Chapter 16
Identification of Helicopter Dynamics based on Flight Data using Nature Inspired Techniques

S. N. Omkar
Indian Institute of Science, India

J. Senthilnath
Indian Institute of Science, India

Dheevatsa Mudigere
Indian Institute of Science, India

M. Vijaya Kumar
Indian Institute of Science, India

ABSTRACT

The complexity of helicopter flight dynamics makes modeling and helicopter system identification a very difficult task. Most of the traditional techniques require a model structure to be defined a priori and in case of helicopter dynamics, this is difficult due to its complexity and the interplay between various subsystems. To overcome this difficulty, non-parametric approaches are commonly adopted for helicopter system identification. Artificial Neural Network are a widely used class of algorithms for non-parametric system identification, among them, the Nonlinear Auto Regressive eXogeneous input network (NARX) model is very popular, but it also necessitates some in-depth knowledge regarding the system being modelled. There have been many approaches proposed to circumvent this and yet still retain the advantageous characteristics. In this paper, the authors carry out an extensive study of one such newly proposed approach - using a modified NARX model with a II-tiered, externally driven recurrent neural network architecture. This is coupled with an outer optimization routine for evolving the order of the system. This generic architecture is comprehensively explored to ascertain its usability and critically asses its potential. Different implementations of this architecture, based on nature inspired techniques, namely, Artificial Bee Colony (ABC), Artificial Immune System (AIS) and Particle Swarm Optimization (PSO) are evaluated and critically compared in this paper. Simulations have been carried out for identifying the longitudinally uncoupled dynamics. Results of identification indicate a quite close correlation between the actual and the predicted response of the helicopter for all the models.

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1. INTRODUCTION

Helicopter system identification is the extraction of system characteristics/dynamics from measured flight test data (Maine & Iliff, 1985; Anon, 1991). The complexity of helicopter flight dynamics makes, modelling and helicopter system identification a very difficult task. Unlike fixed-wing aircrafts, the helicopters exhibits a high degree of inter-axis coupling, highly unstable, non-minimum phase dynamic characteristics and large response variations with flight condition. These characteristics of the helicopter make it a highly non-linear and a complex dynamical system. Further, wind tunnel/flight tests are required for the prediction of the aeromechanical forces - loads on rotor system and main rotor wake interferences with empennage/tail-rotor. But the wind tunnel experimental data suffers from scale effects and model deficiencies. Therefore, a key tool for helicopter flight/ground test correlation is provided by system identification using flight data.

Identification of a system requires picking a function (or model) to approximate the input-output behaviour of the system (the helicopter in this case) in the "best" possible manner. There has been considerable amount of work carried out in this regard, exploring the various methods available for identification of dynamical systems (Miller, Sutton, & Werbos, 1990; Narendra & Parthasarathy, 1989; Narendra & Parthasarathy, 1990; Narendra & Parthasarathy, 1991; Ichikawa & Sawa, 1992; Sastry, Santharam, & Unnikrishnan, 1994; Chen, Billings, & Grant, 1990; Hoskins, Hwang, & Vagners, 1992). Identification of nonlinear physical models continues to be a challenge since both the structure and parameters of the physical model must be determined. Many existing system identification methods are based on parametric identification. Structure determination often uses a trial and error approach to test candidate model structures. Possible structures are deduced from engineering knowledge of the system and the parameters of these models are estimated. But in the case of a helicopter, defining an a priori model is difficult due to interaction between the various subsystems like the rotor, fuselage, power plant, tail rotor and transmission systems (Tischler, 1996) the dynamics are of relatively higher order, and it is difficult to know how many states to include and which states are important. Also, increase in the nonlinearity, uncertainty and complexities of the model together with the stringent specifications of accuracy limits to be maintained renders modelling helicopter systems a daunting task. This initiated an interest among researchers to identify the system characteristics using nonparametric methods.

Artificial Neural Network (ANN) has found widespread application in nonlinear dynamic system identification as universal approximators (Miller, Sutton, & Werbos, 1990; Narendra & Parthasarathy, 1989; Narendra & Parthasarathy, 1990; Narendra & Parthasarathy, 1991; Ichikawa & Sawa, 1992; Sastry, Santharam, & Unnikrishnan, 1994; Chen, Billings, & Grant, 1990; Hoskins, Hwang, & Vagners, 1992). ANNs have also been used for helicopter system identification, Vijaya Kumar et al., (2003) has explored the different Recurrent Neural Networks (RNNs) for the identification of helicopter dynamics and based on the results, the practical utility, advantages and limitations, the models have been critically appraised. The authors after a comprehensive study of the three popular RNN architecture, such as, Nonlinear Auto Regressive eXogenous (NARX) model, Memory Neuron Network (MNN) model and Recurrent Multi-Layer Perceptron (RMLP) model, concluded that the NARX model is most suitable for the identification of helicopter dynamics (Vijay Kumar, Omkar, Ranjan Ganguli, Prasad Sampath, & Suresh, 2003). The NARX model, proposed by Narendra et al., (1989, 1990 & 1991) uses Tapped-Delay-Lines (TDL) and the Multi-Layer Perceptron neural network architecture (MLP) for non-linear system identification. The NARX model is trained using the Back Propagation (BP) algorithm. Although NARX model