Chapter 6

Real time Control of Ship & Aircrafts -Historical perspective

6. *Real Time Control of Ship & Aircrafts –Historical perspective*

In terms of the real time control application of evolutionary algorithm are concerned, there are difficulties with pure Genetic Algorithm implementation, as we discussed in the previous chapters. Hence, we need to embed the evolutionary algorithm to any of the existing intelligent control methods, which in turn will improve the performance of the existing intelligent controller. This intelligent controller might have been designed based on the artificial neural network or fuzzy logic or both. We have discussed various real time applications the previous chapter. Here I am going to discuss the various methods implemented by researchers across the world to implement intelligent controllers for cargo ship steering and fault tolerant aircraft related problems.

6.1 Ship Steering Problem

Although the history of ships and sailing is spread over centuries, the concepts of autopilots are not more than 75 years old. Minorsky's [189] work on automatic ship steering was one of the principal contributions to the early literature in the general field of automatic control. In the same year, Sperry [190] introduced the first automatic steering control system for ships. These early autopilots were purely mechanical in construction and they provided a very simple steering action, the rudder demand being proportional to the heading error. To prevent oscillatory behavior, a low gain was selected which rendered the device useful only in the course keeping mode, where there was no significant desire for a high degree of accuracy in the response. When proportional-derivative-integral (PID) controllers became commercially available, they greatly improved the performance and until the 1980s almost all makes of autopilots were based on these controllers. The main disadvantage of the PID controllers is that they required manual adjustments to compensate for wind, waves, currents, speed, trim, draught and water depth. These adjustments are time consuming and tedious and are usually not optimal for the ship in question. However, the capability for manual adjustments of the parameters of the controller is added to compensate for disturbances acting upon the ship. Once suitable controller parameters are found manually, the controller will generally work well for small variations in the operating conditions. For large variations, however, the parameters of the autopilot must be continually modified. Such continual adjustments are necessary because the dynamics of a ship vary with, for example, speed, trim, and loading. Also, it is useful to change the autopilot control law parameters when the ship is exposed to large disturbances resulting from changes in the wind, waves, current, and water depth. Manual adjustment of the controller parameters is often a burden on the crew. Moreover, poor adjustment may result from human error. As a result, it is of great interest to have a method for automatically adjusting or modifying the underlying controller.

Ship dynamics are obtained by applying Newton's laws of motion to the ship [[191]]. For very large ships, the motion in the vertical plane may be neglected since the "bobbing" or "bouncing" effects of the ship are small for large vessels.

6.1.1 Artificial Neural Network

Artificial neural networks (ANNs) in an early stage of development offered some advantages over other forms of control for ship steering. This is because of their ability to handle variations of plant dynamics without the element of unpredictability that may cause concern when adaptive control is considered for safety-critical applications. Witt et al [[192]] reported that a neuro-controller can improve the profit margin of a vessel and contribute to the safety of the vessel by: (a) reducing manning levels required on the bridge, (b) achieving a fuel saving by allowing the vessel to stay on course with little deviation and (c) providing accurate steering in an environment of increased traffic density and close proximity of obstacles. In an early stage of the neural network based implementation for ship steering control almost all have made use of multi-layered perceptron and have trained the networks by making use of the well known Back-Propagation learning algorithm.

Unar et al [[193],[194]], implemented the ship problem at different speed with the ANN, using multi-layer perceptron as well as radial basis functions (RBFs).

The RBF network is powerful feed forward neural network architecture. The increasing popularity of RBF networks is because of their distinctive properties of best approximation, simple network structure and efficient learning procedure. The only disadvantage is that they require significantly more nodes than MLP networks for comparable performance levels. This affects the amount of computation required for the network to produce a classification.

An RBF network consists of three entirely different layers. The first layer, or the input layer, consists of a number of units clamped to the input vector. The hidden layer is composed of units, each having an overall response function, usually a Gaussian as below:

$$g_k(\vec{x}) = \exp\left(-\frac{\|\vec{x}-\vec{c}_k\|^2}{\sigma_k^2}\right) \qquad \text{...(6.1)}$$

where, $\vec{x}$ is the input vector, $\vec{c}_k$ is the centre of the k^{th} RBF and σ_k^2 is its variance. The centers can be either fixed before the training of the network or learned through the training of the network. The third layer computes the output function for each class as follows:

$$f(\vec{x}) = \sum_{k=1}^{M} W_k \cdot g_k(\vec{x}) \qquad \text{...(6.2)}$$

Where, M is the number of RBFs and W_k is the weight of each RBF. A number of approaches to training RBF networks are available in the literature. Most of these can be divided in to two stages. The first stage involves the determination of an appropriate set of RBF centers and widths and the second stage deals with the determination of the connection weights from the hidden layer to the output layer. Indeed, the selection of the RBF centers is the most crucial problem in designing the RBF network. These should be located according to the demands of the system to be modeled. A number of different approaches are available for the selection of appropriate RBF centers. Orthogonal least square method developed by Chen et al [[195]] is widely used. In the context of a neural network, the OLS learning procedure chooses the RBF centers c_1, c_2, ..., c_M as a subset of the training data vectors p_1, p_2,..., p_N, where M<N. The centers are determined one by one in a well-defined manner, until a network of adequate performance is constructed. At each step of the procedure, the increment to the explained variance of the desired response is maximized. In this way, the OLS learning procedure generally produces an RBF

network whose hidden layer is smaller than that of an RBF network with randomly selected centers.

The results of the simulations by Unar et al [193,194] demonstrated that the RBF networks are potentially useful for ship steering control systems. They yield satisfactory performance even when MLP networks fail. Moreover, their fast training time compare the MLP makes them attractive for the application. The only disadvantage is that they require more neurons in the hidden layer as compared to MLP networks. To minimize the number of neurons in the hidden layer, the data length should not-be too large. The referred simulations do not include the effect of wind disturbances and other noise effects.

In the next chapter, I have simulated the results of the MLP as well as RBF networks for the purpose of comparison.

6.1.2 Fuzzy Controller

Autopilots used for ship steering seek to achieve a smooth response by appropriately actuating the rudder to steer the ship. The presence of unwanted oscillations in the ship heading results in loss of fuel efficiency and a less comfortable ride. While such oscillations, which are closed periodic orbits in the state plane, sometimes called "limit cycles," result from certain inherent nonlinearities in the control loop, it is sometimes possible to carefully construct a controller so that such undesirable behavior is avoided. In order to have proper implementation, we need to use the describing function method for the prediction of the existence, frequency, amplitude, and stability of limit cycles. [196]

Above this if any limit cycles exist in the system and the basic assumptions of the system are satisfied, then the amplitude and frequency of the limit cycles can be predicted by solving the harmonic balance equation.

Designing the simple fuzzy controller as shown in the figure 2.1, using a nonlinear model for a ship [8], the controller surface shows that there is nothing mystical about the fuzzy controller! It is simply a static nonlinear map. For real-world applications most often the surface should have been shaped by the rules to have interesting nonlinearities.

There are several design concerns that one encounters when constructing a fuzzy controller. First, it is generally important to have a very good understanding of the control problem, including the plant dynamics and closed-loop specifications. Second, it is important to construct the rule base very carefully. Third, for practical applications there are problems with controller complexity since the number of rules used grows exponentially with the number of inputs to the controller, if all possible combinations of rules are used. As with conventional controllers there are always concerns about the effects of disturbances and noise on, for example, tracking error. Just because it is a fuzzy controller does not mean that it is automatically a "robust" controller. Analysis of robustness properties, along with stability, steady state tracking error, and limit cycles can be quite important for some applications. As mentioned above, since the fuzzy controller is a nonlinear controller, the current methods in nonlinear analysis apply to fuzzy control systems also to find out how to perform stability analysis of fuzzy control systems. In short one can say that the main advantage of fuzzy control is that it provides a heuristic approach to nonlinear controller construction.

While the fuzzy control has emerged as an alternative to some conventional control schemes since it has shown success in many application areas there are several drawbacks to this approach: a) the design of fuzzy controllers is usually performed in an *ad hoc* manner where it is hard to justify the choice of some controller parameters (e.g., the membership functions), and b) the fuzzy controller constructed for the nominal plant may later perform inadequately if significant and unpredictable plant parameter variations occur. This is the reason that the researchers opted for learning control systems.

The use of a "learning control system" to maintain adequate performance of a cargo ship autopilot when there are process disturbances or variations as mentioned above. In general, a "learning system" possesses the capability to improve its performance over time by interaction with its environment. A "learning control system" is required to be designed so that its "learning controller" has the ability to improve the performance of the closed loop system by generating command inputs to the plant and utilizing feedback information from the plant. The learning control algorithms are based on a direct fuzzy controller.

In general, a "fuzzy controller" utilizes a fuzzy system to capture a human expert's knowledge about how to control a process for use in a computer algorithm. Often, the human expert's knowledge must be known *a priori* for fuzzy controller design. However, the learning control algorithm automatically generates the fuzzy controller's knowledge base on-line as new information on how to control the ship is gathered. The "fuzzy model reference learning controller" (FMRLC) is a (direct) model reference adaptive controller [197]. The term "learning" is used as opposed to "adaptive" to distinguish it from the approach to the conventional model reference adaptive controller for linear systems with unknown plant parameters. In particular, the distinction is drawn since the FMRLC will tune and to some extent *remember* the values that it had tuned in the past, while the conventional approaches for linear systems simply continue to tune the controller parameters. Hence, for some applications when a properly designed FMRLC returns to a familiar operating condition, it will already know how to control for that condition. Many past conventional adaptive control techniques for linear systems would have to retune each time a new operating condition is encountered.

Layne et al [198] presented the architecture of FMRLC and Shah et al [199] implemented the same and found that the FMRLC can automatically synthesize a fuzzy controller for the cargo ship and later tune it if there are significant disturbances/process variations.

The "fuzzy model reference learning controller" (FMRLC) and other adaptive fuzzy control approaches seek to address these issues, they primarily focus on improving existing learning control approaches or introducing new ones. A comparative analysis of the FMRLC and conventional "model reference adaptive control" (MRAC) for a ship steering application shows that the FMRLC has several potential advantages over MRAC including a) improved convergence rates, b) use of less control energy, c) enhanced disturbance rejection properties, and d) lack of dependence on a mathematical model.

The simulation results of the FMRLC are found to be much better compared to the earlier approaches but they are little complex. In the next chapter implementation of the FMRLC and GA – FMRLC for the ship steering application is carried out.

6.2 Aircrafts maneuvering & control

Aircraft maneuvering and control problems are of the similar nature as that of ship steering except that time available for pilot to respond in critical situation is limited as well as there are virtually an unlimited number of possible failures that can occur on sophisticated modern aircrafts. While preplanned pilot executed response procedures have been developed for certain anticipated failures, especially catastrophic and high probability failures, certain unanticipated events can occur that complicate successful failure accommodation. Accident Investigations sometimes find that even with some of the most severe unanticipated failures, there was a way in which aircraft could have been saved, if the pilot had taken proper action in a timely fashion. Because the time frame during the catastrophic event is typically short, given the level of stress and confusion during these incidents, it is understandable that pilot may not find the solution in time to save the aircraft.

Besides the increased usage of control systems, the requirements for a control system increase considerably, resulting in more and more complex control systems. For designing a classical and modern control system, it is necessary to have an accurate mathematical model of the plant, which is to be controlled. In such applications however this is impossible or very difficult to achieve this due to complicated dynamics, severe nonlinearity and / or influence of environmental conditions. Modeling difficulties like these have forced researchers to use simplified or linearized models. However when required operation range is large this model can relax a good nonlinearity and then degraded control performance. Then nonlinear control comes into play. As all the reality aspects are not taken into account in this model and some parameters of the system are poorly modeled, we speaks thus of the uncertain nonlinear model.[199]

The high performance of the first jet aircraft stepped ahead of stability and control technology [[200]], as did the first supersonic flight, where the difference between success and failure was getting the elevators to work. In terms of hypersonic flight control design, the challenges generated are two fold. The first relates to the flight constraints of a highly nonlinear time-varying vehicle performance and the second is due to the degree of uncertainty in the performance of airframe, propulsive and control components. The common theme amongst developments in control theory is therefore the optimal design of a robust controller. Another recognized feature is the integration of guidance and control [201], due to the coupling of airframe and propulsion systems and the sensitivity of both to the flight conditions and vehicle attitude.

6.2.1 Fuzzy Control

Fuzzy control is seemingly well suited to the aircraft control problem due its robustness to variations in the vehicle performance, and the capability of describing a nonlinear control law [74]. There have been many proposals for the application of fuzzy logic based guidance and control, including conventional proportional derivative control, adaptive control, sliding mode control, hierarchical systems, optimal control, and fuzzy gain scheduling [202]. There have been limited studies on the application of fuzzy control to flight control. Christian [203] reported the application of a fuzzy logic controller for the regulation of the acceleration of a hypersonic interceptor. A linearized longitudinal dynamics model was used with the aerodynamic coefficients defined by nonlinear functions of angle of attack, providing an unstable airframe. The primary objective of the study was the design of a broad range fuzzy controller to express the thrust level as a function of acceleration error and pitch rate. It appears that the rules were heuristically determined. That the controller was so effective is probably a reflection of the simple system model used in the analysis. With the addition of an adaptive scheme based on changing the membership functions, the acceleration response showed considerable robustness to large changes in the aerodynamic parameters.

Zhou *et al.* [204] presented an application of fuzzy controller for the purpose of providing longitudinal stability and attitude command tracking. The flight characteristics were defined through the longitudinal linearized equations of motion about a horizontal reference flight condition, with elevator deflection angle as the control variable. Four reference flight conditions were used, the two hypersonic conditions possessing short period modes which were dynamically unstable. Angle of attack and pitch rate were used as inputs, and the rule base was developed according to the behavior of a human pilot. Simulated angle of attack responses depicted a favorable comparison between the fuzzy controller and standard linear proportional-derivative feedback control system, and showed the robustness of the fuzzy controller to variations in the flight condition. The superiority of the fuzzy control law in this case is attributable to the non-linear control law which was generated by localized manipulation of the control surface.

In the most of the existing fuzzy systems, the designing problems can be considered as approximation problems of functions. Before a type of fuzzy systems is put into application, it is helpful if we know clearly the basic mechanism of how they approximate a desired function. Theoretically fuzzy systems are capable of approximating any real continuous function on a compact set of arbitrary accuracy. [205] In addition adaptive control theory has evolved as a powerful methodology for designing feedback controller for nonlinear systems with parametric uncertainties and/or external disturbance. So advanced fuzzy control must be adaptive.

There are two general approaches for the adaptive control, in the first approach the "adaptation mechanism" observes the signals from the control system and adapts the parameters of the controller to maintain performance even if there are changes in the plant. Sometimes, the desired performance is characterized with a "reference model," and the controller then seeks to make the closed-loop system behave as the reference model would even if the plant changes. This is called "model reference adaptive control"[197].

Second general approach to adaptive control, uses an on-line system identification method to estimate the parameters of the plant and a "controller designer" module to subsequently specify the parameters of the controller. If the plant parameters change, the identifier will provide estimates of these and the controller designer will subsequently tune the controller. It is inherently assumed that we are certain that the estimated plant parameters are equivalent to the actual ones at all times. Then if the controller designer can specify a controller for each set of plant parameter estimates, it will succeed in controlling the plant. The overall approach is called "indirect adaptive control" since we tune the controller indirectly by first estimating the plant parameters, as opposed to direct adaptive control, where the controller parameters are estimated directly without first identifying the plant parameters.

6.2.2 Genetic Algorithm based approach

As mentioned earlier, the basis of the control design approach is to use simulated flight responses to guide a parameter optimization procedure. The basic structure of the controllers is predetermined, and the free parameters are then optimized by a genetic algorithm, so that the simulated flight responses for a variety of initial conditions display desirable properties, such as long term stability, fast settling, disturbance rejection and broad range performance.

The genetic algorithm is a zero-order search procedure, where the only information used to direct the search process is a performance measure, referred to as the objective function, computed from a set of simulations. Though the design procedure is essentially a brute force approach, it has been configured, in terms of the controller structure, the search algorithm, and the adaptive performance measure, to moderate the computation time required.

There are a number of advantages to designing the controller with an optimization tool and a performance metric abstracted from the randomly perturbed flight responses. Firstly, it relieves a common issue faced by many control design approaches, namely representing the vehicle mathematically in an appropriate form. The accuracy of the model is a function of available computing power and the knowledge of the vehicle physical properties and the processes governing the performance, rather than being bound by the structure of the control design procedure. In conventional design theories the system is typically assumed to be LTI and, in the case of robust control theory, uncertainty added to the system to account for system nonlinearities and variations with time. Representation of performance uncertainty is critical for the development of a robust control law. Much work in robust control theory is directed towards the development of compatible structured and unstructured uncertainty models. When the simulated flight responses are used, the inclusion of parametric uncertainty can describe the physical process leading to the variations in the vehicle performance, through the inclusion of appropriate simulation models. Another advantage of the design approach is that the control law development is linked directly to the time history responses, allowing stability and performance measures to be easily quantified.

The genetic algorithm does not need the components of the objective function to be the same throughout the design. They too can evolve with the controller design so that as the controlled flight responses improve, greater demands can be placed on the performance of the controller. Though the genetic algorithm is noted for its global search capabilities, it is also extremely opportunistic. Considerable care is therefore needed when defining objective functions, and when combining multiple and possibly conflicting design objectives. However, this is a feature which must be addressed in all optimal control theories. In problems where non commensurate objectives are unavoidable, evolutionary algorithms are considered to be particularly suited since a set of solutions are processed in parallel. One means of dealing with such problems is to use a multi-objective genetic algorithm [179, [206]] to obtain Pareto-optimal solutions. One potential problem in an iterative design approach is the "curse of dimensionality".

As the number of design parameters increases there may be an exponential increase in the effort required to arrive at the solution. Though this can be mitigated by providing some structure to the design, it is important that a large number of design parameters can be dealt with. Evolutionary based search procedures are readily applied to problems of high dimension, and are able to rapidly extract useful designs in spite of the size of the problem. If the absolute global minimum or maximum of a complex multi-modal search space is required, then the computing effort remains considerable. However there are few algorithms capable of performing well on such functions and the notion of an efficient search procedure is still being established.

The focus of this effort is the design of an inner-loop attitude controller which would offer closed-loop vehicle stability, subject to system uncertainties, broad range performance variations, disturbances, sensor noise, and severe operational constraints. In the chapter that follow, a detailed description of the major areas of the research is provided.

6.2.3 Adaptive Critic Network

Recently, Kampmen et al [[207]] proposed a newer method for the control of aircraft dynamics. In that approach they have separated the normal action network and critical network and both are implemented using a separate reinforcement learning controller. This separation of control has the advantage that it is much easier for the individual controllers to learn the correct behavior, because the appropriate control mechanism is automatically chosen. If the control channels are not separated, the controller might learn to regulate the airspeed by changing the elevator deflection, because a change in elevator deflection might have a more immediate effect on the airspeed then a change in throttle setting. The reward function could be shaped in such a way that this effect is reduced, but there will still be extra errors in the controller as a consequence of the cross-coupling.

The disadvantage of using separate channels can be explained using the same argument as above. It is not possible to adapt the control behavior such that there is a switch to a different control mechanism, for example in the case of a complete failure of a specific control mechanism. A single reinforcement learning controller for the two control channels that would be able to perform this switch between control mechanisms is definitely possible given enough training and this should be looked at in further research.

Tangent hyperbolic functions are used to implement the nonlinear properties in the network. ANN with MLP is trained using back propagation algorithm with constant as well as variable learning rate parameters. The simulation results shown are quite comparable with that of Fuzzy controller discussed earlier but the computational complexity has been increased a lot and also the simulation time required is also comparatively larger.

6.3 Summary

Since the early implementation of the ship steering control, the researches have tried and implemented various approaches to design proper control strategies, which is true in case of aircraft as well as helicopter related problems. Every time new methods are suggested there are improvements in either the performance or the structure or complexity in one or other ways. But achieving the real time performance are concerned still it has a long way. In the next chapter, I have tried to answer many of the questions by embedding evolutionary methods for the problems on the hand.