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Advanced Control Technique for Substrate Feed Rate Regulation of a Fed Batch Fermentation

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ABSTRACT

In this study, an advanced control technique for substrate feed rate regulation of fed batch fermentation is developed. It is reliable in dealing with possible variations in the process condition. In this study, neural network and fuzzy logic methods are used in the design. As a case study, the baker's yeast production process is chosen to test these controllers. The evaluation of the performance of the designed controllers is carried out through computer simulation. To obtain a reliable assessment, the results are then compared with those of the PI controller. The results have shown that the proposed approaches can be successfully applied to regulate of fed-batch fermentation to improve the operation of such processes.

Key words: Advanced control techniques, fermentation, feed batch fermentation, fuzzy logic

INTRODUCTION

In recent years, the growth of the fermentation industry has been enormous worldwide. The products coming from this industry cover many sectors such as chemical, pharmaceutical, energy, food and agriculture. All these type of products now command a large industrial market and are essential to modern society. In line with the increase in market competitiveness, the producers are prompted to improve the quality of their products while at the same time reducing the production cost and increasing the yield so as to survive the competition. In this respect, attention on the monitoring and control aspect of fermentation process is necessary. Due to this, a large number of research works on bioprocess control have emerged recently.

In many respects, the engineer concerned with the monitoring and control of a fermentor faces a far more difficult task than those involved in chemical or purely physical processing units. The fundamental distinction between the two is that the fermentor deals with a complex biological system. Of particular importance is the fact that the actual process takes place inside living cells, i.e., microorganisms (Sarkar and Modak, 2003). What makes such a system extremely difficult to describe and hence hard to control is the expanding and self-reproducing nature of the microorganisms as well as their highly sophisticated intracellular control. Consequently, the control system design of fermentation processes faces the following obstacles:

- Due to the involvement of living microorganisms whose behavior is uncertain, the mechanisms ruling these processes are not adequately understood to formulate reliable mathematical models
- Because the actual metabolic processes take place inside individual living microorganisms, it is likely to be impossible to fully influence the cell's internal environment by manipulating the external environment in which they live
- The dynamic behavior of the processes is inherently nonlinear and the variation of the process parameters is uncertain
- Reliable sensors to measure intracellular activities are rarely available, making the process states very difficult to characterize

Control of fed batch fermentation has become the most productive area of research in fermentation control studies. Since it was first devised in the early 20th century, fed batch fermentation technique has been gaining acceptance in performing industrial fermentation processes particularly for those suffering from conflict between productivity and yield. Many, if not most, commercially important products are best produced in this type of ferment or operation. For example, production of baker's yeast and penicillin are among processes dominantly performed through this. The key factor in favour of fed batch fermentation is the enormous flexibility with respect to the regulation of substrate feeding. This, in turn, enables control of the process conditions associated with the variation in substrate concentration in the fermentor to be achieved effectively (Hilaly *et al*., 1994).

Despite their capability, fed batch fermentations rarely achieve their optimal performance in practice. The requirement of a reliable controller for accurate substrate feed rate adjustment becomes the main issue in this respect. As is well known, due to the involvement of living microorganisms as well as the process mechanism, especially due to the effect of increase in culture volume during the operation, fed batch fermentation processes exhibits significant nonlinearity and time variance in their dynamics. The use of linear controller, such as the conventional PID, to deal with such a feature normally results in unsatisfactory performance (Dairaku *et al*., 1983).

Recent decades have witnessed flourishing research efforts in the development of control schemes for the substrate control problem (Rani and Rao, 1999; Lee *et al*., 1999). A survey shows that the use of optimal control strategy, both in open-loop and feedforward schemes, have been attractive (Mahadevan *et al*., 2001; Roy *et al*., 2001). But it is admitted that this strategy exhibits, at least, two fundamental drawbacks. First, the controller is insensitive to the process changes and, second, due to the lack of reliable mathematical model, the calculated optimal feeding profile is likely to perform at sub-optimal levels in practice. To overcome these drawbacks, in line with the immense progress in computer technology, advance control methods, e.g., knowledge-based or intelligent controllers, have been introduced for fed batch fermentation control (Konstantinov and Yoshida, 1992).

Due to their impressive capability in dealing with severe nonlinearity and uncertainty of a system, the application of fuzzy logic and neural network methods for the design of controllers for fed batch fermentation processes has great potential. Generally, the application of these methods in fed batch fermentation control can be realized in two ways, i.e., by indirect and direct ways. In the indirect way, they can serve, for example, as parameter estimators. In the direct way, fuzzy logic and neural networks are used directly as the controller. For example, fuzzy logic controllers are used as compensators for optimal controllers (Honda and Kobayashi, 2000) while neural network controllers are used in internal model control strategies (Schubert *et al*., 1994). However, some difficulties in the application of the fuzzy logic and neural network methods have been observed (Hang *et al.*, 1993). Basically, fuzzy logic and neural network models are developed on the basis of input-output data sets of the process. In other words, this is a black-box approach. So far, these methods lack definitive methodology to develop model for the controllers. Often, trial and error techniques are used to establish the model (determination of the size of the networks for the neural network model and of the fuzzy rules and the tuning of the membership functions for the fuzzy logic model). Despite these shortcomings, the use of fuzzy logic and neural network method still has great aspects to explore. The application of adaptive control technique and hybrid control strategy to these fuzzy logic and neural network controllers to improve their performances still seems to be a potential research area for feed rate control of fed batch fermentation.

FED BATCH FERMENTATION

Fed batch fermentation refers to a technique of fermentation where the nutrients necessary for microbial growth are fed either intermittently or continuously during the course of operation. The reaction mixture is then harvested either fully or partially at the end of the operational period and this whole process may be repeated several times (Parulekar and Lim, 1985). Simply, it can be perceived that fed batch technique is a combination of batch and continuous operation, hence it is sometimes called semi-batch fermentation. Figure 1 shows the diagram of the fed batch fermentor together with its batch and continuous counterparts.

Fed batch fermentation has been found to be particularly effective for processes in which substrate inhibition, catabolite repression and glucose effect are important with respect to the cell growth and/or product formation. In other words, fed batch fermentation is well suited to processes suffering from conflict between productivity and yield.

Historically, fed batch fermentor operation was originally devised by yeast producers in early 1900's to regulate the growth in batch culture of Saccharomices Cerevisieae (Baker's yeast) with malt as a substrate (McNeil and Harvey, 1990). It was recognized that in the production of yeast from malt wort, the concentration of malt wort must be kept low enough so that the yeast is not grown too fast thereby preventing occurrence of anaerobic conditions in the culture and subsequent production of ethanol. Additional wort was added at a rate which was always less than the rate at which the yeast cells could use it. This led to increased yeast yield while obviating production of ethanol. Following successful application to yeast production, fed batch cultures have been applied to other processes such as industrial production of antibiotics, amino acids, enzymes, vitamins, single-cell proteins, biomass and various organic compounds of commercial importance (Parulekar and Lim, 1985).

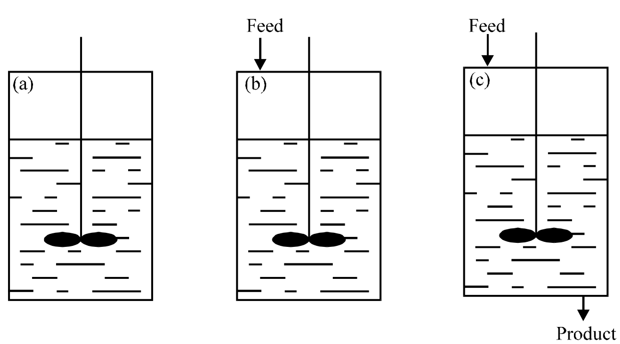

Fig. 1(a-c): Fermentor operations: (a): Batch, (b): Fed-batch and (c) continuous

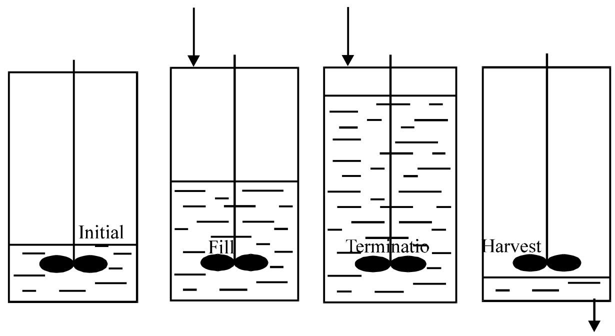

Fig. 2: Schematic of fed-batch fermentation operation

Operational mechanism: The schematic of fed batch fermentation operation is shown in Fig. 2. Basically, the operation of fed batch fermentation begins with a batch culture. In this stage, an initial volume of material, containing cells and substrate in a particular amount, undergoes fermentation process by which substrate is converted into new cells and metabolite products. By the time the batch stage is considered completed, fresh substrate is introduced and the fed batch culture procedure begins. In this stage, the substrate feed rate is regulated based on the process demand in order to achieve the process objective such as to obtain maximum metabolite product or maximum cell production. When this stage is terminated, the fermentation broth is then harvested and the fermentor is ready to run for the next batch. Regarding the time for starting and finishing/harvesting the fed batch fermentation, the criteria for this is very much dependent on the specific cultivation kinetics and the operator's interest. The most commonly used criterion to start the feed is the depletion of the substrate. The fed batch is usually halted when the production slows down due to cell death. Other criteria can be an increase in viscosity that implies an increased oxygen demand or until oxygen limitation occurs.

Associated with harvesting method, two types of fed batch fermentation are known, i.e., single and repeated or cyclic fed batch fermentation (Ferriera, 1999). For the former, the broth is fully removed from the fermentor and the next batch starts from the beginning, i.e., batch culture while for the latter, the broth is partially removed from the fermentor and the operation continues with the fed batch culture procedure on the residual broth.

Besides the variable volume approach as explained above, fed batch fermentation process can also be carried out through fixed volume approach. In this approach, the culture volume is maintained practically constant by feeding a highly concentrated liquid or gas substrate (Ferriera, 1999). The repeated fed batch process for this approach can basically be done as follows. A portion of the broth is removed from the fermentor once the process reaches a certain stage, e.g., when aerobic conditions cannot be maintained anymore and then sterile water or medium containing the feed substrate is added to dilute the cells to the original volume (Na *et al.*, 2002).

FUZZY LOGIC

Concepts: Fuzzy logic refers to a technique used to deal with the concept of the vagueness and uncertainty of linguistic terms, e.g., high, low, big, small, warm, cold, etc. In this technique which originated from the fuzzy set theory (Zadeh, 1965), the ideal and hard-edge classical concept of binary (yes/no, 0/1) logic is softened by taking into account the subtle border between sets of the linguistic terms 9. Figure 3 shows the comparison between the concept of classical logic and fuzzy logic.

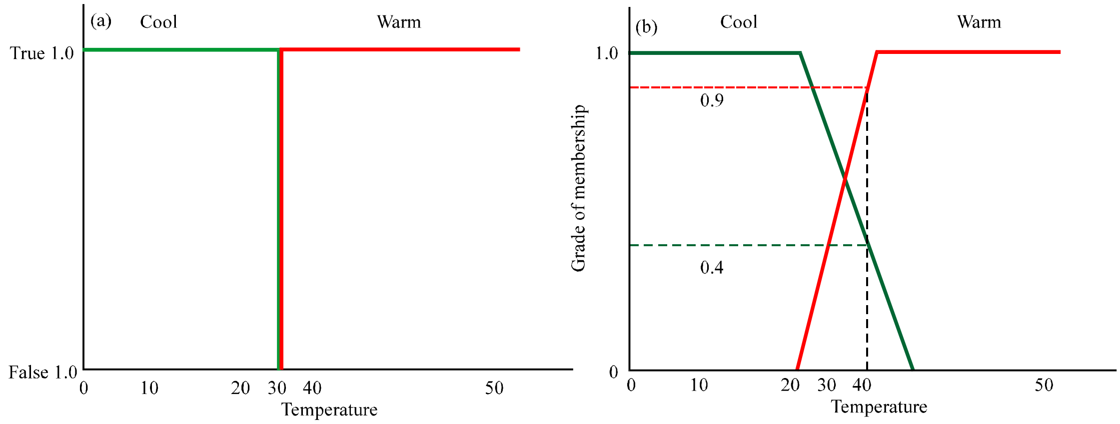

Fig. 3(a-b): Classical (a) fuzzy and (b) sets

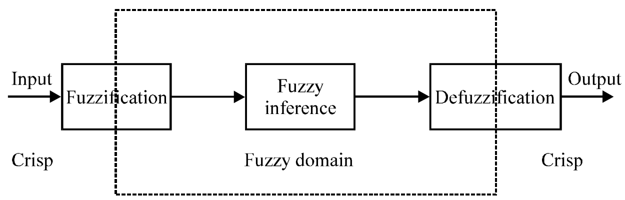

Fig. 4: Data flow in a fuzzy system

Fuzzy logic model design: Usually, a fuzzy model can be constructed by capturing human-expert knowledge and transforming such expertise into rules and membership function. The construction of the model generally involves three main processing elements, i.e., fuzzification, fuzzy inference (if/then rules) and defuzzification. Figure 4 shows the block diagram of this system (Tsoukalas and Uhrig, 1997).

In the fuzzification stage, input variable value is transformed from crisp domain to fuzzy domain, i.e., obtaining the grades of membership of the value with respect to the corresponding fuzzy values. In the fuzzy inference stage, the data is then processed through if/then rules. The rules express the relationship between the input variable(s) and the output variable. The rules can be written in the Mamdani form or in the Sugeno form. In the case of Mamdani-form fuzzy inference, the rules relate the fuzzy values of the input variable(s) with the fuzzy values of the output variable. This is actually the process of transferring the fuzzy value's grade of membership of input(s) to the output one, where in the defuzzification stage they are in some ways manipulated further to obtain the crisp value of the output variable. In the case of Sugeno-form rules, the rules directly relate the fuzzy values of the input variable(s) with the crisp value of the output.

The comparison between fuzzy logic model with Mamdani rules and that with Sugeno rules is illustrated in Fig. 5. In the Fig. 6 x1 and x2 stand for input variables, y is output variable, A, B, C, D and E represent the fuzzy values. In short, the main difference between the two lies in the fact that the consequence part of the Sugeno rules is normally a concrete mathematical function of input variables instead of some fuzzy linguistic variables as used in the Mamdani rules.

The comparison between fuzzy logic model with Mamdani rules and that with Sugeno rules is illustrated in Figure 5. In the figure, x1 and x2 stand for input variables, y is output variable, A, B, C, D and E represent the fuzzy values. In short, the main difference between the two lies in the

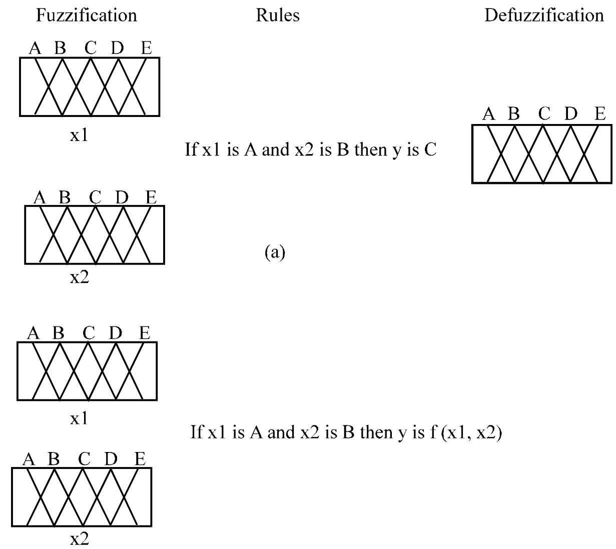

Fig. 5: Fuzzy logic model with (a) Mamdani rules and (b) Sugeno rules

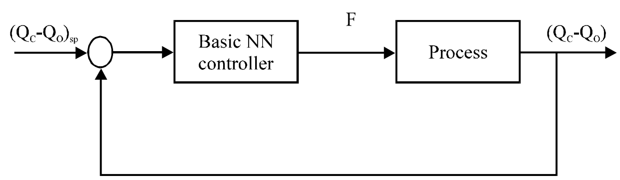

Fig. 6a: Control system with basic neural network controller

fact that the consequence part of the Sugeno rules is normally a concrete mathematical function of input variables instead of some fuzzy linguistic variables as used in the Mamdani rules.

Generally speaking, Sugeno fuzzy rule systems are more flexible and thus has stronger modeling capacity to solve complex problems. Sugeno rules method is also recommended rather than Mamdani rules if computational efficiency and convenience in fuzzy control analysis are very important (Resnik *et al.*, 2000). For this reason, Sugeno fuzzy rule system is, therefore, used in this work.

It should be noted that in establishing fuzzy models, depending entirely upon human knowledge is impractical and dangerous (Hsu and Chen, 1999). even if the ideal expert knowledge exists, the knowledge based is usually incomplete or partially incorrect.

There is no objective way to extract all correct human knowledge. In addition, often different experts give different rules, which may even have conflicts. Therefore, the application of adaptive and hybrid strategies is necessary.

Basic neural network controller scheme: This basic neural network controller refers to the controller using merely a neural network model in its control law. Inverse neural network model with feed forward structure is used as the controller in this case.

Controller design: In the fed-batch fermentation control system, this controller works in a feedback manner. The diagram of the control system is shown in Fig. 6a.

The design of this basic scheme involving a neural network controller covers features essential in the development of the neural network model used. The development includes the selection of input-output variable for the model, the data used for training and validation and neural network model formulation. The elaboration of these features is presented.

Input-output variable selection: The model is considered to consist of three input nodes, i.e., the current difference value of feed rate, the current value of $(Q_c\text{-}Q_o)$ and the one-step-ahead value of $(Q_c\text{-}Q_o)$. The output of the model is the one-step-ahead difference value of feed rate. Mathematically, this input-output relationship is expressed by:

$$\Delta F_t = f\,(\Delta F_{t-1}, \Delta\,(Q_c\text{-}Q_O)_t, \Delta\,(Q_c\text{-}Q_O)_{t+1}) \tag{1}$$

where:

$$\Delta\,(Q_c\text{-}Q_o)_t = (Q_c\text{-}Q_o)_t\text{-}(Q_c\text{-}Q_o)_{t-1} \tag{2}$$

$$\Delta\,(Q_c\text{-}Q_o)_{t+1} = (Q_c\text{-}Q_o)_{t+1}\text{-}(Q_c\text{-}Q_o)_t \tag{3}$$

$$\Delta F_t = F_t\text{-}F_{t-1} \tag{4}$$

$$\Delta F_{t+1} = F_{t+1} - F_t \tag{5}$$

It should be noted that, in the implementation, $(Q_c\text{-}Q_o)_{t+1}$ in Eq. 3 serves as the set point of the neural network controller. The actual controller output, i.e., the manipulated substrate feed rate is then obtained by the following equation:

$$F_{t+1} = F_t + \Delta F_{t+1}$$

Training and validation data: Since the direct inverse model approach is used, the training data sets are prepared based on the process input which, in this case, is the substrate feed rate. Two sets of data are used in the training stage and one data set is used in the validation stage. These data sets are generated through simulating the process under a casual control condition. To obtain different profile of the data sets, disturbances of different types (i.e., the change in glucose concentration of the substrate feed and the changes in the value of process parameter μmax) are introduced in each of three batches of the process. These three data sets are considered as the historical data of the process. The training data sets and the validation data set are shown in Fig. 6b and 7, respectively.

Model development: The following are several features considered in the neural network control model development:

- The model is of layered network type with one hidden layer. Based on Eq. 1, the architecture of the neural network model is shown in Fig. 8. The number of nodes employed in the hidden layer is determined by trial and error method during the training stage. Therefore, it is considered as a training variable

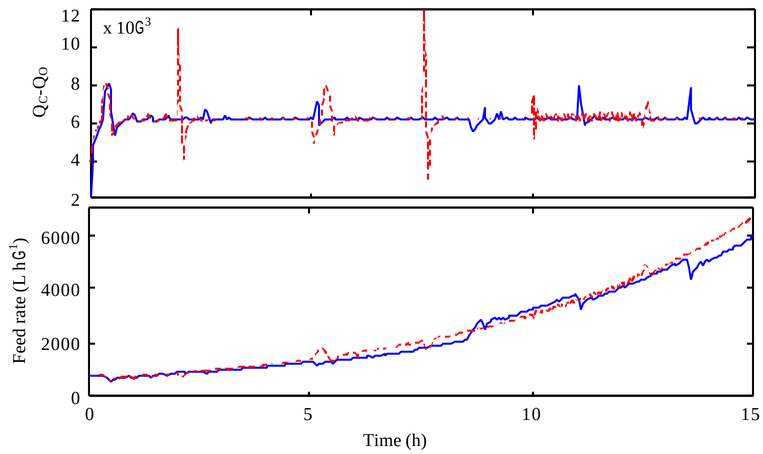

Fig. 6b: Data sets for training neural network control model. Solid line for data set 1 and dash line for data set 2

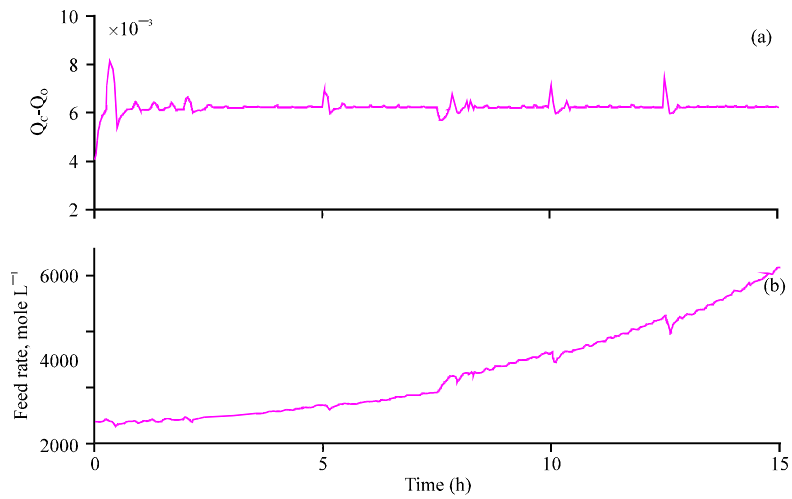

Fig. 7(a-b): Data set for validating neural network control model

- The hyperbolic tangent sigmoidal transfer function (Fig. 3b) is employed in the hidden layer nodes while the linear transfer function (Fig. 3a) is used in the output node. It should be noted that the effective range of the x-axis of the hyperbolic tangent sigmoidal transfer function is within the interval of (-3)-3. To gain the benefit of the curvature of the function, the interval of 0-3 or 0-(-3) is more useful. However, to attain a particular degree of accuracy of the model, a sub-interval within this interval is needed to consider. Hence, scaling the training data into a certain range within the interval is necessary. The formula for the scaling is shown below:

$$sv = \left[\frac{uiv - liv}{\max(av) - \min(av)}.(av - \min(av)\right] + liv \tag{6}$$

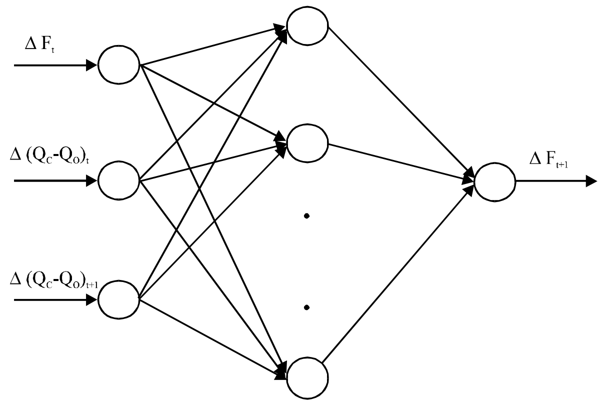

Fig. 8: Typical architecture of the neural network control model

where, sv, av, uiv and liv stand for the scaled, actual, upper and lower interval values, respectively. The scaling parameters, i.e., the interval's lower and upper values, are then considered as variables in the training

- The model is trained, which is the determination of the optimum weighting coefficient values of the interconnections among the nodes, by using Levenberg-Marquardt method (Edgar *et al.*, 2001).

Controller design: As seen in the preceding section, due to its fixed gain, the neural network controller with the basic scheme performed unsatisfactorily. The inclusion of adaptive feature is found necessary for the controller to keep up with the change in the process gain. Suppose **δ** is a factor denoting the gain of the neural network controller, then Eq. 5 can be rewritten as follows:

$$F_{t+1} = \delta\ (F_t + \Delta F_{t+1}) \quad (7)$$

The value of the factor **δ** in the basic controller scheme was actually fixed over the operation and assumed to be unity. In this adaptive scheme, this factor is made adjustable.

As mentioned in before that since the change in process gain of the process is associated strongly with the change in the biomass concentration in the culture, it is reasonable to use the biomass concentration as the reference variable to adjust this factor during the process. Hence, the idea was that the value of factor **δ** should be changed according to the change in the biomass concentration. Fuzzy logic methodology is then utilized to determine this change in the factor's value. In fact, it can be said that this is a kind of gain scheduling method. Unlike the interval-based gain scheduling method applied for the PI controller in which the controller gain changes abruptly, this fuzzy logic-based adaptive strategy implements smooth changes in the controller gain. The development of the strategy is described below.

Four fuzzy membership functions of biomass concentration are considered, i.e., low, medium, high and very high. The design of the membership functions is as shown in Fig. 9. In the rule part, the Sugeno fuzzy inference method is applied where the biomass concentration acts as the antecedence and the adaptive parameter, i.e., the gain factor, acts as the consequence. Before describing the design of the fuzzy rules, an important issue, i.e., the initialization of the gain factor, needs to be addressed.

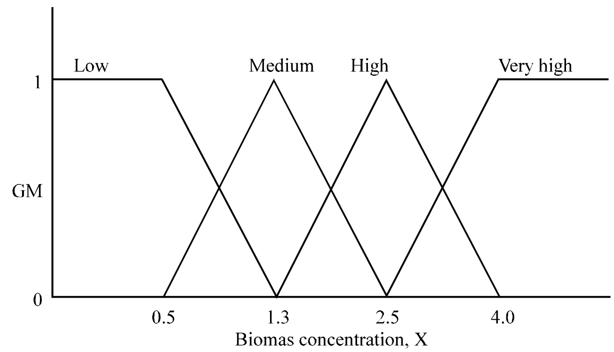

Fig. 9: Fuzzy membership functions of biomass concentration

Initialization of the gain factor is required to ensure the stability of the control system when it starts running. Recall that the gain of the basic controller is represented by the value of the gain factor of 1. As shown in the previous section, the control action of the basic controller is aggressive in the early period of the process. Since the stability of the control system in this period is obtained as the dynamics of the controller matches that of the process, it makes sense to reduce the value of the gain factor down to the value representing such a condition. It is found that such a condition is achieved when the value of the gain factor is set to be 0.33 which is used as the initial value of the gain factor.

Based on its initial value, it is logical to assign maximum value of the gain factor for each of the membership function according to the trend of biomass profile during the process. As shown in Fig. 3.4b, it is seen that the increase in biomass concentration is almost linear in trend. Hence, as initial setting, the values of 0.33, 0.9, 1.5 and 2.1 are assigned for the membership functions of low, medium, high and very high, respectively. A series of simulation is carried out to check and correct these values. Finally, it is found that the appropriate maximum gain factor values for membership functions of low, medium, high and very high are 0.35, 0.9, 1.5 and 2.1, respectively. Hence, the fuzzy rules are established as follows:

$$\begin{aligned}
&\text{If X is low then } \delta = 0.35GM_{Low} \\
&\text{If X is medium then } \delta = 0.9GM_{Medium} \\
&\text{If X is high then } \delta = 1.5GM_{High} \\
&\text{If X is very high then } \delta = 2.1GM_{Very\ High}
\end{aligned} \tag{8}$$

where, X and GM_i are biomass concentration and the grade of the membership of the function i, respectively.

Controller performance: The following is the simulation results of the implementation of the indirect adaptive scheme neural network controller in the fed-batch fermentation control. The performance of the controller is investigated through studies of nominal operating condition, set point change tracking and disturbance rejection. The process operating values for the studies has been given in Table 1. The results of this controller in dealing with the given process conditions are shown in Fig. 10-14, respectively while the calculated IAE is given in Table 2.

Figure 10 shows the performance of the controller in maintaining the nominal operating condition. The oscillations observed in the basic neural network controller are totally removed by

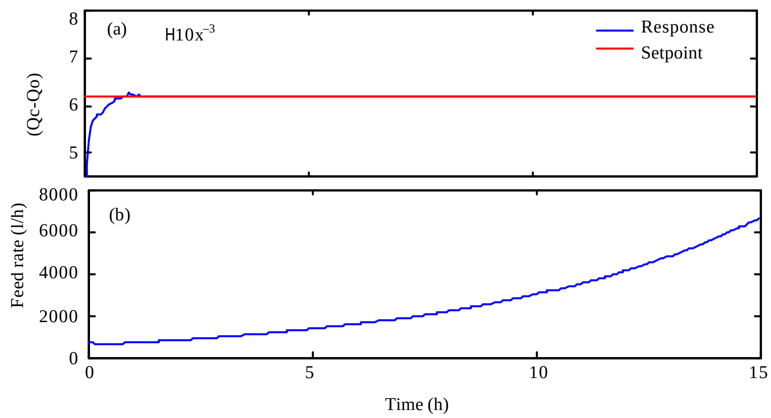

Fig. 10(a-b): Process and controller response of indirect adaptive neural network controller for nominal operating condition study

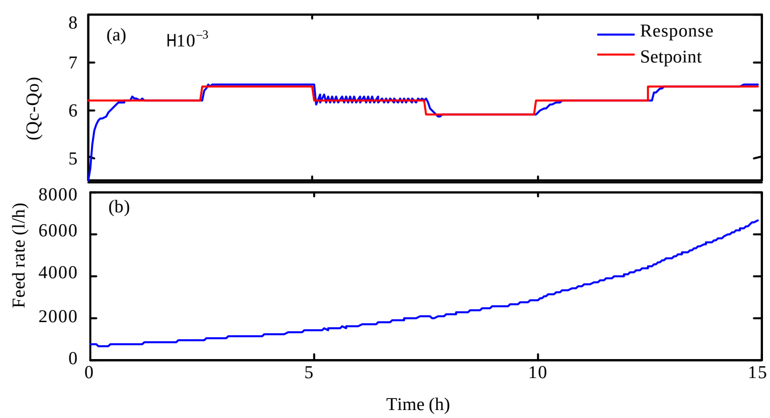

Fig. 11(a-b): Process and controller response of indirect adaptive neural network controller for set point tracking study

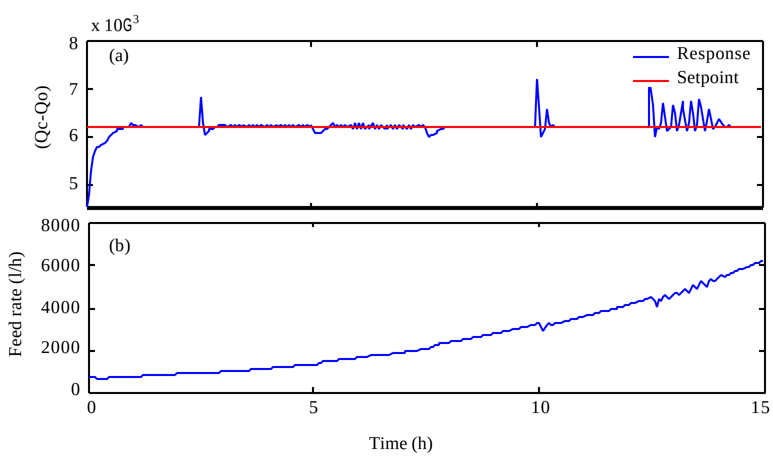

Fig. 12(a-b): Process and controller response of indirect adaptive neural network controller for external disturbance rejection study

Table 1: Operating values of process variables used in the controller performance in the controller investigation

	Process variable			
	Set-point, (Q_c-Q_o)	External dist., C_s^f	Internal dist., Q_s^{max}	Mixed dist., C_s^f, Q_s^{max}
Nominal operating condition	0.0062	1.6	0.06	1.6, 0.060
Varying operating condition:				
t: 0-2.0 h	0.0062	1.6	0.06	1.6, 0.060
t: 2.0-5.0 h	0.0065	1.7	0.065	1.7, 0.065
t: 5.0-7.5 h	0.0062	1.6	0.060	1.6, 0.060
t: 7.5-10.0 h	0.0059	1.5	0.055	1.5, 0.055
t: 10.0-12.5 h	0.0062	1.6	0.060	1.5, 0.060
t: 12.5-15 h	0.0065	1.7	0.065	1.7, 0.065

Table 2: Integral absolute error of process response under indirect adaptive neural network controller

Studies	IAE
Nominal operating condition	0.0117
Set point changes	0.0175
External disturbance changes	0.0339
Internal disturbance changes	0.0253
Mixed disturbance changes	0.0369
Average	0.0251

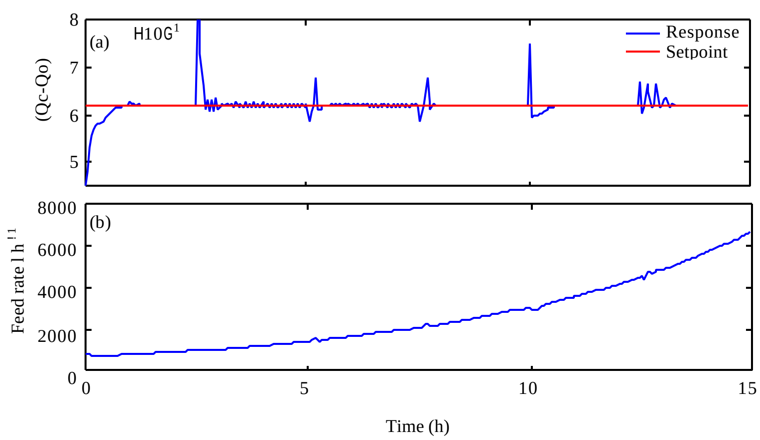

Fig. 13(a-b): Process and controller response of indirect adaptive neural network controller for internal disturbance rejection study

this controller. In dealing with the variation of set point (Fig. 11), the controller is able to bring the process to follow the given set point changes. However, in the early half of the operation period, the controller responds fast to the deviation occurring, i.e., around t = 2.5 h and t = 5.0 h. The controller is a bit aggressive in this period as indicated by the occurrence of small oscillations observed in the interval of 5 to 7.5 h that is, when the set point turns back to its nominal value. In the subsequent period, the controller becomes sluggish in responding to the pertubations. This can be seen from the process response around t = 10 h and t = 12.5 h.

In the study of external disturbance rejection (Fig. 12), it can be seen that the controller is successful in rejecting the disturbances at t = 2.5, 5 and 7.5 h. But at t = 10 h and t = 12.5 h,

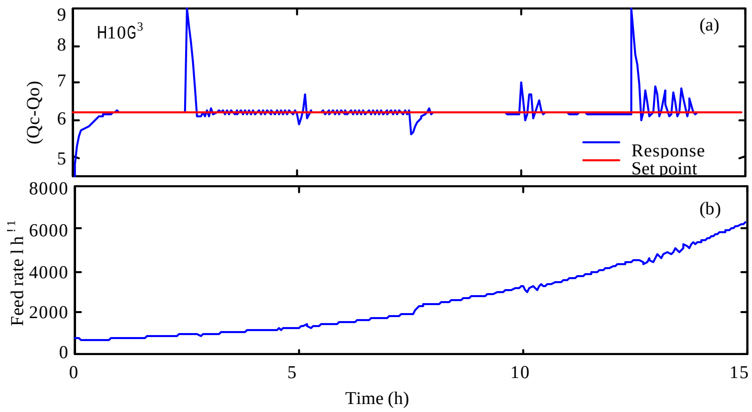

Fig. 14(a-b): Process and controller response of indirect adaptive neural network controller for mixed disturbance rejection study

especially for the latter, the controller over acts and causes the process response to severely oscillate. In addition to this, small oscillations are observed in the interval 5 to 10 h. In dealing with the internal disturbances (Fig. 13), the performance of this controller seems reasonable in some sense. Small oscillations also appear in the 2.5 to 7.5 h period. Sluggish control action is observed around t = 10 h causing the controlled variable to take a significantly long time to reach the set point, i.e., when it moves from a state below the set point. Severe oscillatory process response is observed around t = 12.5 h. In the mixed disturbance rejection study (Fig. 14), it can be seen that the controller performs reasonable when responding to deviations at t = 5, 7.5 and 10 h. However, it becomes sluggish when responding to large deviations in the process response as noticed in the figure around t = 2.5 h and t = 12.5 h.

From the results shown above, it can be concluded that, since no significant oscillation and offset are observed in the process response in the study of nominal operating condition, the controller is capable of following the time-varying characteristics of the process. The controller seems capable of dealing with the process nonlinearity as indicated by its ability in tracking set point changes. However, these capabilities do not cover a wide control range. The occurrence of oscillations in the process response when dealing with disturbances in the last 5 h confirms this observation. In spite of that, compared to the results of the basic scheme, a large improvement is observed with this control scheme. This can be seen from the integral absolute error values (Table 2) which are very much lower compared to that of the basic neural network controller scheme. Improvement achieved by this adaptive neural network controller is 43.74% on the average.

In view of the above, the use of biomass concentration as the adaptation reference variable as well as the lack of comprehensive fuzzy membership functions and rules for the adjustment of the gain factor is the most likely reasons for its performance. As previously mentioned, the change in biomass concentration during the process is associated with the process gain changes. So, the use of biomass concentration as the adaptive reference variable is beneficial only to prevent the deviation due to the time-varying process changes but is not sufficient and reliable to prevent the deviation due to changes in process operating conditions. Therefore, the application of a direct adaptive approach to cater for this consideration is given in the next section.

CONCLUSION

This study aims at designing advanced controllers for substrate feed rate regulation of fed-batch fermentation. Production of baker's yeast is used as the process under study. Since it is characterized by nonlinearity in its dynamics, control of substrate feed rate to baker's yeast fed-batch fermentation is difficult. It has been shown that conventional fixed-gain and scheduled-gain PI controllers result in unsatisfactory control performance when dealing with this process. Significant offset and oscillations are observed in the process response and the controller action suffers from fluctuations when the input control signal is corrupted by noise. The development involves the design of the basic, adaptive and hybrid control schemes for both the neural network and fuzzy logic controllers. This design and application is an important contribution of this work.

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