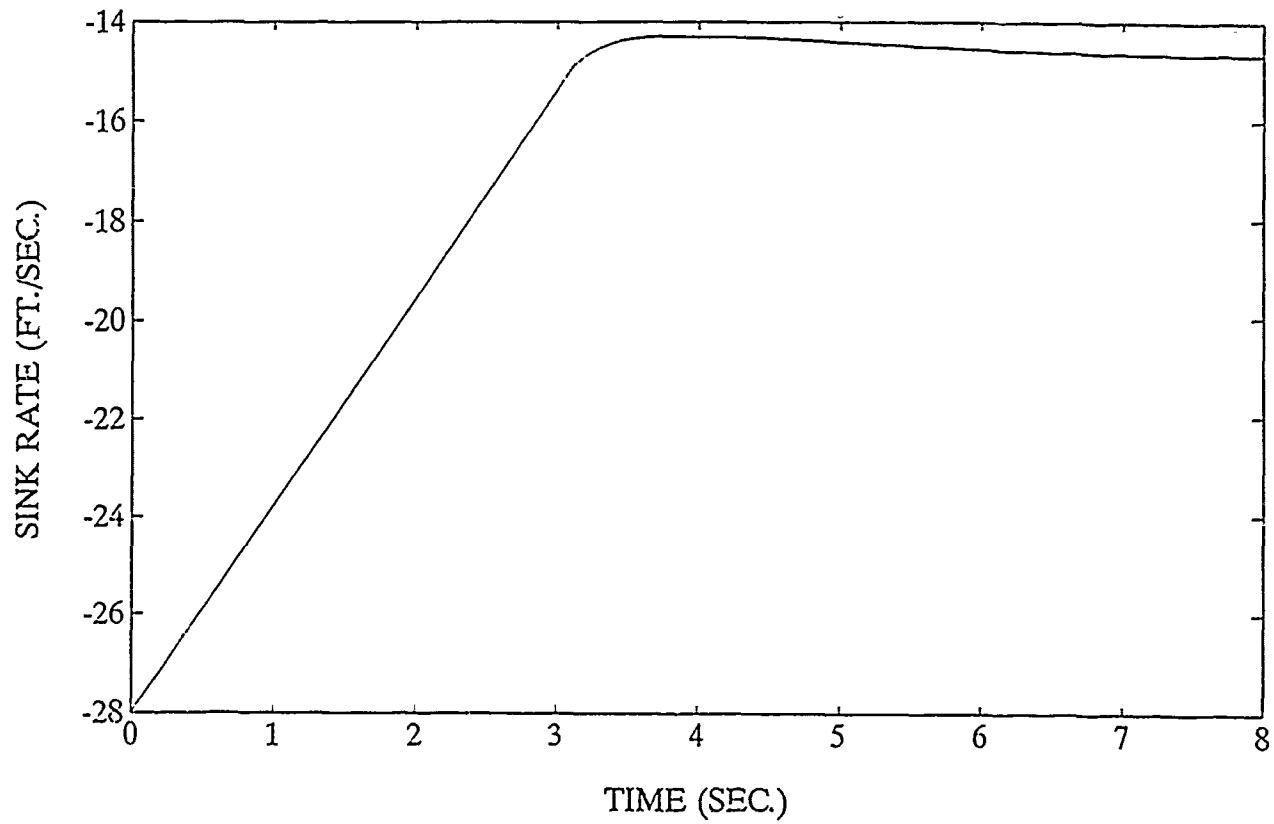Princeton, NJ   08544
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