CHAPTER II

LITERATURE REVIEW

2.1 Literature review on pervaporative membrane reactor

Most of published work on membrane reactor is in the field of biotechnology. Recently, extensive studies involved membrane reactors applied to catalytic dehydrogenation, hydrogenation, and decomposition reactions. However, fewer recent researches have been reported on liquid-phase reversible reactions but lack of suitable membranes with good permselectivity and solvent resistance. Ultrafiltration membranes are too porous to effect efficient separation of small liquid molecules, while reverse osmosis membranes are likely to require high operation pressure because of osmotic pressure of the reaction mixtures.

Pervaporation, an emerging membrane process specially used for organic-water and organic-organic separations, seems to be an appropriate choice (Feng and Huang, 1996). In this process, the mass transport through the membrane is induced by maintaining a low vapor pressure on the downstream side, thereby eliminating the effect of osmotic pressure.

In 1960, Jenning and Binning investigated the using of pervaporation to remove by-product species from reaction mixtures was proposed in the early stage of pervaporation research. However, the interest in pervaporative membrane reactors was only rekindled recently when pervaporation has been proven to be a viable separation technique in the chemical industry. Presently, pervaporation is best applied to dehydration of organic solvents, and the dehydration membranes normally work best when water content in feed mixture is not high. Thus, reversible reactions that produce by-product water are a niche of pervaporation for reaction enhancement.

Esterification represented a significant group of the reactions commonly found in the chemical industry. The use of pervaporative membrane reactor for esterification was different from the combination of reactive distillation and pervaporation in which water was externally removed from the top or bottom stream. In the pervaporative membrane reactor, the product water was simultaneously removed from the reaction zone while the reaction took place. A number of reactions have been tested in this reactor.

David and coworkers (1991) studied the esterification of 1-propanol and 2-propanol with propionic acid to produce propyl propionate and iso-propyl propionate. Pervaporation with PVA membranes was externally added to the reactor. It was revealed that the hybrid process was governed by four main parameters that influenced the conversion rate: in order of significance, these were temperature, initial molar ratio, membrane area to reaction volume ratio, and catalyst concentration.

Okamoto and coworkers (1993) investigated the pervaporative membrane reactor for esterification of oleic acid and ethanol to produce ethyl oleate, in the presence of *p*-toluenesulfonic acid. Polyimide, chitosan, nafion, polyetherimide and perfluorated ion-exchange were used as membranes. Among these membranes, polyimide showed the highest selectivity. High yields could be obtained when the large excess of ethanol is used.

Chompunut (1994) studied the pervaporation of butanol in dilute aqueous solution by using silicone rubber tubular membrane. The experiments were performed at various concentrations of butanol, temperatures and permeate pressures. The experimental results showed that the butanol flux increased with increasing temperature, concentration of butanol in feed solution, and with lowering permeate pressure. The water flux was constant in each temperature and increased with increasing temperature and with lowering permeate pressure. In addition, butanol concentration in feed solution or temperature had slightly effect on separation factor due to dilute butanol concentration. The slower permeation flux obtained with thicker (1 mm.) membrane was due to greater resistance in membrane

Keurentjes and coworkers (1994) studied the kinetic parameters for the esterification of tartaric acid with ethanol. Both concentration-based as well as activity-based reaction rate constants and equilibrium constants had been determined. Reaction rate constant determined in dilute solution are capable of describing the reaction in a concentrated environment. When pervaporation is used to remove the water produced in the reaction, the equilibrium composition could be shifted significantly towards the formation of the final product diethyltartrate.

Matouq and coworkers (1994) proposed a process- layout combining an external pervaporation process using hydrophilic polyvinyl alcohol (PVA) membranes with reactive distillation for the production of MTBE. Two types of catalysts i.e. ion exchange resin Amberlyst 15 and heteropoly acid for the reaction of methanoi and TBA to form MTBE were investigated. HPA showed higher selectivity than the ion exchange resin. It was found that the hybrid process using pervaporation might be effective in removing water.

Feng and Huang (1996) studied a parametric to provide a fundamental understanding of reactor behavior. A batch reactor integrated with pervaporation unit was selected as the model system. The simulation results showed that conversion exceeding equilibrium limits could be achieved by using pervaporation to remove water from reaction mixture, and that complete conversion of one reactant was obtainable when the other was in excess. Membrane area, permeability and the volume of the reaction mixtures to be treated were important operating parameters influencing the reactor behavior. Operating temperature influenced both the reaction rate and membrane permeability.

Waldburger and Widmer (1996) presented a review on membrane reactors with special emphasis on membrane-assistance of esterification reactions and a continuous tube membrane reactor for the pervaporation-assistance of the esterification. The heterogeneously catalyzed esterification of ethanol and acetic acid to ethyl acetate and water was investigated as a typical chemical equilibrium reaction. The selective and simultaneous water separation from the reaction mixture of the esterification with polyvinyl alcohol pervaporation membranes was considered to be an interesting process alternative to the conventional distillation process. Compared to the distillation process, for the pervaporation-assisted process a decrease of the energy input of over 75% and of the investment and operating costs of over 50% each was calculated.

Zhu and coworkers (1996) studied on a continuous pervaporative membrane reactor of esterification reaction between acetic acid and ethanol, by using a polymeric/ceramic composite membrane. The membranes showed reasonable fluxes and separation efficiencies toward water, a product of reaction. During water removal in experiment, reactor conversions were observed which were higher than the corresponding calculated equilibrium values.

Pichai (1997) investigated the effects of barakol extraction from Cassia siamea Lamk. and concentration by pervaporation. It was found that the extracted solution containing barakol was concentrated by pervaporation process in tubular silicone module. The operating conditions were carried out at various feed temperature, permeation pressure. It was showed that the permeation flux was increased with increasing feed temperature. And the permeation flux was decreased with increasing permeation pressure. The permeability of ethanol was higher than water and barakol. The result indicated that the performance of ethanol separation was better than water and barakol, respectively. The membrane selectivity of ethanol was higher than water. The increase of concentration was resulted from ethanol vaporization and permeation of water and ethanol.

Lalita (2000) studied the suitable condition for removing water from crude extract from Cassia siamea by pervaporation process by using crosslinked polyvinyl alcohol with glutaric acid membrane. Firstly the systhesized membranes were prepared and tested with sorption process. It was found that sorption ability of water and crude extract in membrane were better than ethanol. Secondly, The removal of water from crude extract from evaporation process by pervaporation process in plate and frame module was performed at various operating parameters. It was found that water permeation flux was increased with increasing feed temperature and with lowering permeate pressure. Barakol in crude extract from Cassia siamea can not permeate through the membranes because of its molecular size and complex structure.

Liu and coworkers (2001) developed a kinetic model for the coupling esterification of acetic acid with n-butanol catalyzed by $Zr(SO)_4$-$4H_20$ with pervaporation. Experiments were conducted to investigate the effects of several operating parameters, such as reaction temperature, initial molar ratio of acetic acid to n-butanol, ratio of the membrane area to the reacting mixture volume and catalyst concentration, on the coupling process.

3 Assabumrungrat, Kiatkittipong, and Praserthdam (2003) studied the synthesis of ethyl tert-butyl ether (ETBE) from a liquid phase reaction between ethanol (EtOH) ethyl and tert-butyl alcohol (TBA) in pervaporation membrane reactors (PVMRs). Three modes of PVMR operation; semi-batch reactor (SBR), continuous stirred tank reactor (CSTR) and plug flow reactor (PFR) were modeled using kinetic parameters of the synthesis over beta-zeolite and permeability data for a polyvinyl alcohol (PVA) membrane. The study focused on comparing PVMR performances between two modes of continuous flow operation for various operating parameters. It was found that the CSTR mode shows superior performance to the PFR mode only within some ranges of operating conditions. To obtain high ETBE yields, it is best to operate the PVMRs at low temperature with a high ratio of membrane area to catalyst weight and with the feed ratio of EtOH and TBA at the stoichiometric value or slightly higher.

Assabumrungrat, Phongpatthanapanich and Praserthdam (2003) investigated the synthesis of methyl acetate (MeOAc) from methanol (MeOH) and acetic acid (HOAc) in pervaporation membrane reactors (PVMRs). Semi-batch (SB-PVMR), plug-flow (PF-PVMR) and continuous stirred tank (CS-PVMR) were modeled using the kinetic parameters of the reaction over Amberlyst-15 and permeation parameters for a polyvinyl alcohol (PVA membrane). The PVA membrane shows high separation factors for HOAc and MeOAc but very low for MeOH. The study focused on comparing PVMR performances between two modes of continuous-flow operation for various dimensionless parameters, such as Damkohler number (Da), the rate ratio, the feed composition and the membrane selectivity. Flow characteristic within the reactors arisen from different operation modes affects the reactor performance through its influences on the reaction and permeation rates along the reactor. There are only some ranges of operating conditions where CS-PVMR is superior to PF-PVMR.

Kittisupakorn and coworkers (2003) studied on hybrid pervaporative membrane reactor for esterification of butanol and acetic acid. Optimization framework was formulated to determine an optimal temperature policy maximizing a desired product. The optimal temperature profile obtained was controlled using generic model control (GMC) technique incorporated with data reconciliation-based estimator. The implementation results provided satisfactory control performance. It was also found that the estimator showed an estimation of heat released by reaction.

2.2 Literature review on Neural Networks

2.2.1 Origin of Neural Networks

At the beginning of the chronological overview of neural network research, the work by McCulloch and Pitts , in 1943 essentially stared the modern age of neural networks. The McCulloch and Pitts neuron was very simple neuron, which had a linear activation function with a threshold value to produce an output. The network was a two-layer network, and there were no training of these neurons. However, the McCulloch and Pitts neuron model laid the foundation for future developments in neural networks.

In 1949, Hebb described a learning process that was postulated from neurobiological viewpoint. The information was stored in the connections of the neurons and postulated a learning strategy for adjustment of the connection weights. This was the first time a learning rule was presented that allowed for adjustment of the synaptic weights.

Later, in 1985, Rosenblatt developed the original concept of perceptron and demonstrated that perceptrons can generalize and learn. The perceptrons consisted of neuron-like processing units with linear thresholds, and were arranged in layers similar to biological system. They used the Hebbian learning rule for training. This rule reinforces active connections only-weight were increased when the outputs are active, and decreased when the outputs are inactive.

In 1962, Widrow and Hoff developed the Adaline (adaptive linear element). The Adaline was trained by the least mean square (LMS) learning, closely resembles Rosenblatt's perceptron. The Adaline used target value to calculate the prediction error and moves the weight values in the direction of negative gradient of the error.

In 1969, Minsky and Papert proposed that single layer neural networks had limited capabilities. One such example was the inclusive XOR problem. The neural network research slowdown in this period.

In 1972, Kohonen published his paper on correlation matrix memories. Later, in 1974, Werbos proposed the backpropagation algorithm for training multilayer feedforward perceptron. Multilayer perceptrons with nonlinear activation functions were capable of solving nonlinear problems.

In 1987, Carpenter and Grossberg developed self organizing neural networks based on adaptive resonance theory (ART).

2.2.2 Chemical process modeling, identification and estimation with neural network

Bhat and McAvoy (1989, 1990) discussed the use of backpropagation neural net for dynamic modeling and control. In which an isothermal CSTR reactor was considered and MFFN was trained to optimize the reactor yield, by using backpropagation algorithm. Bhat and McAvoy (1989,1990) and Saint- Donat, Bhat, and McAvoy (1991) used a MFFN for the dynamic modeling of a simulated nonlinear pH system.

Narenda and Parthasarathy (1990) introduced the models that MFFN and recurrent neural network (RNN) were interconnected in novel configuration for both identification and control. It was found that the neural networks could be used effectively for the identification and control of nonlinear dynamical systems.

Ungar, Powell, and Kamens (1990) modeled a bioreactor with two controlled variables and one manipulated variable using MFFN.

Chitra (1992) described an application of MFFN for developing chemical kinetics of a catalytic process. The neural network model was better in several temperature and catalytic loading regions, compared to a statistical power-law model quadratic model.

Nahas, henson, and Seborg (1992) utilized the three layer feedforward networks trained with conjugated gradient algorithm to model the continuous stirred tank reactor (CSTR) and the pH neutralization process and implement them in the nonlinear internal model control (NIMC).

Pollard et al. (1992) demonstrated that MFFN models could be built for real industrial processes. They conducted experiments on distillation column unit with one input (column reflux flow rate) and one output (tray temperature) and obtained a neural network dynamic model. They also demonstrated the utility of cross validation.

Psichogios and Ungar (1992) develop a hybrid model for a fedbatch bioreactor. The hybrid model combined a partial first principles model, which incorporated the available prior knowledge about the process being model, with a neural network which served as an estimator of unmeasured process parameters that are difficult to model from first principles. The training method for the neural network was the error backpropagation algorithm. They found that the hybrid model had better properties than standard black-box neural network model in that it is able to interpolate and extrapolate much more accurately. Furthermore, it was easier to analyze and interpret and required significantly fewer training examples.

You and Nikolaou (1993) utilized the recurrent neural network (RNN) to model static and dynamic relationship of a pH CSTR and a biochemical batch reactor. They found that the modeling capabilities of RNN were comparable to those of the MFFN, but the training of RNN took longer time.

Kurtanjek (1994) studied the use of MFFN to model the baker's yeast production. This study was found that the network was effective tool for modeling of complex system such as biological processes.

Thompson and Kramer (1994) presented a method for synthesizing chemical process model that combined prior knowledge and artificial neural networks. The examples of case study were model synthesis of fed batch penicillin fermentation.

MacMurray and Himmelblau (1995) examined a number of different types of artificial neural networks, including MFFN, externally recurrent network (ERN), internally recurrent network (IRN), diagonally recurrent network (DRN), and combinations of ERN and IRN, to model the packed distillation column. They found that externally recurrent network (ERN) had the best performance in predicting the process output many time step ahead in the future, furthermore, the network model was as good or better than a simplified first proncíples model when used for model predictive control.

Lou and Perez (1996) used the backpropagation algorithm in conjunction with Kalman filtering in order to establish a new self-learning technique of MFFN. They found that this new technique was faster and more stable than the classical backpropagation algorithm for training MFFN. Moreover, it was less sensitive to the initial weights and to the learning parameters.

Nikravesh et al. (1996) adopted the MFFN in conjunction with recursive least squares to identify the model of a nonisothermal CSTR with time varying parameters. They found that their technique could be used effectively for model identification of nonlinear time variant processes.

Emmanouilides and Petrou (1997) used the MFFN to identify and control anaerobic digester process. Adaptive online training with random search optimization techniques, random search and chemotaxis, as well as backpropagation algorithm were applied to improve the modeling and control performance. From the results, the random search techniques converged much faster than the backpropagation algorithm.

In 1997, Sabharwal and coworker used the approach that integrated a neural network and dynamic simulation modeling to achieve quality control and increase throughput. It was developed for the no. 2 XY splitter of the xylene distillation unit as part of a new advanced quality control (AQC) project in the Japan Energy Corp. Mizushima Oil Refinery.

Lanouette and coworker (1999) improved the modeling of complex processes when only small experimental data sets were available. Feed-forward and radial basis function neural networks was used in this problem. In addition, the influence of activation functions, the number of levels in stacked neural networks and the composition of training data set were studied. The study showed that the use of neural network was a powerful tool for modeling complex processes even when only a small set of data was available for training. A higher number of stacks led only to increase of the confidence level. However, radial basis function presented some weakness for modeling properly a process when data landscape lacked smoothness.

Shene and coworker (1999) designed two different neural network to predict the state variable (biomass, substrate and ethanol concentration) of *Z. mobilis* CP4 batch fermentations. The designed networks were black-box neural networks and the combination of neural network and a mathematical model. Experimental data recorded from batch fermentations carried out under different condition were used to train the net and test its prediction. From the results presented, The error for utilizing the combination of neural network and a mathematical model was higher than black-box neural network. Anyhow, the prediction of using both cases could be carried out using neural networks.

Aziz and coworker (2000) investigate the performance of different types of controllers in tracking the optimal temperature profiles in batch reactor. That the neural network was used as the online estimator the amount of heat release by hemical reaction within the GMC algorithm. The GMC controller coupled with a neural network based heat release estimator was found to be more effective and robust than PI and PID controllers in tracking the optimal temperature profiles.

Gontarski and coworker (2000) presented the way to predict the environmental properties of output stream from the wastewater plant.The industrial plant produces purified terephtalic acid and generates wastewater that should be treated in an activated sludge system. The influence of input variables was analysesd, and satisfactory predicted results were obtained for an optimized situation.

Nongluk (2001) investigated the neural network to predict melt index and density in polyethylene plant. The parameters, online temperature, pressure, flow rate and gas composition were input data of neural network. These adjustable parameters were updated online using infrequent laboratory measurements and error backpropagation and Lavenberge-Marquart techniques. It was shown that both melt index and density which were key index of product quality could be successful predicted.

2.2.3 Neural Network Applications in Control Systems

Artificial neural networks can be used as a representation framework for modelling nonlinear dynamic systems. It also possible to incorporate these nonlinear models within nonlinear feedback control structure. Neural networks are often used in many control configurations, for example, model predictive control, inverse-model-based control, and adaptive control.

- **Model predictive control**

Psichogios and Ungar (1991) utilized a neural network model of a continuous stirred tank reactor (CSTR) to control the product composition in.the conventional model predictive scheme where they found that steady state offsets were obtained during set point tracking. However, they made corrections to the output, accounting for modeling error and unmeasured disturbances entering the process, and obtained offset-free tracking in this case.

Lee and Park (1992) applied neural network in DMC configuration. The neural network was taught to learn about the relationship between the disturbance pattern and the desired control actions by minimizing the controller output due to unmodeled effects. In this case the neural network basically acts as a feedforward controller to cater for unknown disturbances in the system. This scheme was then applied to control the product compositions in a distillation column under disturbances and plant-model mismatches. They found that the neural scheme performs better than the conventional feedforward DMC controller.

In 1994, Wormsiey and Henry used neural-network models within a model predictive control scheme to control the distillate temperature in a laboratory-scale distillation apparatus separating methanoi and water. An exhaustive search method was used for optimization and they obtained good set point and disturbance-rejection results in their study.

Temeng, Schnelle, and McAvoy (1995) used a recurrent network to model an industrial multi-pass packed bed reactor which is then used in conjunction with an optimizer to build a nonlinear model predictive controllers. The controller was then used to regulate the temperatures within the reactor under disturbance rejection cases.

The closed loop results they obtained indicate that the neural network-based controller could achieve tighter control than is possible with decentralized single loop controllers.

VanCan et al. (1995) utilized a neural network by numerically inverting the forward model and implementing it as a predictive controller. This was implemented on a laboratory pressure vessel to control the pressure by manipulating the inlet air flowrate. Experiments were done for set- point tracking and comparisons were made with the PI and linear model-based controllers. They found that the response of the neural network based controller was faster than the conventional approaches especially at larger set point changes.

Tsen et al. (1996) used a hybrid neural-network that integrates experimental information and knowledge from a mathematical model for control of quality in an experimental batch polymerization reactor. The hybrid model is utilized for identifying the unknown and unmeasured disturbances in the initial charge of the batch reaction, which is formulated in a model predictive control strategy. The strategy was applied on a real experimental system to achieve the desired product conversion in the least possible time.

Emmanouilides and Petrou (1997) utilized neural networks in a model predictive scheme to control the substrate concentration and pH of a complex nonlinear anaerobic digestion system. In his implementation, the neural network models were adapted online. The simulation results showed that the control strategy gave desired set point tracking and regulation even under process input variations and process parameter changes.

- **Adaptive control techniques**

In 1995, Boslovic and Narendra applied both the conventional multilayered neural network and radial basis function networks in an adaptive control scheme, which updates the unknown parameters online, for production of baker's yeast in a fed-batch fermentation process. They considered the set point regulation of the system under no-noise and Guassian noise cases. They found that the conventional multilayered network gave superior performance over the RBF and other nonlinear techniques such as the nonlinear adaptive and inverse dynamics controller.

In 1995, Lightbody and Irwin used a neural network in parallel with a fixed gain linear controller in a direct model-reference adaptive control configuration to control the product composition in a CSTR system. Another neural network in parallel to the nonlinear system is used to generate the plant jacobians for updating the neural network controller online. They showed that this method provided greatly improved performances over the conventional PI controller under linear model reference output tracking.

Loh, Looi, and Fong (1995) used neural networks in conjunction with a PID in a model reference adaptive strategy to control a process pH. In this case the network consists of a cascade of two single hidden layer nets: the first being a recurrent network to reflect the dynamic nature of the neutralizing reactor and the second net is a static one to reflect the static nature of the titration characteristic. Their results indicated good set point tracking performance even under external load disturbances.

Chovan, Catfolis, and Meert (1996) used neural networks in a clustered scheme (combination of clusters of neural network controllers and models) within the indirect adaptive control method. They adopted real-time learning with the controller trained by backpropagating the error through the network model. They performed set point tracking for the control of cell mass yield in a bioreactor system with successful results.

Syu and Chang (1997) utilized a recurrent backpropagation neural network for online adaptive control of a penicillin acylase fermentation process. In enhancing the effective online learning of the network, moving data scheme was supplied to train the network. The pH of the system was well controlled in their experiments with maximum optical density achieved under different types of disturbances.

- **Inverse model based techniques**

Psichogios and Ungar (1991), who utilized an internal model control (IMC) approach to control product concentration in a nonisothermal CSTR with first order irreversible reactions by manipulating the inlet feed temperature. Their control strategy was concerned with disturbance rejection where the disturbance was the change in feed concentration. The inverse-model-based controller was obtained by inverting the neural network model, describing the process dynamics, using Newton 's method numerically. However, they obtained unstable results when directly utilizing the inverse neural network models as the controller in the IMC configuration.

Nahas, Henson, and Seborg (1992) also utilized the IMC approach to control the effluent concentration in a CSTR, with first order irreversible exothermic reactions. The inverse model was obtained by numerically solving for the control action, from the formulation of the network forward model. Filtering action and time delay compensation, in the form of a Smith predictor, were also used an offset-free results were obtained in both the set point tracking and disturbance rejection cases. They also implemented the same strategy in controlling the base flow rate. Offset-free results were also achieved here for set point and disturbance rejection cases.

Nikolaou and Hanagandi (1993) used a recurrent neural network within a state feedback linearizing control strategy to control the temperature of a non-isothermal CSTR system. In this case the recurrent neural network acts as the open-loop observer supplying the network states to the linearizing control formulation. An external linear controller was also applied to the system and the whole strategy, implemented for set-point tracking and disturbance-rejection studies, showed better performance than the linear, optimally tuned controller.

Scott and Ray (1993) developed recurrent neural networks (which also have direct connections from inputs to outputs) where the topology and initial weights of the network were determined from an approximate linearized model of the system. These networks were then consequently prune to remove the weights with negligible values and these networks were then applied in various model-based control methods such as the direct control and IMC methods. These methods were applied to the task of controlling both the concentration and temperature of a non-isothermal CSTR under set-point regulation, plant-model mismatches and disturbance-rejection studies. They showed that these neural network based controllers perform was better than the linear methods in controlling the process over a wide range of conditions.

In 1994, Dayal, Taylor, and MacGregor also implemented the IMC approach for the control of a jacketed CSTR, with first order irreversible reactions, to keep the reactor conversion at its desired setting. A feedback as well as reference model filter was used in this case. In their study they compared the usage of a numerically inverted neural network inverse-model controller for set point as well as disturbance rejection studies. They found that the directly framed neural-network inverse-model as the controller case gave better results overall (except for a slightly bigger oscillation at the step changes) than the numerically inverted inverse-model method, with yet less computational time. They also incorporated a feedforward-feedback strategy to improve on the disturbance-rejection results. However, for the non-monotonic case (i.e. process has well-defined maximum conversion and the steady state gain changes sign) the directly trained neural network inverse-model gave unstable results, which they accounted to the presence of input multiplicity in the reactor behavior.

In 1994, Seborg used a neural network with radial basis function activation to control the pH in a two-tank neutralization system. An internal model control structure was utilized with the controller designed to minimize some performance criteria. The experiment was performed to regulate the pH under disturbances in the acid and buffer flow rate. They found that the results gave significant improvements over the PI control action.

Dirion et al. (1995) used neural networks as direct-inverse controllers to control temperature in a bench-scale semi-batch jacketed glass reactor equipped with a mono-fluid heating-cooling system. Simulations and experiments were done for set point tracking of the temperature profile in this semi-batch set up with reasonably good results.

Hussain, Kershenbaum, and Allwright (1995) utilized a neural-network-based IMC strategy for controlling the temperature of a partially simulated reactor in a pilot plant. They implemented the strategy for set point tracking, disturbance rejection and regulation under plant-model mismatches. The results obtained were found to be comparable with the conventional cascade method with, however, less fluctuations in the control action demanded.

In 1995, Lightbody and lrwin developed a novel nonlinear model control strategy which utilized the nonlinear neural network model of the plant to act as a medium for the estimation of the parameters of the linear discrete- time model (assumed for the plant). This linear model is then utilized in conjunction with Kalman 's method to design the inverse controller, wherein the parameters of this controller are adapted at each sample instant. They used this approach for set point tracking of concentration in a CSTR system, which outperformed the conventional PID control system.

Ramchandran and Rhinehart (1995) used a neural-network inverse model to estimate the reflux and the holdup rate, which was then incorporated in the Generic Model Control (GMC) strategy to control the top and bottom composition in a distillation column. The GMC technique basically involves incorporating the nonlinear process model directly in the formulation of the control algorithm (Lee and Sullivan, 1988). This was done for set point tracking and disturbance-rejection cases and the technique was found to be better than the PI controller with feedforward features.

Aoyama, Doyle, and Venkatasubramaniam (1996) used a neural network to construct a minimum-phase model of a non-minimum phase system in conjunction with the analytical inverse of the system model within the IMC strategy. This scheme was applied successfully to control the system composition in a Van de Vusse reactor and a bioreactor system under set point and disturbance-rejection cases.

Santi (1996) used recurrent feedforward neural network (RFNN) as modeling of gravity flow tank process and CSTR. In addition, the inverse models were designed as controllers. Both RFNN model and controllers were trained by backpropagation algorithm. That the neural networks based controller, namely, adaptive neural network controller without error, adaptive neural network, nonlinear internal model and simple feedback neural network controllers were proposed; and their performance were compared with PID controller.

Juthatip (1999) utilized the multilayer feedforward networks for system identification. The industrial front-end acetylene hydrogenation system was studied in this case. For system identification, neural networks were trained by plant input-output data to learn the plant dynamics. Error backpropagation and Lavenberge-Marquardt algorithm were employed to train the networks. It was found that the neural network provided good prediction results. Furthermore, the neural networks were used as a function approximation in GMC method. The use of neural network as a nonlinear controller in nonlinear internal model control algorithm was also investigated. The CSTR system was studied in last two cases. For function approximation of neural network in GMC, it was found that control performance of GMC was improved in the presence disturbances and plant-model mismatch. In the neural network acted as controller, the results showed that the neural network used as controller in NIMC could control reactor temperature at its set point. However it produced some off set when tested with disturbances rejection.

Hussain, Kittisupakorn and Daosud (2001) investigated the use of neural network based inverse model control strategy to control an exothermic reactor. The utilization of inverse model schemes namely the direct inverse control and the internal model control methods were shown for both set point and disturbance injection cases.

The overall results for set point tracking were good in both control strategies but direct inverse control method had limitation when dealing with disturbances.

Kittisupakorn and coworker (2001) used neural networks in conjunction with GMC and PI controller. The CSTR system was studied. The neural network is used as a function estimator in GMC method and as a model and controller in IMC-PI method. Various simulation involving set point tracking and disturbance rejection under nominal and model mismatch. The results of hybrid controller were found to be better than conventional PID and GMC methods.

Aziz, Hussian and Mujiba (2003) used neural network inverse model based control (NN-IMBC) to track the optimal reactor in complex exothermic batch reactor. It was also evaluated through a few robustness tests. Furthermore, neural network estimator was embedded to strategy as the online estimator to estimate the amount of heat release by the chemical reaction The NN-IMBC was found to be well performed in tracking both set point and accommodating changes within its range of training. It also promised robust controller if it is trained with a wide range of reactor temperature covering all possible condition.