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Review of the applications of neural networks in chemical process control — simulation and online implementation

Mohamed Azlan Hussain*

Chemical Engineering Department, University Malaya, 50603 Kuala Lumpur, Malaysia

Abstract

As a result of good modeling capabilities, neural networks have been used extensively for a number of chemical engineering applications such as sensor data analysis, fault detection and nonlinear process identification. However, only in recent years, with the upsurge in the research on nonlinear control, has its use in process control been widespread. This paper intend to provide an extensive review of the various applications utilizing neural networks for chemical process control, both in simulation and online implementation. We have categorized the review under three major control schemes; predictive control, inverse-model-based control, and adaptive control methods, respectively. In each of these categories, we summarize the major applications as well as the objectives and results of the work. The review reveals the tremendous prospect of using neural networks in process control. It also shows the multilayered neural network as the most popular network for such process control applications and also shows the lack of actual successful online applications at the present time. © 1998 Elsevier Science Ltd. All rights reserved.

Keywords: Chemical process control; Neural networks; Simulation; Online application

1. Introduction

In recent years an active interest in the development and application of nonlinear control methodologies has emerged. Nonlinear control now occupies an increasingly important position in the area of process control engineering as reflected by the tremendous increase in the number of research papers published in this area recently. However, in many nonlinear systems it is extremely difficult and expensive to obtain an accurate model of the process from first principles. This difficulty has limited the usage of nonlinear models to regions and systems where the model obtained is reliable. In fact, one of the chief barriers to the more widespread use of nonlinear models in advanced modeling and control techniques in the chemical/petroleum industry is the cost of model development and validation. Normally modeling costs account for over 75% of the expenditures in the design of an advanced control project.

At the same time, the recent upsurge in research on neural networks, has made it readily available as an attractive method for identifying nonlinear processes. Since neural networks can learn by example, they offer a cost-effective method of developing useful process models. These connectionist models also have the ability to learn the frequently complex dynamic behaviour of a physical system. In fact recent work, e.g. Cybenko [1] and Hornik et al. [2], have proved that any continuous functions can be approximated to an arbitrary degree of exactness on a compact set by a feedforward neural network comprising two hidden layers and a fixed, continuous non-linearity.

Although neural network application in various aspects of engineering have been around for some time, there have been a 'explosion' of its applications in areas relevant to chemical engineering only recently. This can be attributed to many reasons, some of which are as follows:

1. The tremendous hardware advances in digital technology over the past decade or so have enabled simulations of neural nets to be made both economically and with relative ease and speed. Although neural networks are parallel devices, the majority of their simulations at present are being simulated sequentially on serial computers. Neural networks will be more efficiently utilized as parallel computing technology becomes more readily available.
2. Application of neural networks for sensor pattern classification have been found to be superior to the traditional algorithmic techniques or the expert system approaches.

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* Corresponding author. Fax: 00 603 759 5319; e-mail: azlan@fk.um. edu.my

3. Neural networks offer the promise of being able to extract information from plant in an efficient manner with normal availability of rich data. In some cases, it may not be cost effective to develop models from first principles at all times, especially those dealing with severe/unknown non-linearities commonly found in chemical process systems. Neural networks offer a simpler and efficient alternative.

4. Some practitioners contend that neural networks may be easier to use and apply in the real process plant, with difficult to handle nonlinearities, as compared with the modeling approach which can be subjected to various modeling errors.

5. Finally the versatility in structure and application of neural networks enables them to be utilized in the middle ground between conventional model-based approaches and black box approaches for solving many classes of problems. These hybrid-type approaches have been another factor which have further attracted their use in chemical process systems recently.

Although they have been successfully used for a number of chemical engineering applications such as sensor data analysis, fault detection and process identification, its widespread use for chemical process control has only emerged lately. This paper intends to review all such process control application in the chemical engineering field in recent years. Although there have been some isolated reviews previously [3, 4], this paper presents an extensive review of its application in chemical process control presented in the open literature. Our survey in this paper involves its incorporation in three major categories of control i.e. inverse-model based, predictive and adaptive control techniques, both in simulation and online applications. Under these different control techniques, we will only discuss the general description of their methods as the detailed discussion of these various techniques utilizing neural networks can be found elsewhere [5]. In general, the predictive control methods have the advantage of being stable with less drastic control actions, but with more computational time required. The inverse-model-based control methods have the advantage of giving faster implementation, but require more drastic control actions which tend to lead to instability problems. The adaptive control methods on the other hand are suitable for models with varying parameters but they are also prone to instability problems especially in nonlinear systems.

The majority of the neural networks utilized in these applications are the multilayered feedforward type inclusive of the radial basis function networks. Numerous references can be found in the literature on their properties, advantages and limitations [6–10]. The other types of networks used are the recurrent networks and the vector quantizing network (VQN). Various references are also available on these recurrent networks [11–13] while some overview and references on VQNs will be given later. There is no clear advantage of one network over the other as well as of one activation function over the other. This will very much be dependent on the user and their application and has to be looked on a case-to-case basis. Some comparisons between the different types of networks can be found in [14, 15] while the comparisons between the conventional sigmoidal and the radial basis function activation functions can be found in [16–18].

The applications utilizing these neural-network-based strategies are wide ranging but involve typical chemical process systems ranging from the linear to the highly nonlinear systems. The detail description and characteristics of these processes can be found in standard textbooks [19–23]. However, the most common systems used are the distillation columns and the reactor systems (continuous stirred tank reactors, bioreactors and the neutralizing reactors). These are multivariable, nonlinear systems, which are highly suitable for testing such control algorithms in chemical process systems. Neural networks have also been used for other specific purposes such as the auto-tuning of PID controllers [24] and have also been incorporated with other types of techniques, such as the cerebellar model articulation controller (CMAC), the B-splines network [25] and fuzzy systems [26], which are, however, beyond the scope of this review.

2. Neural network in model-predictive control techniques

2.1. General description

The most commonly found control technique, which uses neural network models is the predictive control technique. It is defined as a control scheme in which the controller determines a manipulated variable profile that optimizes some open-loop performance objective on a time interval, from the current time up to a prediction horizon. Nonlinear model prediction control refers to the general case in which the model, performance objective and constraints are nonlinear functions of the system variables. In this case, neural networks are used as convenient identified models to replace the normal first-principle-models in the optimization formulation. The increasing popularity of the neural-network-based-predictive-technique is due to the attraction of using neural network models instead of other forms of model to effectively represent the complex nonlinear systems within the predictive methodology [24]. Some of the advantages of using neural networks in optimal control strategies over other conventional and linearly parametrized models are also given in the paper of Edwards and Goh [17].

This predictive control algorithm basically involves minimizing future output deviations from the set point whilst taking suitable account of the control sequence necessary to achieve the objective and the usual constraints imposed upon it (see Fig. 1). This multistep predictive control strategy has been shown to perform well in unstable operating
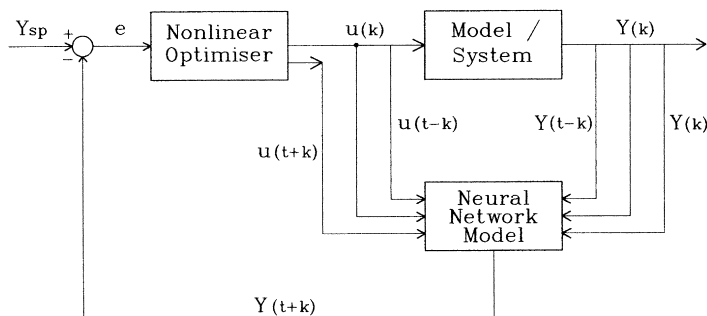
Fig. 1. Neural networks in general model predictive control strategy.

regimes and inferential applications, but at the expense of extra computational time. Neural networks are highly suitable for incorporation in this approach as it is known to be able to predict multistep ahead output values. The neural network predicts the outputs for some k time step into the future ($y(t + k)$) and the normal cost function, J is used to obtain the optimal sequence of control actions given by,

$$J = \sum_{k=N_1}^{N_2} [e(t + k)]^2 + \sum_{i=1}^{N_3} [q_i \delta u(t + i)]^2$$

where N_1, N_2 define the prediction horizon, N_3 define the control horizon, e is the error between target and prediction, q is the weighting factor and δu are the change in control sequences. The first term is a measure of the distance between network prediction and desired future trajectory and the second term penalizes excessive movement of the manipulated variables. This methodology is very similar to the classical optimal control strategy except that the forward neural net model is utilized in the equality constraint equations instead of the nominal plant model. The gradient and hessian matrix used for solving the optimization using 2nd order methods are normally formulated in terms of the structure of the neural network i.e. weights and biases [27, 28].

The different advanced techniques, which have been used by many researches for incorporating neural networks models within their formulation include the general predictive control (GPC) [29], dynamic matrix control (DMC) [30] and receding horizon control (RHC) [31] techniques. These techniques are very similar in their overall approach and objective with the differences occurring in the sequence of control implementation and in the underlying formulation of the models and constraints. The GPC approach is formulated with the models based on a difference-equation scheme while the DMC approach is based on a step-response model. In the RHC technique, feedback is incorporated in the predictive control scheme by using the measurement to update the optimization problem for the next time step, when the control action is also implemented. Note that the description of all abbreviations can be seen in Table 1.

2.2. Applications in chemical process systems

Most of applications under the predictive control scheme utilizes the multilayered feedforward neural network type while a couple utilizes the recurrent type and the VQN type, respectively. These applications, with their objectives, system and type of network are summarized in Table 2. The major applications are described in further details later, beginning from the multilayered type.

In one of the earliest reported simulation work, Psichogis and Ungar [32] 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 errors and unmeasured disturbances entering the process, and obtained offset-free tracking in this case. Willis et al. [33], Turner et al. [34], and Hunt and Sbarbaro [35] also estimated the plant–model mismatch at each sampling instant and utilized it to correct the predictions from the model in their model predictive control schemes. They implemented their control action using the receding horizon method. Willis et al. implemented the scheme for the control of concentration in a CSTR; Turner implemented it for the control of concentration in a distillation column while Hunt implemented it for the control of pH in a neutralizing reactor. Offset-free set point tracking results were obtained by them in all these cases. Gokhale et al. [36] used a steady-state multilayered neural-network model to replace the tray-to-tray model used in a predictive model based controller to control the product compositions in a propylene–propane splitter. They found that the neural-network scheme, with online filtering, performed slightly better than the nonlinear model-based controller for set point changes in the top and bottom compositions (with sluggish response for the bottom composition). Emmanouilides and Petrou [37] 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

Table 1
Description of abbreviations

Abbreviations	Description
Control technique	
D. Inv	Direct inverse
M. Pred	Model predictive
Adap	Adaptive
FBC	Feedback controller
Pb Adap	Pattern based adaptive
GPC	Generalised predictive controller
IMC	Internal model controller
Infer	Inferential
PI	Proportional integral
Hybr	Hybrid
Em	Emulate
DMR	Direct model reference
Adapt	Adaptation
DMC	Dynamic matrix control
Ext. DMC	Extended dynamic matrix control
GMC	Generic model control
FFd	Feedforward
LC	Linearising controller
Objective/system	
Temp	Temperature
Press	Pressure
Thick	Thickness
Prod	Product
Conc	Concentration
Comp	Composition
CSTR	Continuous stirred tank reactor
Dis	Distillation
Neut	Neutralising/neutraliser
MW	Molecular weight
Poly	Polymerisation
Neural network type	
Ml	Multilayer
Sig	Sigmoidal
Hyp	Hyperbolic
RBF	Radial basis function
Tanh	Tangent
Sym	Symmetric
Log	Logarithmic
VQN	Vector quantizing network
Ellp	Ellipsoidal
Robustness	
Set pt.	Set point
Dis	Disturbance

desired set point tracking and regulation even under process input variations and process parameter changes.

Two studies utilizing neural networks in the dynamic matrix control (DMC) algorithm have also been reported. Hernandez and Arkun [38] applied neural networks to estimate the disturbance due to the presence of nonlinearities. This was then added to the linear model in the DMC formulation with online learning of the neural network models. This algorithm was applied for control of concentration in a CSTR system (with multiple steady states) for set-point tracking and disturbance–rejection case studies. They achieved better results in both cases as compared with the conventional linear DMC method. In the work of Lee and Park [39] 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 unmodelled 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 compositions in a multiple reaction CSTR system and 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.

The use of recurrent neural networks in these model predictive schemes were reported in two cases. Macmurray and Himmelblau [40] used an external recurrent neural network to predict and control the product compositions in a packed distillation column within the model predictive control strategy. This was done for set-point and disturbance–rejection studies. They obtained the same results as those obtained using first principles model, but with less computation time when using the neural network model. Tan and VanCauwenberghe [41] compared three different optimizing methods for the design of an external recurrent neural network predictive controller based on Smith-type prediction. They used this technique successfully to compensate for large time delays in the control of an anaerobic digester process under set point tracking.

The vector quantizing neural networks (VQN) were applied by Megan and Cooper [42] to analyse both the input and output behaviour of a process resulting from a perturbation to the process. The VQN's are basically discrete pattern classifiers that compare an incoming pattern to a library of example patterns and assign the incoming patterns to the class of example pattern which is most similar to it. Like the feedforward networks, it consists of nodes but every node in a VQN receives the entire incoming pattern and produces an output of the network. The details of the VQNs can be seen in [43, 44]. The work by Megan and Cooper focuses on making model adaptations following a load disturbance to a reactor under concentration control and is also applied within a DMC algorithm for multivariable composition control of a distillation column, with successful results.

3. Neural networks in inverse-model-based techniques

3.1. General description

Two approaches utilizing neural networks in the inverse-model-based strategy are the direct inverse control and the internal-model control (IMC) techniques. In the direct inverse control technique, the inverse model acts as the

Table 2
Summary — applications of neural networks in predictive control strategies

Control technique	Objective	System	NN type	Robustness	Ref.
M. Pred	Prod. Comp.	Dis. column	Ml/Sig	Set pt./Dist.	[33]
M. Pred. w/Feedback	Prod. Conc.	CSTR	Ml/Sig	Dist.	[32]
M. Pred.	Strip Thick.	Rolling mill	Ml/RBF	Set pt.	[50]
M. Pred.	Prod. Conc.	CSTR	Ml/Sig	Set pt.	[27]
M. Pred.	pH control	Neut. reactor	Ml/Sig.	Set pt.	[28]
DMC w/NN FFd	Prod. Comp.	Dis. column	Ml/Hyp. Tanh	Dist.	[39]
Ext. DMC	Prod. Conc.	CSTR	Ml/Sig.	Set pt./Dist.	[38]
M. Pred.	Prod. Quality	Autoclave batch curing	Ml/Sig.	Dist.	[96]
M. Pred.	pH control	Neut.	Ml/Sig.	Set pt.	[75]
M. Pred. w/Adapt.	Level	Conical tank	Ml/Sig.	Set pt./Dist.	[94]
M. Pred. w/Adapt.	Multivariable	Evaporator	Ml/Sig.	Set pt./Dist.	[94]
M. Pred.	pH control	Neut.	Ml/RBF	Set pt.	[35]
M. Pred.	Prod. Comp.	Packed column	Recurrent/Sig.	Set pt./Dist.	[40]
M. Pred.	Prod. Comp.	Dis. column	Ml/Sig.	Set pt.	[36]
M. Pred.	Press.	Dis. column	Ml/Dynamic filter	Set pt.	[34]
M. Pred.	pH control	Neut.	Ml/Sig. and RBF	Set pt.	[97]
M. Pred.	Temp.	Anthracene crystal process	Ml	Set pt.	[98]
D. Pred.	Conc.	Digester	Recurrent	Set pt.	[41]
DMC	Conc.	Dis. column	VQN	Dist.	[42]
M. Pred	pH	Neut.	Ml/RBF	Set pt./Dist.	[99]
M/ Pred w/Adapt.	Conc./pH	Anaerobic digester	Ml	Set pt./Dist.	[37]

controller in cascade with the system under control, without any feedback. In this case the neural network, acting as the controller, has to learn to supply at its output the appropriate control parameters for the desired targets at its input. In this control scheme the desired set point acts as the desired output which is fed to the network together with the past plant inputs and outputs to predict the desired current plant input [45]. A much more robust and stable strategy is that of the nonlinear internal model control technique, which is basically an extension of the linear IMC method [46] (see Fig. 2). The IMC approach is similar to the direct inverse approach above except for two additions. First is the addition of the forward model placed in parallel with the plant, to cater for plant or model mismatches and second is that the error between the plant output and the neural net forward model is subtracted from the set point before being fed into the inverse model. The other data fed to the inverse model is similar to the direct method. A filter can be introduced prior to the controller in this approach to incorporate robustness in the feedback system, especially where it is difficult to get exact inverse models.

In most cases, presented in the literature using this approach, the necessary control signals, from the neural network inverse-model is computed by numerically inverting the neural network forward model at each interval by Newton's method or substitution methods based on the contraction mapping theorem [47]. The first derivative with respect to the control input can be computed in these techniques by the usual backpropagation method. These numerical techniques are, however, computationally intensive and time-consuming, they are very sensitive to the initial estimates and they may not necessary give the global and unique solution. A couple of cases have, however, utilized the output, from the offline-trained neural network inverse model, directly as the control input into the plant without numerical computation.

3.2. Applications in chemical process systems

All applications under this category except for two cases reported utilizing multilayered feedforward neural network and a summary of these applications utilizing neural networks in inverse model-based control methods can be seen in Table 3. They are described in further details later, beginning first with those utilizing the multilayered networks. One of the earliest reported work in process systems was done by Psichogios and Ungar [32], who utilized an internal model control (IMC) approach to control product concentration in a nonisothermal CSTR with first order reversible 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 et al. [48] also utilized the IMC approach to control the effluent concentration in a CSTR, with first order
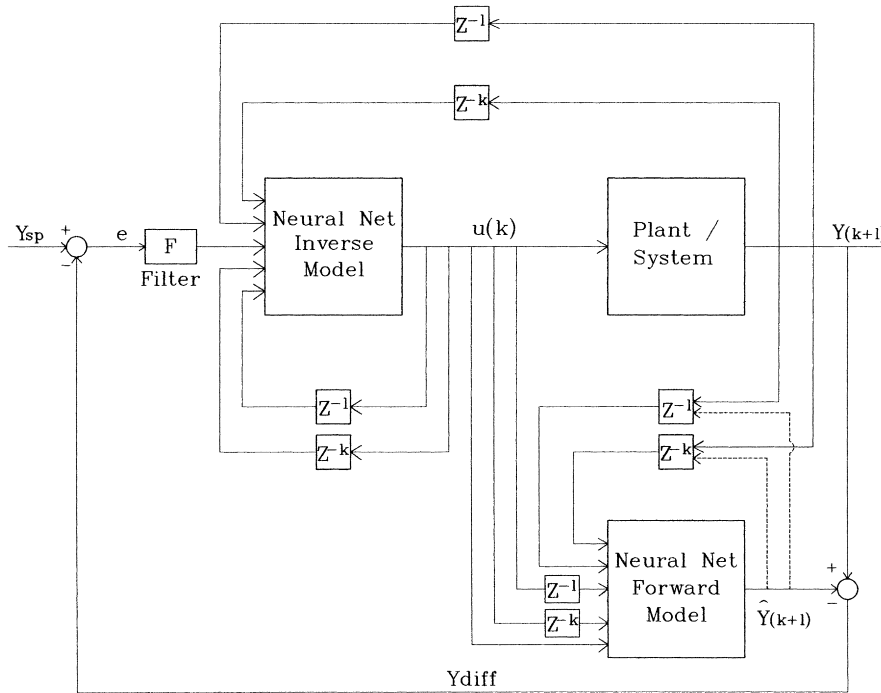
Fig. 2. Neural networks in internal-model-control strategy.

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 and offset-free results were obtained in both the set-point and disturbance–rejection cases. The same strategy was implemented by them in controlling the effluent pH in a neutralization system by manipulating the base flow rate. Offset-free results were

also achieved here for set-point and disturbance–rejection cases.

Dayal et al. [49] 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 controller and that of a directly trained neural network inverse-model controller

Table 3
Summary — applications of neural networks in inverse-model based control strategies

Control technique	Objective	System	NN type	Robustness	Ref.
IMC	Prod. Comp.	CSTR	Ml/Hyp. Tanh	Set pt./Dist.	[48]
IMC	Prod. Comp.	Neut.	Ml/Hyp. Tanh	Set pt./Dist.	[48]
IMC	Prod. Comp.	CSTR	Ml/Sig.	Dist.	[32]
IMC	Strip Thick.	Rolling mill	Ml/RBF	Set pt.	[50]
Inverse w/PI	Strip Thick.	Rolling mill	Ml/RBF	Set pt.	[50]
D. Inv	Prod. Conc.	Fed batch bioprocess	Ml/Sym. Log.	Set pt.	[95]
IMC	Prod. Comp.	CSTR	Ml/Sig.	Set pt./Dist.	[49]
IMC	pH	Neut.	Ml/RBF	Set pt.	[35]
Inv w/GMC	Prod. Comp.	Dis. column	Ml/Hyp. Tanh	Set pt./Dist.	[51]
Hybr. Inv	Conc	Van de Vusse/bioreactor	Ml/Ellp.	Set pt./Dist.	[53]
IMC	Prod. Comp.	Dis. column	Ml/Sig.	Set pt.	[54]
IMC	Conc./Temp.	CSTR	Ml	Set pt.	[59]
IMC	Temp.	Lime kiln	Ml	Set pt./Dist.	[93]
IMC	Conc.	CSTR	Ml/Hyp. Tanh	Set pt.	[56]
Hybr. Inv	Temp.	CSTR	Ml/RBF	Set pt.	[57]
GMC/IMC	Temp.	CSTR	Ml/Sig.	Set pt.	[55]
LC	Temp.	CSTR	Recurrent	Set pt./Dist.	[58]

for set-point as well as disturbance–rejection studies. They found that the directly trained 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 feed-forward–feedback strategy to improve on the disturbance–rejection results. However, for the nonmonotonic 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 multiplicities in the reactor behaviour.

Sbarbaro et al. [50] utilized the neural network inverse models, acting as a controller, in different ways to control the strip thickness in a steel rolling process, under normal process disturbances. They utilized the inverse model in series with a PI controller, in parallel with an integrator (I) and in the IMC configuration, respectively. Comparisons were also made with the PI and Model Predictive techniques. They found the inverse model in parallel with the integrator gave the best results but with the IMC and MPC techniques giving equally good control. In another work with Hunt [35], they utilized multilayered neural networks with radial basis functions, in the IMC strategy to perform set-point tracking of the pH in a neutralizing reactor. They found in this case that the control system provided very close tracking performance with considerable improvement over a linear controller type.

Ramchandran and Rhinehart [51] used a neural-network inverse model to estimate the reflux and 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 [52]. This was done for set-point and disturbance–rejection cases and the technique was found to be better than the PI controller with feedforward features. Aoyama et al. [53] 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. Basualdo and Ceccato [54] used the neural networks in single-input single-output (SISO) and multiloop IMC structures for controlling the product compositions in a distillation column. In this method the inverse neural network model acts as feedforward compensation for nonlinearities for both the controller and the internal model and for adapting the gains of the controller and model online. They obtained good results in set point tracking in conjunction with the conventional PI controller in the feedback loop.

Piovoso et al. [55] utilized neural networks in the GMC and IMC strategies, respectively, to control the reactor temperature in a first-order, non-adiabatic CSTR system. In the GMC approach, they used a neural network to approximate the functional form of the nonlinear function describing the energy balance which is required in the controller formulation. In the IMC strategy, they however utilized a PI controller (tuned on the neural network forward model) to estimate the needed control input to produce the required output. They performed set point tracking studies, for the ideal case and with model-mismatch, and found that the neural-network-based methods gave comparable results to the pure GMC and global linearising feedback techniques. Lightbody and Irwin [56] developed a novel nonlinear model control strategy which utilizes 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 is 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. Shah and Meckl [57] used a neural net in parallel with a proportional controller to control temperature in a CSTR. The neural network they used consists of Gaussian activation functions and is trained to learn the inverse dynamics of the CSTR with and without parameter variations. Their simulation results for pseudo-step changes indicate that the neural network can be applied online, even with parameter variation, provided the input trajectory sufficiently excites the system under consideration.

Two applications using recurrent type networks are described as follows: Nikolaou and Hanagandi [58] used a recurrent neural network within a state feedback linearising 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 linearising 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 [59] 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 linearised model of the system. These networks were then consequently pruned 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 much better than the linear methods in controlling the process over a wide range of conditions.
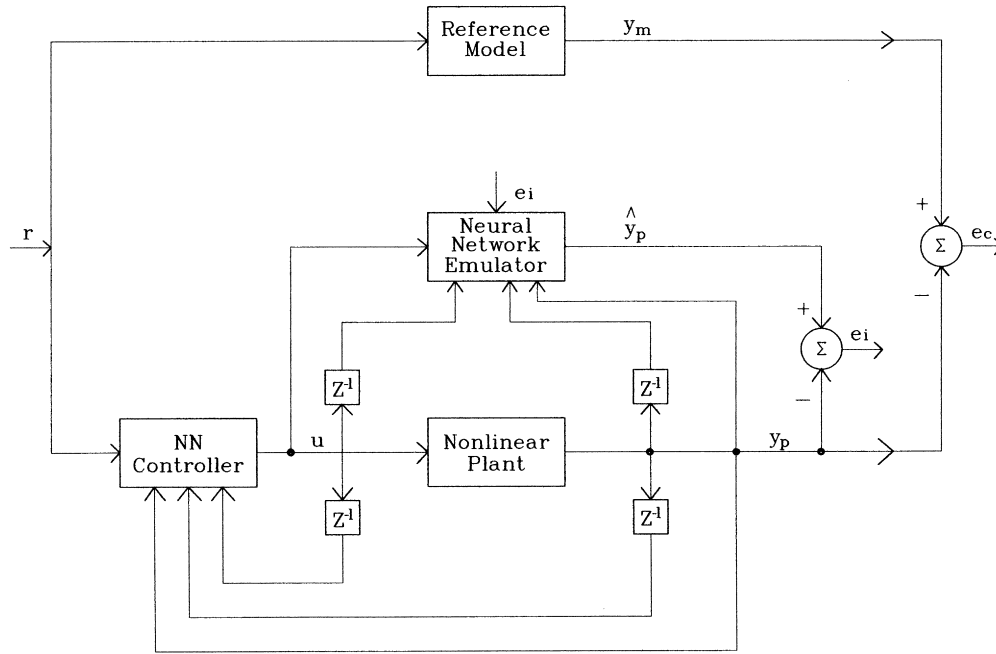
Fig. 3. Neural networks in indirect adaptive control strategy.

4. Neural networks in adaptive control techniques

4.1. General description

As with other techniques, neural networks can also be adopted into the conventional adaptive control structures in the control of nonlinear dynamic systems. These adaptive methods are normally categorized into two approaches i.e. direct adaptive and indirect adaptive schemes. In the direct adaptive control scheme, there is no explicit attempt to determine the model of the system; instead the controller parameters are directly adjusted on-line to achieve the necessary tracking and stability of the closed loop system. In this scheme involving neural networks, the weights of the neural network, acting as the controller, are adjusted on-line to control the plant by minimizing some cost function involving the plant output and desired response. A possible adjustment algorithm for the weights of the neural controller can be based on gradient descent such as in the backpropagation technique, which provides the necessary gradient of the cost function with respect to the network parameters [60]. In fact this approach is closely similar to the direct inverse-model control method with the main difference being that the controller is adjusted on-line using a model reference signal in this approach.

In the indirect adaptive control scheme, a neural network is used to identify an unknown part/function of a nonlinear plant online (see Fig. 3). The objective of the control strategy in this case is to make the plant output follow the reference output. The control action can be then computed from the knowledge of the required output and that of the nonlinear plant, made up of the known function of the

model and the neural network model emulating the unknown part/function of this plant. Control action is normally initiated once the plant is identified to the desired level of accuracy so that the output of the plant follows the output of the stable reference model. In this way, both identification and controls are performed simultaneously with the time interval for updating the identification and controls chosen carefully to achieve stable results. Details of this scheme can be found in the seminal paper of Narendra and Parthasarathy [61]. Improvements to this basic approach by adding a sliding control term to the neurocontroller have also been proposed by Sanner and Slotine [62], to increase the region of operation.

4.2. Applications in chemical process systems

All the applications in this category utilized the feedforward multilayered neural network are summarized in Table 4. They are described in further details later. Ydstie [63] utilized neural networks in direct adaptive and indirect adaptive control type techniques for a CSTR with second order reactions occurring between sodium thiosulphate and hydrogen peroxide. Their control objective was achieved successfully in making the temperature follow a predetermined reference by controlling the reactant flow rate. In the direct adaptive method, the neural network with linear bypass was used as the controller. In the indirect adaptive method, the control action was solved by numerical techniques at each step and implemented as a one-step-ahead predictive method. The network was trained by what they called as the 'error-broadcast' algorithm. Lightbody and Irwin [64] used a neural network in parallel with a fixed

Table 4
Summary — applications of neural networks in adaptive control strategies

Control technique	Objective	System	NN type	Robustness	Ref.
Adap w/Inv	Temp.	CSTR(isothermal)	Ml w/linear bypass	Set pt.	[63]
DMR w/online adapt	Prod. Conc.	CSTR	Ml/Hyb. Tanh	Set pt	[64]
Adap	Conc.	Fermentation	Ml/Sig. and RBF	Set pt.	[65]
Adap	Level	Tank	Ml/Sig.	Set pt.	[66]
Adap	Cell mass yield	Bioreactor	Ml/Sig.	Set pt.	[66]
Adap	pH,	Neut.	Ml w/recurrent	Dist	[67]
Adap	Cell Conc.	Bioreactor	Ml/Sig.	Set pt.	[68]
Adap	MW Prod. and Temp.	Poly. reactor	Ml	Set pt.	[69]

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.

Boslovic and Narendra [65] 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 Gaussian 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. Chovan et al. [66] 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 level in a tank and the control of cell mass yield in a bioreactor system with successful results.

Loh et al. [67] 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. Yang and Linkens [68] developed an adaptive online neural network-based controller where the neural network controller is adapted online by error signals from the neural network model emulating the plant. The neural network is used to model the time varying properties of the plant. This scheme is used to control a bioreactor with time-varying characteristics and nonlinearity. They obtain good results for set-point tracking, disturbance–rejection and regulation under noisy signals but with extensive

computational time. Watanabe [69] also utilized an adaptive control scheme where the neural network inverse models acting as the controller were updated on-line in the special inverse and error feedback learning method respectively. These methods were applied successfully in a multiple-input multiple-output (MIMO) continuous polymerization reactor to control the number average molecular weight of the polymer product and the temperature in the reactor under set-point tracking conditions.

5. Online applications of neural network-based control strategies

This section reviews all those application utilizing these neural-network-based control strategies in online situations. A summary of these online applications is given in Table 5. The majority of these online application utilizes the multi-layered feedforward network while a few others utilize the recurrent and state feedback networks. We will discuss them, beginning with those using the feedforward multi-layered networks first, in detail later.

Dirion et al. [70] used neural networks as direct inverse controllers to control temperature in a bench-scale semi-batch jacketed glass reactor equipped with a monofluid 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. Khalid and Omatu [71] used the neural network to learn the inverse dynamics of a bench-scale heated water bath and then configured it as a direct controller to control its temperature. Studies on set-point tracking, disturbance–rejection and the effect of dead time on the control action were done in this work. Khalid et al. [72] used an adaptive neural network controller, where the weights were adapted on-line, to control the temperatures within a multiple-input multiple-output (MIMO) bench-scale furnace. The weights were adapted online by backpropagating the errors through a forward neural network acting as the emulator. Studies for set point tracking, disturbance rejection and the effects of parameter changes were also done in this case. In both applications they obtain better results than those obtained using the conventional PI controller.

Table 5
Summary — neural-network-based control methods in actual online applications

Control technique	Cont. objective	System	NN type	Robustness	Ref.
D Inv.	Temp.	Semi-batch reactor	Ml/Sig.	Set pt.	[70]
Pred.	Level	Two-tank-in-series	Ml/Sig.	Set pt.	[74]
Adap.	Temp.	Bench-scale furnace	Ml/Sig.	Set pt.	[72]
Em. FBC	Level	Tank system	Ml	Set pt.	[75]
Pred	Press.	Pressure vessel	Ml/Hyp Tanh	Set pt.	[73]
D Inv.	Temp.	Water bath	Ml/Sig.	Set pt./Dist.	[71]
GPC Adap.	Level	Two-tank-in-series	VQN networks	Set pt.	[91]
GPC Adap.	Temp.	Bench scale heated tank	VQN networks	Set pt./Dist.	[92]
Infer.	Prod. Comp.	Stabilizer plant	Ml/Sig.	Set pt.	[77]
Pred.	Distillate Temp.	Dis. column	Ml/Sig.	Set pt./Dist.	[78]
Pred.	Prod. maximisation	Semi-batch reactor	State feedback	Set pt./Dist.	[89]
Pred.	pH	Tubular Neut. reactor	Ml/RBF	Dist.	[79]
IMC Adapt	Temp.	Oven system	Ml/RBF	Set pt.	[80]
Inv. w/GMC	Temp.	Heater	Ml/Hyp. Tanh	Set pt.	[81]
Pred.	Temp.	Packed bed reactor	Recurrent/Sig.	Dist.	[88]
IMC	pH	Neut.	Ml/RBF	Dist.	[82]
Adap.	Flow	Process control unit	Ml/Hyp. Tanh	Set pt./Dist.	[83]
Pred.	Prod. quality	Poly. reactor	Ml	Optimal time	[85]
Ext. DMC	pH	Neut. reactor	Ml/Sig.	Set pt./Dist.	[84]
Pred.	Temp.	Furnace	Ml	set pt.	[76]
IMC	Temp	Partially simulated reactor	Ml/Sig.	Set pt./Dist.	[86]
Pred	Melt flow rate	Poly. reactor	Ml	Set pt.	[87]
Adap.	pH	Fermentor	Recurrent	Dist	[90]
Inv. w/GMC	Temp	Heat exchanger	Ml/Sig	Set pt./Dist	[100]

VanCan et al. [73] 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 flow rate. Experiments were done for set-point tracking and comparisons were made with 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. Evans et al. [74] developed a neural-network model of a laboratory process i.e. two non-interacting tanks in series, and incorporated it in a predictive control strategy, where the network was used to predict future process outputs up to a set horizon. Experiments for set point tracking of the level in the second tank were performed in this study. Their comparison with the conventional PID controller show better performance, in terms of sluggishness and control movements.

Langonet [75] utilized neural networks to copy the dynamic behaviour of conventional controllers, tuned for different operating conditions (corresponding to different valve openings), for the control of the level in a tank by manipulating the output flow. The neural network was able to control the system satisfactorily when switching from one operating condition to another without any need for retuning. Sheppard et al. [76] applied neural networks for the control of temperature in a 175 kW experimental furnace system. In this case the neural network model was

incorporated into an explicit generalized predictive control scheme. They performed set point tracking of the temperature and the results obtained showed poor tracking at the start of the experiment but excellent tracking towards the end, even with the small possible amount of data gathered.

Baratti et al. [77] used neural networks to estimate the distillate and bottoms composition of a gasoline stabilizer tower in a refinery plant. This was utilized for inferential control of the isopentane composition in the column in conjunction with a PI control system. They found that this method outperformed the normal way of using the temperature for inferential control of the system. Wormsley and Henry [78] used neural-network models within a model predictive control scheme to control the distillate temperature in a laboratory-scale distillation apparatus separating methanol and water. An exhaustive search method was used for optimization and they obtained good set-point and disturbance–rejection results in their study. Doherty et al. [79] used an RBF-based neural network to model an online pH process and used it within a model predictive control scheme to control the pH of the outlet stream. They used a transport lag volume array method to compensate for the dead time in the tubular reactor. They employed their scheme successfully to regulate the pH under various disturbances and used a filter to improve robustness to noise effects. Dubois et al. [80] used an adaptive IMC control strategy, where the model was updated online, to control the temperature in an oven system. However, they could

not get an accurate inverse model from training it with the plant data and resorted to training the inverse model using the data from the neural network model instead. An RBF-based neural network model was used in this scheme to control the oven to follow various desired temperature trajectories satisfactorily.

Dutta and Rhinehart [81] used neural networks to model the steady state inverse of a laboratory-based electrically-heated feed preheater system. This was cascaded with a GMC controller in a reference system synthesis approach and used to control the feed temperature of the system. They found the step point tracking results using this approach to be better than the conventional PI and the model-based IMC and MPC approaches. Seborg [82] 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. Noriega and Wang [83] used a direct adaptive neural network to control the flow rate of a bench scale flow-process control unit. The control signals in this experiment was generated directly by the well established gradient descent rule. The system was tested for set point changes with fixed and changing network learning rates and for disturbance–rejection cases with successful results.

Draeger et al. [84] utilized a neural-network-based model predictive control scheme to control pH in a laboratory-scale neutralization reactor. They used the neural network as the nonlinear prediction model in an extended DMC algorithm to control the pH-value. The training data set for the neural network was obtain from online measurements of the inputs and outputs of the plant operating under a PI controller. The results obtain for set-point tracking and disturbance–rejection cases showed better results than with the conventional PI controller. Tsen et al. [85] 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.

Hussain et al. [86] 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. Only recently a nonlinear predictive control technique employing neural networks have been implemented, through a software called Process Perfector, in an industrial polypropylene plant. The model predictive control technique utilize a neural network steady state model and a dynamic process model with the dynamic optimization program to perform the control calculations. The objective of the installation was to control the melt flow rate in the polypropylene polymerization reactor. The managed to get good set point tracking results, much better than the traditional linear model predictive method [87].

Temeng et al. [88] 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 controller. 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. Schenker and Agarwal [89] used what they called the state-feedback neural networks (i.e. networks fed with states from the dynamic model) within a predictive control scheme for product maximization in a bench-scale semi-batch chemical reactor, where reactions with complex kinetics occurs within it. They compared this method with the feedforward-network method for controlling the system under various operating conditions, disturbances and model mismatches. They found that their method demonstrate superiority over the conventional feed-forward-network-based method. Recently, Syu and Chang [90] 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.

Cooper et al. [91] utilized a vector quantizer network (VQN) within an adaptive generalised predictive control (GPC) strategy to correct for the initial underestimates of the model gain and recognize controller error patterns to restore desired controller performances after few adaptations. This method basically takes advantage of the pattern recognition capabilities of neural networks. The scheme was carried out successfully for set-point tracking of level in a two-tanks-in-series system in a laboratory experiment. This methodology was also extended for parameter tuning of a PI controller to control the temperature in a bench-scale heated stirred tank system under set-point and disturbance rejection cases with good results [92].

6. Concluding remarks

The review in this paper has highlighted the broad, extensive and continuing increase in the application of neural network in many chemical process control applications, both online and in simulation. Other than showing the

successful application of neural networks in these various control strategies, they also reveal several other points such as:

1. Neural networks are versatile in that they are capable of being incorporated in various well-known nonlinear control methods and strategies.
2. Multilayered feedforward with sigmoidal or hyperbolic activation functions is still widely used in most of these applications. This demonstrates their sufficiency and capability for performing systems identification and controls for wide range of problems, although there are many other types of networks and activation functions available currently.
3. Many online chemical process control applications have been reported in the literature, but they are mostly for miniature laboratory-scale equipments. Only a couple of applications on pilot plants have been performed and a few recent industrial applications, utilizing the predictive method, have been reported but with few published results. This opens the scope for more applications on pilot plants and actual systems using these neural network-based control strategies especially the inverse-model-based schemes, which is the ultimate test of robustness.

Acknowledgements

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