# Chapter 1

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Implementation of the state-feedback control solution requires access to all the state variables of the plant model. In many control situations of interest, it is possible to install sensors to measure all the state variables. This may not be possible or practical in some cases. e.g. if the plant model includes non-physical state variables, measurement of these variables using physical sensors is not possible. Accuracy requirements or cost considerations may prohibit the use of sensors for some physical variables also.

The input and the output of a system are always physical quantities, and are normally not easily accessible to measurement. We therefore need a sub-system that performs the estimation of state variables based on the information received from the input and output. This sub-system is called an 'observer' whose design is based on observability property of the controlled system.

In order to employ a state variable feedback, it is necessary that all the states are accessible. In case where they are not accessible, it is necessary to obtain estimates of inaccessible states using observer-estimator [1] [2]. A reduced order stochastic observer-estimator may be designed Observer output may be noisy with noise having zero mean. For exact estimation the state of the observer, from noisy output, optimal estimator can be used.

Observer design and adaptive control for nonlinear systems have both been very active fields of research during the last decade. The introduction of geometric techniques has led to great success in the development of controllers for nonlinear systems. Many attempts have been made to achieve results of equally wide applicability for state estimation and adaptation. The observer problem has, however, turned out to be much more difficult than the controller problem [3], [4].

Lots of work has been done in the control system in 60's and 70's. After arrival of computers and PC's the work in the field of control system is multiplied and the branch of control system is widened and now penetrated in all branches of engineering. A number of practical systems such as biochemical process, nuclear fission processes, physiological

processes, population of species, thermal control processes, complex power systems, automobile, air craft etc. exist in bilinear and linear time varying nature[5],[6],[7]. The aim is to develop a design procedure to design optimum reduced order observer-estimator for linear time varying systems.

According to Webster's dictionary, to adapt means *"to change (oneself) so that one's behavior will conform to new or changed circumstances."* So we can say the 'adaptive system' means the *"self-learning system"* i.e. the system will adjust it self when there is change in operating or environmental condition.

An adaptive observer performs the twin tasks of state estimation and parameter identification. The two tasks are performed simultaneously and cannot be separated. The identification algorithm has to be defined using access to only the measured outputs and the estimated states. The state estimation algorithm has to work in the presence of uncertain parameters. This makes the problem very challenging.

The design of an adaptive observer for a linear time invariant system has been well analyzed [8]. [9] describe the use of parameter adaptive controller obtaining asymptotically exact cancellation for the class of nonlinear systems which can be feedback linearized. Adaptive observers [10], [11] use a coordinate transformation so that the estimation error dynamics would be linearized in the new coordinates, however the construction of the observer still remains a difficult task due to the need to solve a set of simultaneous part differential equations to obtain the actual transformation function. [12] deal with a fairly general class of nonlinear systems, in which the nonlinearities are assumed to be Lipschitz.

A systematic algorithm is provided which checks for the feasibility of an asymptotically stable adaptive observer. If the feasibility condition is satisfied, the algorithm provides the observer gains.

Since existing adaptive observers for nonlinear systems may generate unbounded parameter estimates in the presence of bounded disturbances, robust adaptive observers are presented which prevent parameter estimate drift. In addition the input to state stability of the error dynamics with respect to disturbances and parameter time-derivatives is guaranteed by generalizing a persistency of excitation result. Asymptotic convergence of state estimation errors is still achieved for systems in adaptive observer

form when disturbances are not present, by a suitable extension of Barbalat's Lemma [13].

Disturbances caused by unmeasured inputs, plant perturbations or faulty actuators degrade the robustness and performance of both control and diagnostic systems. These disturbances can be known or unknown. When the disturbances are known, extensive techniques exist for accommodating them, while only weaker techniques exists for estimating and accommodating faults of unknown origin and unknown dynamics. Techniques for the accommodation of unknown disturbances must be considered. It is also essential that the designed system must exhibit robustness. The procedure is expected to incorporate the robust behavior.

Observers designed by engineers to implement controllers or fault detectors have been utilizing precise numerical equations to model the system and characterize inputs and disturbances. With these quantitative methods an observer can be designed to reject any single disturbance that can be described quantitatively. However, if the disturbance disappears or changes, the observer can not dynamically compensate for the change. Classical approaches to rejecting disturbances for state observes have been under development for the last half century.

When the parameters of the system are unknown or time varying, an adaptive observer must be used. The adaptive observer, in addition to estimating the system states, must now also estimate the system parameters. Achieving this added requirement, while maintaining stability, has resulted in the development of significantly complex observer structure.

Because prediction error can no longer be unambiguously associated with errors in estimating state, a *persistently exciting signal* must be generate to insure the stability of the adaptive observer. Even with this persistently exciting plant signal, the adaptive observer has significant difficulty distinguishing between the effects of inaccurate parameter estimates and measurement disturbances.

The corresponding observer for a stochastic system containing additive noise processes, with known parameters, is a stochastic observer with a structure attributed to Kalman . This **Kalman filter** is a recursive solution to Gauss's original least squares estimation problem and builds on the work of Norbert Wiener in estimating the

underlying signal from a noisy time series. The Kalman filter is the optimum estimator when the corrupting noise has a Gaussian probability distribution. Like the Luenberger observer, the Kalman filter also includes a correction factor to insure stability and convergence, but for the Kalman filter it is based on the variances of the noise processes. If accurate estimates of the variance are not available, optimal observer performance is not obtained.

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When the disturbances are known, extensive techniques exist for accommodating them, while only weaker techniques exists for estimating and accommodating faults of unknown origin and unknown dynamics. Disturbances can be either stochastic or deterministic. While stationary stochastic input processes with a zero-mean Gaussian distribution can be effectively rejected by a Kalman filter when accurate noise statistics are available, fixed non-stochastic disturbances can only be rejected when the observer is augmented with a dynamic model of the disturbance. Time varying disturbances of either type that can not be modeled as a linear system are difficult if not impossible to reject. Any ability to compensate for either stochastic or deterministic disturbances is called **disturbance rejection**. However, this dissertation will use the term disturbance rejection only for the rejection of deterministic disturbances, while the term **noise rejection** will used for the rejection of stochastic disturbances.

The **Classical techniques** use **Adaptive Observers** to estimate and accommodate disturbances, while **Qualitative models** and uses stability and tracking behaviors, implemented with fuzzy rules, to achieve robust rejection of disturbances.

Faults are often detected by monitoring the measurement residuals of state observers. Excessive measurement residuals are interpreted as being indicative of a fault. A tradeoff, however, must be made between detecting all faults and creating an excessive number of false alarms since measurement residuals can also be generated by unmodelled plant dynamics, parameter mismatch or plant input disturbances. Disturbance decoupling is required in order to distinguish between true faults and the effects of disturbances .

Accurate estimation and robust accommodation of actuator faults can greatly increase the reliability and flexibility of control systems. Estimation allows for the characterization and classification of the fault, while actuator fault accommodation increases the robustness of the control system and allows time for diagnostic evaluation of the fault mechanism. With sufficiently accurate fault estimates and robust accommodation, the dynamics of a fault can be closely monitored and used for the preemptive scheduling of repairs, without interrupting normal plant operation. Robust accommodation also allows for the utilization of less expensive actuators. High accuracy and performance can thus be achieved with components that previously were not precise enough and did not have sufficiently stable performance characteristics.

Currently no simple scheme exists for the design of a controller that both estimates and accommodates for unknown actuator faults. If the type of fault is known, and has a priori been characterized by a piecewise linear model, adaptive techniques exist for estimating the parameters of the fault model . Other techniques can accommodate, but not estimate, a class of faults with a known $H^{\infty} / H^2$ bound and much work has been done in accommodating actuator faults in systems with redundant actuators. More complex methodologies have also been developed that use computer-automated reconfiguration of control laws to accommodate for a set of known actuator faults. Fuzzy logic is used to compensate the nonlinearities. Results have also been obtained using single layer / Two layer fuzzy compensation for a single known actuator fault. Performance of the compensator is investigated for a typical PID controller.

Qualitative models and machine learning techniques are used extensively in industry to tune linear systems. Undergraduate control courses introduce tuning by teaching the Ziegler-Nichols tuning rules for PID controllers. These heuristics adapt the three PID controller parameters based on the step response of the compensated system. When first developed in 1942, these heuristics were manually employed by an engineer to tune a PID controller. Recently, most of the tuning systems developed for industrial controllers rely on qualitative reasoning or machine learning techniques to automate the pattern recognition needed for tuning.

Qualitative tuning is also used to adapt many other types of linear and non-linear dynamic systems. Most relevant to this dissertation is the work on tuning fault detectors and Kalman filters.

Disturbances caused by unmeasured inputs, plant perturbations or faulty actuators degrade the robustness and performance of both control and diagnostic systems. These disturbances can be known or unknown. A variation of the linear state observer to estimate disturbances may be used to reject the effect of the disturbances. **Qualitative Robust Control (QRC)** uses qualitative models, based on linguistic terms, which capture the structure of the plant and subsume perturbations and faults. The QRC methodology is validated with the popular 1992 American Control Conference (ACC) Robust Control Benchmark.

In contrast to the classical quantitative techniques, people in daily life often utilize symbolic reasoning and a fuzzy abstraction of a system to ascertain a system's hidden states. These abstractions are frequently created using fuzzy logic and are represented as **symbolic linguistic models**. These models provide a convenient mechanism for tuning quantitative observers and improving their disturbance rejection properties. In addition to providing a mechanism for tuning quantitative observers fuzzy logic can be used to build fuzzy observers. An observer based on abstractions of the system and its disturbances functions over the entire range of system and disturbance configurations. The symbolic linguistic model effectively improves the robustness of the derived observer.

Qualitative approaches to observer design, fault detection and control requires creation of qualitative models of the underlying quantitative system. These qualitative models must be designed so they support reasoning that is consistent with the quantitative system. This coupling of consistent qualitative models with a continuous, quantitative plant is called a **hybrid system**. In contrast, many intelligent systems do not use qualitative models of the underlying quantitative system. As an example, intelligent systems based on ANN often learn to recognize patterns, and reason about the recognized patterns, but never develop a qualitative model of the patterns.

An ARTIFICIAL NEURAL NETWORK (ANN) [14-24] is an attempt, to mimic the action of the brain using simple structure. The ANN is built up using a class of adaptive machine that perform computation through process of learning. The large

number of inter-connected artificial neurons forms the network. Thus neural network consists of massively parallel distributed processors which have a neural propensity for storing experienced knowledge and making it available for use.

Input output relations (mapping) in the form of traditional mathematical modeling is replaced by ANN learning the synaptic weights by undergoing a training process. ANN has built in adaptability or can be trained to modify the weights with the change in environment. The ANN can deal naturally with contextual information. Since knowledge ·is represented by the regular structure and activation state of network. Every neuron is potentially affected by the global activity of all other neurons. ANN can be trained to make decisions and they are also fault tolerant in the sense that if a neuron or connecting link is damaged, recalling a pattern will be impaired in quality but due to distribution of information in the network damage has to be extensive for overall degradation. Since neurons are the common ingredients for all ANN, it is possible to Share the algorithm and structures in different applications. So it is possible to have a seamless integration of modules. The ANN is suitable in the following situation:

Correct model of process may not be available or mode may be, complex with to many unacceptable assumptions The classical modeling algorithm may not respond well to the measurement noise in sensors or performance through classical algorithms may not be adequate.

The FUZZY LOGIC based systems [25- 28] may be developed to overcome classical algorithm problems. There are many - similarities between ANN and FUZZY CONTROLLERS. The fuzzy logic frees us from the true/false reasoning of logical system of type that are used in symbolic languages.

Fuzzy linguistic models hold the promise of providing a finite qualitative partition of a quantitative dynamic system while being applicable to any system that can be described in linguistic terms. Fuzzy models provide a succinct and robust representation of systems that lack a complete quantitative model or have uncertain system perturbations. Consistency in reasoning, however, has not yet been proven for a fuzzy linguistic representation of a quantitative system.

Fuzzy linguistic models use fuzzy sets to create a finite number of partitions MBF of the inputs, outputs and states of a quantitative system. Currently most fuzzy models are

implemented as a set of **if-then** rules, where the system input is used to evaluate the rules' antecedents and the model's output is the combined output of all the rules evaluated in parallel . This simple logical system, a Fuzzy Inference System (**FIS**) , does not implement inference chaining and can only evaluate a simplified qualitative model of a plant. Recent work has expanded the usefulness of this structure by providing machine learning methodologies to adapt and **tune** fuzzy linguistic models and to automatically generate new models through **self-organization.**

Learning or tuning allows the initial linguistic fuzzy model developed from heuristic domain knowledge to be optimized. Learning is achieved by using a neuro-fuzzy structure and exploiting the supervised learning strategies originally developed for neural networks. These strategies include gradient descent back-propagation , least-mean-squares, and a hybrid methodology that combines least-squares to optimize linear parameters and back-propagation to optimize the nonlinear parameters. These same supervised learning methodologies can automatically learn any arbitrary nonlinear mapping between input and output without an initial linguistic fuzzy model . The resulting self-organized fuzzy models do not necessarily have a linguistic interpretation that would be recognized by a human expert. Often systems developed through self-organization are never interpreted linguistically, but are utilized effectively for pattern matching and curve fitting. Fuzzy networks are often preferred for curve fitting because the fuzzy rules used by the network have only a local effect, in effect providing an adaptive mechanism for implementing B-splines.

It is possible to integrate the fuzzy logic controller with ANN [ 29-31]so that the expression for the knowledge used in the systems is understood by humans. This reduces difficulties in describing the ANN. Fuzzy controller learns to improve its performance using ANN structure & thus learns by Experience. Neuro-computing is fast compared to conventional computing because of massive parallel computation. Besides, it has the properties of fault tolerance and noise filtering. Here neural network is used as if estimator. Neural network-based control strictly does not need a mathematical model of a plant like a conventional control method does with the required precision.

The recent work published in the national/ international journals, from the seminars on control system, ANN/AI, fuzzy rule extraction, development of rules for the

network, adaptation of new rules from the knowledge gained, various learning algorithm, various learning methods using computer programming various transform for learning are developed.

The above mentioned research work has inspired the author to work in this direction and to think of better alternatives for implementation of adaptive and robust observers, Estimators, Controllers and compensator for linear, Nonlinear or time varying process control systems using current soft computation techniques such as Fuzzy logic, Artificial Neural Network, Adaptive Neural Fuzzy Inference systems (ANFIS).

The research work aims at developing a classical algorithm for designing robust observer-estimator with/ without noisy output for time invariant as well as time varying systems. Since in many cases it may not be possible to have an exact model for noise, an alternative model in terms of neuro-fuzzy estimator may be designed and implemented on digital computer. The use of software development support tools [32] such as MATLAB, SIMULINK and Tool Boxes [33-39] makes simulation study as well design of graphical user interface simpler.

The work described in the thesis includes:

- Observer design for a time varying/Bilinear system using Dynamic programming and Method of Generalized Inversion [40].

- Development and Implementation of Single layer and Two layer Fuzzy compensator for the estimation and removal of nonlinearity for a process control system using PID controller. MATLAB/SIMULINK/Fuzzy/Neural Network are used for testing and Implementation a robust adaptive observer. Application of the designed observer for the control of Induction Machines employing ANN.

- Development of a robust state-feedback fuzzy controller that that incorporates robust stability and tracking behaviors

- Development of a robust hybrid output-feedback controller that combines the fuzzy controller with a robust PFI observer

**The contents of following chapters of the thesis are summarized as follows:**

**Chapter: 2**   Background: Describes the survey of current trend in design of robust adaptive observer and controller using classical methods. A Design of a reduced order observer for linear time varying/ Bilinear system using method of generalized inverse and dynamic programming described. MATLAB is used for testing the design with various set of parameters.

**Chapter:3**   The general preview of the soft computing fields such as: Fuzzy logic, Artificial Neural Network and ANFIS provided in this chapter with reference to observer, estimator and Controllers. It also describes the software tools available for development of ANN models and to carryout their simulation study. Single Layer Fuzzy compensator for Non-linearity compensation and Two layer for pre-compensation is developed. SIMULINK is used for testing the performance of the compensator.

**Chapter: 4**   It provides a comprehensive study of the work done by the researchers using soft computing techniques for the design and development of robust observer based control systems.

**Chapter: 6**   It provides a comprehensive study of the applications of soft computing techniques in control system.

**Chapter: 7**   Describes control of Induction machines and a comprehensive study of the work done by the researchers.

**Chapter: 8**   ANN model for control of Induction Machine is developed. It describes the design of GUI for the application suing MATLAB.

**Chapter: 9**   It contains discussion of the results and   conclusions as well as  scope of future work

**Chapter:10**   It contains Bibliography.