CHAPTER II

LITERATURE REVIEW

2.1 Adaptive control

An adaptive control of input-output linearizable systems, together with an extended Kalman filter (EKF), was applied to a simulated batch polymerization reactor to realize the output (monomer conversion) tracking in the presence of model parameter uncertainties (Wang et al., 1993). Simulation results showed that this technique was robust and the output tracking performance could be ensured even in the presence of large model parameter errors and disturbances.

An adaptive nonlinear control strategy, based on a modified input-output linearization approach, for a bench-scale pH neutralization system was developed and experimentally evaluated (Henson M.A. and Seborg D.E., 1994). Experimental tests demonstrated the superior performance of the adaptive nonlinear controller as compared to a non-adaptive controller and conventional PI controller.

Wang et al. (1995) applied a technique of adaptive control of linearizable systems, together with an extended Kalman filter, to a simulated batch styrene polymerization reactor to realize the output (extent of reaction) tracking in the presence of model parameter uncertainties and disturbances. Simulation results show that the robustness of the controller is good and the tracking performance is guaranteed when there are disturbances and two model parameter uncertainties, the first one being the gel effect, the other one the heat transfer coefficient, which is better than in the case of a nonadaptive input/output linearizing controller.

Kosanovich et al. (1995) presented a linearizing feedback adaptive control structure and its application to the control the CSTR in two instances. The first is when there is full state feedback and the second when only temperature measurements are available. In the latter a nonlinear observer is constructed to infer conversion.

Simulation results verify the overall control performance to be satisfactory and that the parameters converge to their true values. Good performance of the proposed controller could be achieved for almost all values of the adaptation gains and pole location of the feedback linearized system.

Pringle and MacGregor (1997) considered the temperature control of semi-batch polymerization reactors by using a nonlinear adaptive controller which consisted of a nonlinear controller coupled with an extended Kalman filter and compared to a feedback PID controller and a feedforward-feedback PID controller. A nonlinear adaptive controller was shown to provide excellent control in all the situations.

Xie et al. (1999) proposed a new approach to Adaptive Generic Model Control (AGMC), based on the theory of Strong Tracking Filter (STF). Two AGMC schemes were developed. The first was a parameter-estimation-based AGMC. After introducing a new concept of Input Equivalent Disturbance (IED), another AGMC scheme called IED-estimation-based AGMC was further proposed. The unmeasurable disturbance and structural process/model mismatches could be effectively overcome by the second AGMC scheme. The laboratory experimental results on a three-tank system demonstrated the effectiveness of the proposed AGMC approach.

Mclain and Henson (2000) presented nonlinear adaptive control strategy based on radial basis function networks and principle component analysis to reduce the system dimension. The simulation results shown that the computational enhancements enable the nonlinear model reference adaptive control strategy to be successfully applied to nonlinear processes of moderate complexity.

Guo et al. (2001) developed an adaptive scheme that combined the generic model control algorithm (GMC), with a nonlinear observer, which was able to track changes in the process model. Two examples demonstrated the effectiveness of this scheme. The first example was a simulation of an exothermic batch reactor where the algorithm was used for set point trajectory tracking and calorimetric estimation. The second example was a real-time application to a laboratory pressure tank, which was effectively controlled over a wide range. Both examples illustrated the ability of this nonlinear adaptive control strategy to provide good estimation and control of these nonlinear processes.

Knapp et al. (2001) applied to a CSTR process an adaptive algorithm with a neural network model. This work demonstrated that the combination of linear and nonlinear functions in the networks resulted in better convergence when the system operated for long time around the same condition. The combination also proved to provide better performance when the system was operated in a large window of operation requiring a smaller dead zone to stabilizer the controller. Furthermore the adaptive algorithm proved to be superior than PI controller tuned with IMC design ruled and a self tuning PI.

Conradie et al. (2002) introduced the Adaptive Neural Swarming (ANS) method to test in a real-world task of controlling a simulated non-linear bioreactor. They found that ANS was able to adapt to process changes while simultaneously avoiding hard operating constraints.

Wang et al. (2004) proposed Adaptive Generic Model Control (AGMC) for a class of nonlinear time-varying processes with input time delay. Furthermore modified strong tracking filter (MSTF) was adopted to estimate the time- varying parameters of nonlinear processes, and the state estimates are utilized to update the plant models used in the NSP and MSTF parameter. The computer simulation result demonstrated effectiveness of the proposed AGMC.

Czeczot (2006) presented B-BAC (balance-based adaptive control) methodology and its application to the control the non-isothermal CSTR. By the B-BAC methodology combined simplicity and generality, characteristic for classical PI controller, with very good control performance and robustness resulting from its adaptability and feedforward action. The simulation results proved that B-BA controller was very good control performance in comparison with PI controller when the disturbance changes and the significant uncertainly on the measurement data were presented.

Boling et al. (2007) developed a multi-model adaptive PID controller and evaluated in two simulation studies for a nonlinear pH neutralization process that included comparisons with three other PID controllers: a re-tuning adaptive controller and two nonadaptive controllers. The simulations indicated that the multi-model controller was quite effective over wide ranges of unmeasured disturbances and process changes. The re-tuning strategy also performed very well, but was slower to respond to sudden disturbances.

2.2 Extended Kalman Filter

In most industrial processes, the state variables are not all measurable or, not with sufficient accuracy for control purposes. Furthermore, measurements that are available often contain significant amounts of random noise and systematic errors. For these situations, an estimator has been applied to estimate state variables. In 1960, Kalman published a famous paper describing a recursive solution to the discrete data linear filtering problem. The Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation.

Myers and Luecke (1991) described and illustrated an efficient new algorithm on process examples for solution of the extended Kalman filter equations for a continuous dynamic system with discrete measurements. Implicit simultaneous methods, which were powerful in terms of accuracy and efficiency, were utilized for numerical integration. At the internal integration step level, the new algorithm exploited the decoupled nature of the state estimate and error covariance equations along with the symmetry of the error covariance matrix. The error control strategy included both the state estimates and error covariance.

Tan et al. (1991) applied two estimation techniques, the extended Kalman filter (EKF) and the iterative extended Kalman filter (IEKF), to a nonlinear time-varying system that had non-measurable state variables. An iterative solution to a fedbatch fermentation process was reported using the EKF based on measurements of the oxygen and carbon dioxide concentrations. The results demonstrated that this estimation technique could be successfully applied to complex biological processes.

Kershenbaum and Kittisupakorn (1994) studied a temperature control of a batch reactor using GMC controller. The amount of heat released by the reactions had been estimated online using an extended Kalman filter, and incorporated into the GMC algorithm. Simulation results had shown that the Kalman filter gave an accurate estimate of the amount of heat released and together with the GMC controller, gave reliable robust control. An experimental extension of the work using the PARSEX reactor showed that the extended Kalman filter was rather more sensitive to plant/model mismatch than would have been predicted from simulations alone.

Gudi et al. (1995) presented the design and development of a multirate software sensor for use in the chemical process industry. The measurements of process outputs that arrived at different sampling rates were formally accommodated into the estimation strategy by using the multirate formulation of the iterated extended Kalman filter. Measurement delays associated with some of the process outputs were included in the system description by addition of delayed states. Observability issues associated with state and parameter estimation in a multirate framework were discussed and modified measurement equations were proposed for systems with delayed measurements to ensure relatively strong system observability.

Zhao and Kummel (1995) presented an application of state and parameter estimation techniques in an altering activated sludge process with regard to biological phosphorus removal. A simplified model describing the phosphorus dynamics in an alternating activated sludge process was proposed based on insight into the process with a mechanistic activated sludge model. State and parameter estimation problems relating to the non-measurable dynamics of a most important limiting substrate polyhydroxy-alkanoate (PHA) were formulated and discussed. Several schemes were presented which involved a state estimator designed with the extended Kalman filter algorithm, two specific parameter estimation procedures and an adaptive scheme for simultaneous state and parameter estimation.

Phupaichitkun (1998) studied the temperature control of a batch reactor with exothermic reaction and compared the performance of MPC with GMC. In addition, since both MPC and GMC were the model based controllers and needed the measurement of all states as well as the value of process parameters Kalman Filter was used to estimate the heat released of chemical reactions.

State estimation methods, like the extended Kalman filter (EKF) were used for obtaining reliable estimates of the states from the available measurements in the presence of model uncertainties and unmeasured disturbances. The main open issue in applying EKF was the need to quantify the accuracy of the model in terms of the process noise covariance matrix, Q. Valappil and Georgakis (1999) proposed two methods that utilized the parametric model uncertainties to calculate the Q matrix of an EKF. The first approach was based on a Taylor series expansion of the nonlinear equations around the nominal parameter values. The second approach accounted for the nonlinear dependence of the system on the fitted parameters by use of Monte Carlo simulations that were easily be performed on-line. The value of the process noise covariance matrix obtained was not limited to a diagonal and constant matrix and was dependent on the current state of the dynamic system. The application of these techniques to an example process was discussed.

Russell et al. (2000) investigated a model-based inferential quality monitoring approach for a class of batch systems. First, an extended Kalman filter based fixedpoint smoothing algorithm was presented and compared to a popular approach to estimating the initial conditions. Subsequently, a nonlinear optimization-based approach was introduced and analyzed. A sub-optimal on-line approximation to the optimization problem was developed and shown to be directly related to the extended Kalman filter based results. Finally, some practical implementation aspects were discussed, along with simulation results from and industrially relevant example application.

Siripun (2000) presented the implementation of Globally Linearizing Control (GLC) together with an extended Kalman filter to control pH of the wastewater treatment process that was a part of an electroplating plant. The extended Kalman filter had been applied to estimate unavailable or unknown states and parameters and these estimates were incorporated in the control action determination in the GLC algorithm.

Lersbamrungsuk (2000) designed and developed two software programs based on Kalman filter. The first one, named kSTAPEN+, was a software component based on Kalman filter. In kSTAPEN+, users could define their own systems including states and parameters to be estimated. After running the program, estimation results are given. The estimates obtained from the kSTAPEN+ had been compared to those obtained from the program written on Matlab. Furthermore, the program had been tested with a heater, a stirred-tank reactor and a microfeeder. In kSTAPEN-C, the component had been developed by using Component Object Model (COM) technology. The estimates obtained from kSTAPEN-C had been compared to those obtained from kSTAPEN+. Results had shown that both kSTAPEN-C and kSTAPEN+ were equivalent.

Moolasartsatorn (2002) used an extended Kalman filter to estimate the heat release of pervaporative membrane reactor. A generic model control (GMC) coupled with an extened Kalman filter is implemented to track both optimal temperature set point and optimal temperature profile obtained in the off-line optimization. Application of these control strategies to control the pervaporative membrane reactor shows that the proposed control strategy provides good control performances in a nominal case. The GMC coupled with Kalman filter has been found to be effective and robust with respect to changes in process parameters.