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Developing A Decision Support System for Operation and Control of the High-Purity Oxygen Activated Sludge Process

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Civil Engineering

by

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Dedicated to my wife Jie and son Youshi,

and my family,

especially to my parents

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ABSTRACT OF THE DISSERTATION

Developing A Decision Support System for Operation and Control

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Operation and control of the high-purity oxygen activated sludge process (HPO-AS) are more complex than for conventional open-air activated sludge process. The objective of this research is to provide both quantitative and qualitative support to the operators in their decision-making process. To realize this goal, a decision support system is developed in this investigation. The system consists of five major components: operator's interface, process simulator, on-line state and parameter estimator, knowledge base and data managing utilities. This dissertation presents the framework of the system.

The decision support system developed in this study is superior to a conventional expert system since it can quantify the operation and control, besides performing process diagnosis. The operator can obtain more information and has more choices when he/she is

making operational changes to the process, so that the correct decision is more likely to be made.

A process simulator was built into the system. It consists of a group of ordinary differential equations. The operator can simulate and test the operational strategies before they are applied to the process operation. In this way, the strategies can be evaluated and refined. The simulator is a valuable tool for training new operators.

An on-line estimator was constructed to estimate biomass and substrate concentrations, maximum and specific growth rates of biomass, and oxygen uptake rate, based upon measured dissolved oxygen concentration in each stage. These estimated states and bio-kinetic parameters are very valuable to the operator, and provide important information for advanced process controls. The estimator is assisted by fuzzy estimations of influent substrate and effluent total suspended solids concentrations. The convergence of the estimator is fast and stable. The estimated values reasonably well agree with both steady state plant data and hypothetical data with artificial noise.

Two kinds of knowledge were formulated in the knowledge base: fuzzy knowledge for gas phase control and conventional knowledge for process diagnosis. Four fuzzy control strategies were developed to perform gas phase control. The results show that all four strategies are superior to the conventional proportional integral derivative (PID) control system in terms of stable oxygen feed, reducing dissolved oxygen oscillation and resisting process disturbances. The fuzzy control system also has the ability to adapt to process upsets, such as storm and extremely dry weather conditions.

A conventional rule-based knowledge base was developed specifically for the HPO-AS process operation. It can be executed in either on- and off-line modes. The arrangement of the logic trees has the advantages of easy maintenance and extendibility. More than 200 rules were formulated in the knowledge base.

1. INTRODUCTION

1.1 Statement of the Problem and Previous Work

The activated sludge process has emerged as one of the major wastewater treatment methods since its invention in 1912. Thousands of plants use this process for secondary wastewater treatment in the United States. However, according to a survey conducted by the General Accounting Office (1980), 87% of the wastewater treatment plants involved in the survey had failed to meet the National Pollutant Discharge Elimination System (NPDES) permits. Another study, conducted by Junkins *et al.* (1983), showed that most of the violations of NPDES permits were due to poor operating practice and inadequate process control techniques. Appropriate operation and control of wastewater treatment plants have become a major issue in the wastewater engineering field.

The high purity oxygen (HPO) activated sludge (AS) process, a special version of the activated sludge process, is more complex than the conventional AS process. The complexity is due to 1) the nature and configuration of the process, which uses high purity oxygen, covered tanks and tanks in series, and 2) highly stochastic inputs to the process, such as hydraulic and substrate shock loadings. These complexities require greater operator sophistication, and more quantitative support for the operators. Improved operation and control of this process is a difficult task for process operators and control engineers. The major difficulties are 1) uncertainty involved in the bio-treatment process and model, and 2) lack of on-line and reliable measurements which result in poor observability over the process. A large number of previous investigations has been focused on these topics.

Biological systems are one of the most poorly understood systems among the engineering fields (Karplus, 1976). The evolution of the activated sludge model can be traced from single substrate and single organism models to structured multiple component models. The single substrate model was developed by Monod (1942). To overcome the problems associated with this model, structured multiple substrates activated sludge models were developed by the Andrews' group (Blackwell, 1971; Busby, 1973; Busby and Andrews, 1975; Stenstrom, 1976; Clifft, 1980; Clifft and Andrews, 1981). The most important concept of these models is the substrate storage function: the particulate substrate is first entrapped in bio-floc and becomes "stored substrate". The stored substrate is then converted to stored mass which is readily biodegradable by the bacteria. This concept was later adopted by Ekama and Marias (1979), and Dold *et al.* (1980). The latest structured activated sludge model was developed by the IAWQ Tasking Group (1987), IAWQ Activated Sludge Model No. 1. The stored mass concept was not used in this model. An excellent review of the evolution of the activated sludge model was presented by Yuan (1994). None of the activated sludge models have addressed the uncertainties involved in the structure and bio-kinetic parameters of the model. This is one of the major obstacles for the application of the models to the operation and control of the activated sludge process.

There are no major differences between the biological portion of the HPO and activated sludge models, except for the parameter values. However, differences do exist between the two process models, since the HPO process uses covered tanks. The first person who systematically presented an HPO model was Mueller *et al.* (1973). This model is a conventional activated sludge model based on Monod kinetics, in which the total pressure in each stage was assumed constant. This assumption is far from reality since the total pressures in the gas phase usually vary with the biological activities and the process inputs. A generalized mathematical model describing the multi-component mass transfer in the HPO process was formulated by McWhirter and Vahldieck (1978). This model was developed primarily for the process design and is a steady-state model. Clifft and Andrews (1986) applied a structured activated sludge model to the HPO process. In their model, the total pressure of each stage was no longer assumed constant, which is one step closer to reality. Stenstrom (1990) proposed a structured HPO model and tested the model using pilot plant data. The model was further calibrated and verified by Tzeng (1992) and Yuan (1994) for a full-scale HPO treatment plant. The latest HPO process model was developed by Yuan (1994), who modified the IAWQ activated sludge model (1989) and applied it to the HPO process. Yuan concluded that the modified IAWQ model is compatible with Clifft and Andrews, and Stenstrom HPO models.

Beside the poorly understood bio-kinetics and models, lack of on-line measurement for some of the very important process states has created difficulties for operation and control of the HPO-AS process. This poor observability of the system causes poor controllability of the system, which results in poor performance. To compensate for the lack of on-line measurements, an on-line estimator (observer) to estimate the unmeasured states from the measured ones, can be developed. The on-line estimator compensates for some of the disadvantages of poor absevability. Several techniques are available to design the estimator. Among these, the exponential method (Williamson, 1977), Extended Luenberger Observer (ELO) and Extended Kalman Observer (EKO) (Aborhey and Williamson, 1978), and Asymptotic Observer (Bastin, 1988), are most frequently used in the control field.

Estimators have been used previously in the environmental engineering field. Holmberg (1982) used a simple dynamic model to estimate the influent BOD-load and effluent BOD. A recursive algorithm was used to predict oxygen uptake rate (OUR) and K_La. Holmberg and Olsson (1986) presented a simultaneous estimation scheme for K_La and OUR based on a linear Kalman filter, taking advantage of the differing time scale of the two variables. Marsili-Libelli (1990) constructed an on-line estimator to predict K_La and OUR using linear approximation. The estimator was coupled with a self-tuning PID controller. In all cases efficient estimates were obtained.

The lack of on-line and reliable measurements requires operators to rely heavily on their personal experiences to operate their treatment plants (Patry and Chapman, 1989).

Expert systems have been developed to assist operators with treatment plant control. The first person to use the expert system-type rules for treatment plant operation was Beck *et al.* (1978). Johnson (1985) developed a prototype expert system to diagnose the presence of toxic material in the plant's influent. An expert system developed for operation of an anaerobic digester was developed by Barnett and Andrews (1987). A combination of rules and fuzzy logic knowledge was used in the knowledge base which could detect and prevent process failure of an anaerobic digester. Berthouex *et al.* (1988, 1989) used a statistical model to assist expert systems in making control decisions and to perform process diagnosis. Fuzzy terms, such as high, medium and low, were used to define the state limits and to detect abnormal states of the process. These fuzzy terms were statistically based on plant data. Parker and Parker (1989) developed an expert system to address sludge settling problems, such as filamentous bulking, floating sludge, ashing, etc. Koskinen (1989) reported the use of an expert system as a top level controller for an activated sludge treatment plant. Gall and Patry (1988) presented a knowledge-based system for diagnosis of activated sludge plant.

A new development in the expert system approach is to incorporate a process model into the expert system. Ozgur and Stenstrom (1994) have developed an expert system with some simple process models. The system is used for diagnosing nitrification problems for a refinery activated sludge treatment plant.

Most of the expert systems described above are process diagnosis-oriented. The results of the diagnosis are usually linguistic or semi-quantitative recommendations. It is difficult to quantify these recommendation into control actions. A fuzzy logic algorithm overcomes this difficulty, and provides a better way to combine human heuristic knowledge with both quantitative and qualitative system inputs, and to produce quantitative control output for the process.

Fuzzy logic is a useful tool to handle processes where the process mechanism is not well understood, but empirical knowledge about the process exists. Fuzzy logic theory was first introduced by Zadeh (1965), and has emerged as one of the most fruitful fields in artificial intelligence. The applications are primarily focused in the process control area. The description of fuzzy logic algorithm is given in Chapters 4 and 5. The first application of a fuzzy logic algorithm to control the activated sludge process was reported by Tong *et al.* (1981). They concluded that the algorithm works well and that a fuzzy controller would be a useful and practical way of regulating the activated sludge process. Another investigation was conducted by Chen *et al.* (1990). They developed more than 100 fuzzy rules to control the sludge recycle rate, sludge conditioning time and air supply rate for a full scale treatment plant. Significant improvement in process performance of the plant has been achieved as compared with the conventional control method.

1.2 Objectives and Scope of the Work

The ultimate goal of this study is to develop a decision support system (DSS) to facilitate the operation and control of the high-purity oxygen activated sludge processes (HPO-AS). It includes the following sub-objectives:

- performing problem diagnosis using a conventional knowledge base;
- estimating the unmeasured process states and parameters using the process estimator;
- simulating the control and operational alternatives before they are applied to the process;
- issuing quantitative control outputs through fuzzy logic reasoning;
- process data entry and retrieval, and trending data using a spreadsheet-like window;
- training new operators.

A framework of a DSS for operation and control of the HPO-AS process is developed in this study. The decision support system consists of 5 major components (modules): operator's interface, process simulator, state and parameter estimator, knowledge base and data managing utilities. The system was planned for implementation into a computer software, G2 (Gensym, 1992) and G2 Diagnosis Assistant (GDA) (Gensym, 1992). G2 and GDA are a real-time expert system shell and on-line process diagnosis tool, respectively. Originally the system was developed for both HPO and open-air activated sludge processes. Due to the time limit and quantity of the work, the system was narrowed to HPO-AS only. However, with some minor modifications, the system can also be applied to the open-air activated sludge process.

The development of the DSS is divided into two phases. In phase 1, the overall system structure is developed and each system component is tested individually. In phase 2, all system components are integrated into G2 and GDA, and the system is tested. Because of the time limits and available computer software (G2 and GDA), only phase 1 is completed. Part of phase 2 has been completed, such as developing the menu systems and operator's interface to access each system component. However, this work will not be presented in this dissertation. The interested reader is referred to Yuan *et al.* (1993) for the description of the data managing utilities.

The framework of the DSS is presented in this dissertation (mostly the work completed in phase 1). It includes the overall system structure and the interface between each system component, the process simulator, the on-line estimator, and the conventional expert system and fuzzy knowledge bases. All the algorithms involved in these system components are thoroughly tested and discussed in the dissertation.

1.3 Organization of the Dissertation

This dissertation is organized based on several papers that are published or submitted for publication. Each paper specifically describes a certain aspect of the DSS or a system component. As stated in the Objectives and Scope of Work section, there are 5 system components and three out of five components (modules) will be presented in the dissertation: process simulator, on-line state and parameter estimator, and knowledge base.

Figure 1.3.1 shows the organization of this dissertation. A system overview paper is presented first at the beginning of this dissertation (Chapter 2). It describes the overall structure of the system, the function of each component, and the interactions among its components. A process simulator for a typical HPO-AS process is described in Chapter 3. The simulator was developed based on an existing HPO process model (Stenstrom, 1989 and 1990). To compensate for the unmeasured state variables and parameters in the liquid phase of the HPO-AS process, an on-line estimator is developed, which is described in Chapter 4. The estimator can provide quantitative support to the other system components, such as the simulator, fuzzy logic gas phase control and process diagnosis, etc. In Chapter 5, the development of a fuzzy logic control system to perform gas phase control of the HPO process is presented. An adaptive fuzzy logic control system was developed specifically for dealing with extreme weather flows. This is one part of the knowledge base. Another part of the knowledge base, developed specifically for the HPO-AS process, addresses conventional problem diagnosis for both liquid and gas phases, and is presented in Chapter 6. The detailed and complete logic trees and inferencing results of the knowledge base are presented in the Appendix. Finally, the conclusions of this study and future work are presented in Chapter 7 and 8, respectively.

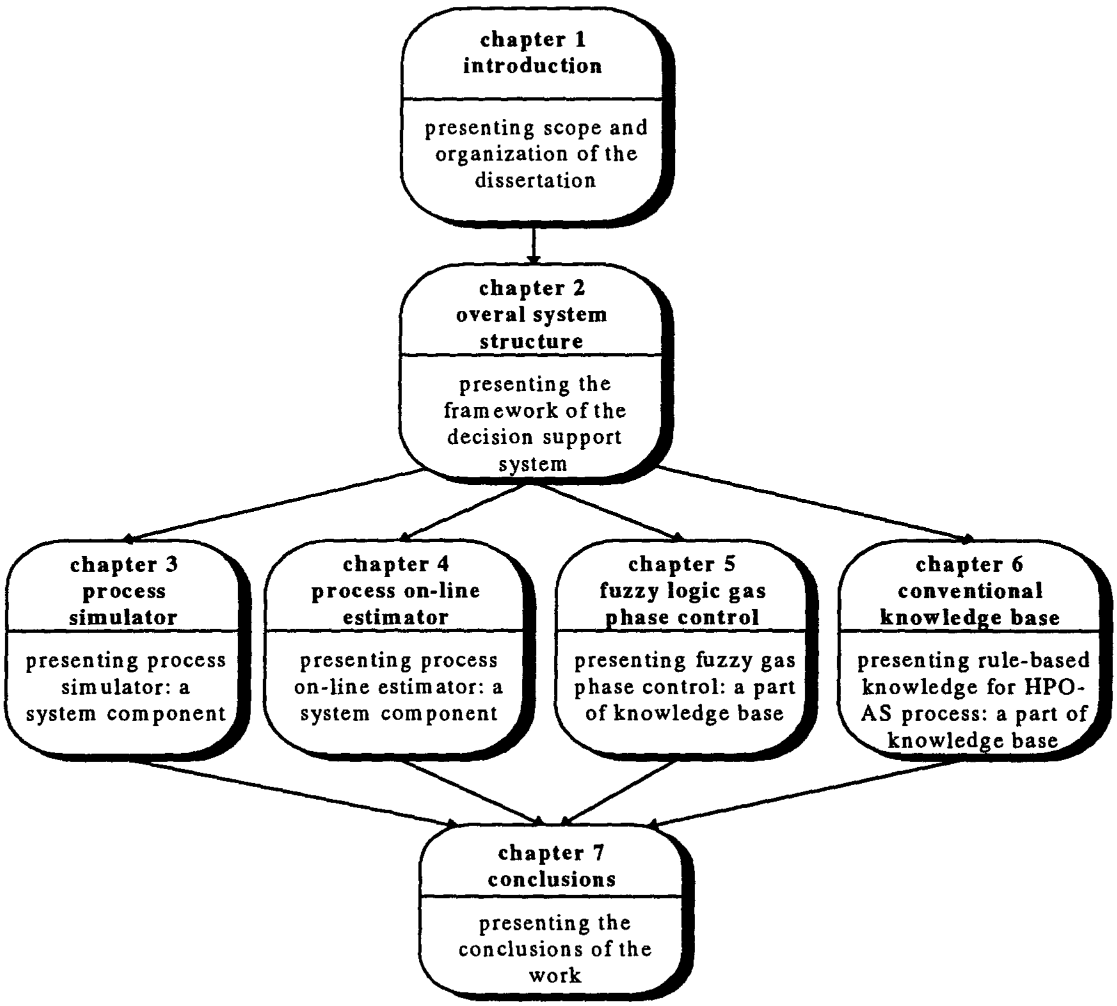

Figure 1.3.1 Organization of the Dissertation

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2. A DECISION SUPPORT SYSTEM FOR WASTEWATER TREATMENT PLANT OPERATIONS

Abstract

A framework of a decision support system for wastewater treatment plant operation is presented in this paper. The process simulator, state estimator, data management utilities along with the knowledge base provide the operator with both qualitative and quantitative support for making decisions. The preliminary results have shown the system is superior to the conventional diagnosis-oriented expert system.

2.1 Introduction

Appropriate operation of wastewater treatment is one of the most challenging tasks faced by process operators and operational engineers. The main difficulties are the inputs to the treatment process, such as influent flow rate and loading, which are highly stochastic, and our partial understanding the process dynamics under transient conditions. The problems are further complicated by the fact that there are few on-line available or reliable measurements (Patry and Chapman,1989). The operator must heavily rely on his or her personal experiences. Several "expert systems" have been developed over the last decade using such experiences (Beck *et al.*,1978, Johnson,1985, Berthouex *et al.*,1988, Barnett *et al.*,1987, Gall and Patry,1988, Koskinen,1989, Parker *et al.*,1989 and Ozgur and Stenstrom, 1994). Most of the previously described systems are process diagnosis-oriented, which still have difficulty satisfying the day-to-day operational needs. This is especially true when the linguistic results are interpreted quantitatively.

To overcome these problems, a decision support system is developed in this investigation. This support system makes full use of the features of expert systems and couples the expert system with process models. It takes full advantage of the expert system shell and creates a user's friendly environment for the operator. The system can perform the following tasks:

- performing conventional problem diagnosis;
- estimating the unmeasurable states using the process estimator;
- simulating options before the control action is applied to the treatment process;
- data entry, retrieving and data trending via a spreadsheet-like window;
- detecting and alarming potential process upsets through either simulation or real operation;
- issuing quantitative control outputs through fuzzy reasoning;
- training new operators.

The preliminary results have shown that this system can provide more information to the operator than an expert system. With the aid of the system, the appropriate operational decisions are more likely to be obtained.

The system is developed using G2, a real time expert system shell (Gensym Corporation, 1992), and G2 Diagnostic Assistant (GDA) which is a separate product of

G2. GDA is designed specifically for process diagnosis, fuzzy reasoning and other advanced controls.

This paper describes a framework of a decision support system for wastewater treatment plant operation. In the following sections, we first present the system structure and discuss the interactions among the system components. The functions of each system component are introduced next. Finally the integrity of the system and the summary are presented.

2.2 System Structure

Determining the system architecture is a critical step in developing a decision support system. The system should be arranged such that the operator can access any system component to obtain necessary information when needed. The information should also flow freely among the system components for ease of use. Based on this information the operator can make decisions under transition states.

Figure 2.2.1 shows the structure of the system, which is designed in a hierarchical format with three levels. The connections between the levels are established through a menu system (workspace in G2). There are four major components beside the operator interface: knowledge base, process simulator, state estimator and data management utility. Each component is designed as an individual module. The information exchange between the modules is through rules, procedures and relations which are standard functions

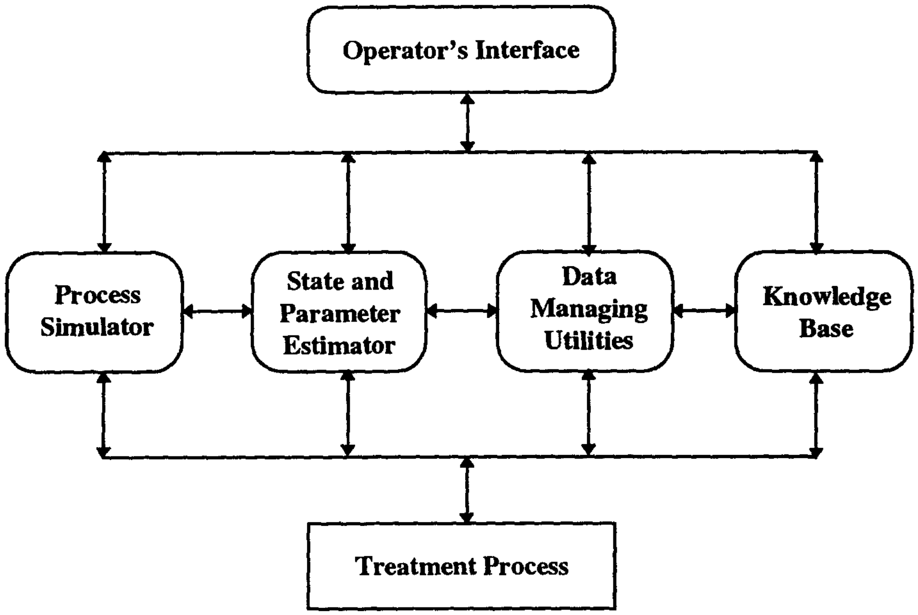


Figure 2.2.1 Structure of the Decision Support System

provided by the expert system shell (G2). For example, the initial conditions for the simulator are provided by the state estimator when it is active, or provided by the data server in the database when the estimator is inactive. The simulated results are graphically displayed to the operator and fed to the knowledge base. The operator starts or stops each functional module based on his needs. For example, when the fluid color or the foam in the aeration tank is abnormal, the operator may start the knowledge base to diagnose the causes of the abnormal color.

To allow the operator to conveniently work among the system modules, a user friendly and easy-to-use interface is crucial important. It should have the ability to extract information, access to each module freely, and perform the specific tasks within each module. As illustrated in Figure 1, the operator interface is on the top of the three level structure. Under the G2 developing environment, the operator interface is designed as several menus under the root menu. The operator starts the module by opening that module menu using the action button. Each module has its own sub-menu system. In this way, the operator can freely access all parts of the system.

In the following sections, we discuss each system module individually. It should be noted that the modules of the system were originally designed for a high-purity oxygen and a refinery activated sludge processes. With some simple modifications, they are readily applicable to any open-air activated sludge processes.

2.3 Process Simulator

A process simulator is designed to enhance the system performance. It takes advantage of our partial knowledge about process kinetics and provides the operator with an inside view of the process. A simulator can simulate the control strategies before they are implemented and allows the operator to review the predicted results. The control strategy may be modified and resimulated. In this way, better control is obtained. In addition, the process simulator can generate deeper knowledge for forming new rules, or generate fuzzy rules for advanced control techniques. The process simulator can also imitate different operational scenarios such that new operators are exposed to a wide spectrum of operational problems and gain operating experience in a relatively short time.

The simulator, based on the High-Purity Oxygen process models (Stenstrom *et al.*, 1989, 1990, Tzeng, 1992 and Yuan 1994), has been incorporated into the system using the built-in simulation utilities of G2. It can run in parallel with the system. "Simulated" data can be intrinsically interfaced with the knowledge base and dynamically displayed to the operator.

There are three major parts in the simulator: a group of ordinary deferential equations describing the process; graphical display of the simulation results, and a control panel which allows the operator to make changes and explore alternatives. Figure 2.3.1 shows the control panel for a High-Purity Oxygen Process. The operator can change process operating mode by regulating the valve openings in the graph. There are four wastewater feeding valves corresponding to four stages of the aeration tanks in series on the upper-left corner of the graph. Different combination of the valve openings forms different step-feed modes. For example, the raw water could be fed completely into the first stage by giving 100% opening to the first valve, and zero openings for the rest of the valve, or a reaeration mode could be established by given 100% opening to the second valve. Similarly, the oxygen feed flow rate can also be regulated by changing the slider of the openings of the oxygen feeding valve. In this way, the operator can evaluate alternate strategies, observe the process responses and make improved operational decisions.

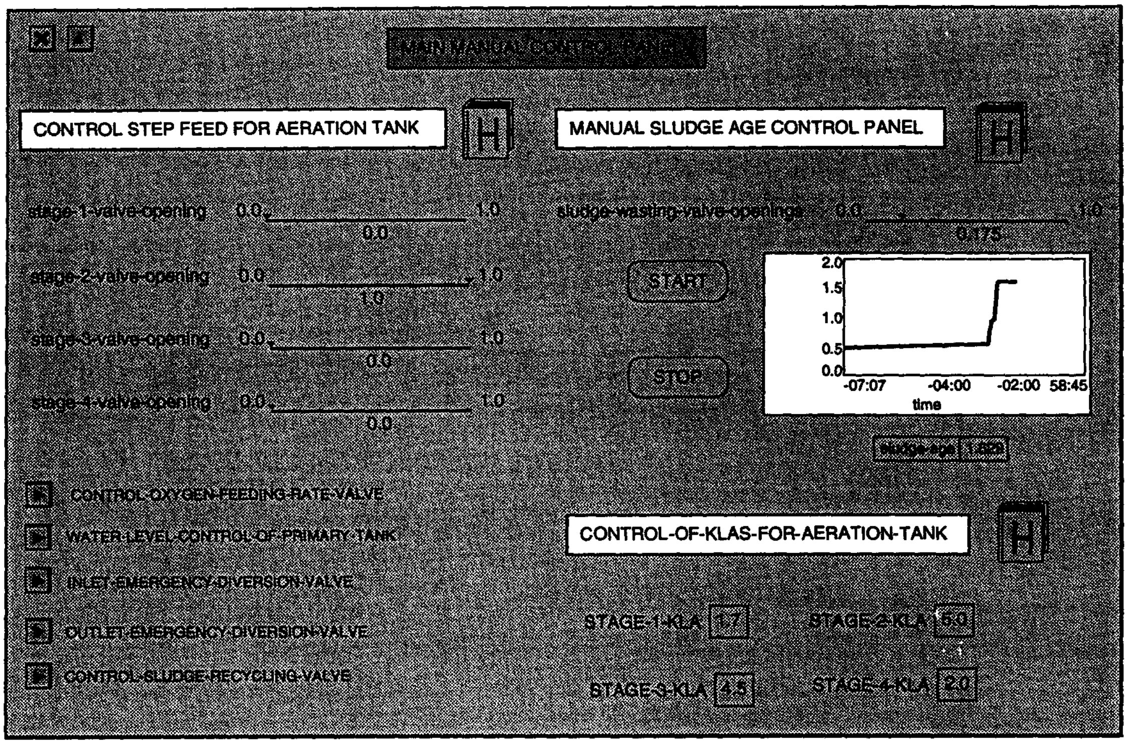


Figure 2.3.1 Process Control Panel of the Simulator

2.4 State Estimator

Among the most difficult problems in the operation of wastewater treatment are the lack of on-line and/or unreliable measurements. Many investigators have discussed this problem (Marsili-Libeli, 1982, 1990, Holmberg, 1982, 1986). One of the solutions to this problem is to design a state estimator (or observer) to estimate the unmeasured states from the measured ones. The estimated state can assist the operator in understanding process conditions and facilitating decision making process.

A prototype state estimator was designed and tested for estimating the sludge and substrate concentrations in the aeration tanks of a HPO-AS process. The estimator is based on the HPO-AS models (Stenstrom *et al.*, 1989, Stenstrom 1991) expressed in as follows:

$$\frac{d\xi}{dt} = \mathbf{K}\mu(\xi) - \mathbf{D}\xi + \mathbf{F} + \mathbf{TR}(\xi) \qquad 2.4.1$$

where ξ is a state vector, **K** is a coefficient matrix which includes stoichiometric and yield coefficients, $\mu(\xi)$ is a reaction rate vector which depends on the substrate and sludge concentrations, **F** is a feeding vector, **D** is the dilution rate vector and $\mathbf{TR}(\xi)$ is the species transfer rate vector between liquid and gas phases. An asymptotic algorithm is used in the estimator (Dochain *et al.*,1992). This method is simple and the convergence occurs faster than with the other methods. The non-linearity of Equation 2.4.1 is approximated by a linear combination process. Figure 2.4.1 shows the estimated four stage sludge concentrations based on the measurements of the gas purity in the gas phase and the DO concentrations in each stage. As expected, the convergence occurs after 40 hours and the estimated sludge concentrations reasonably agreed with the measured pilot plant data.

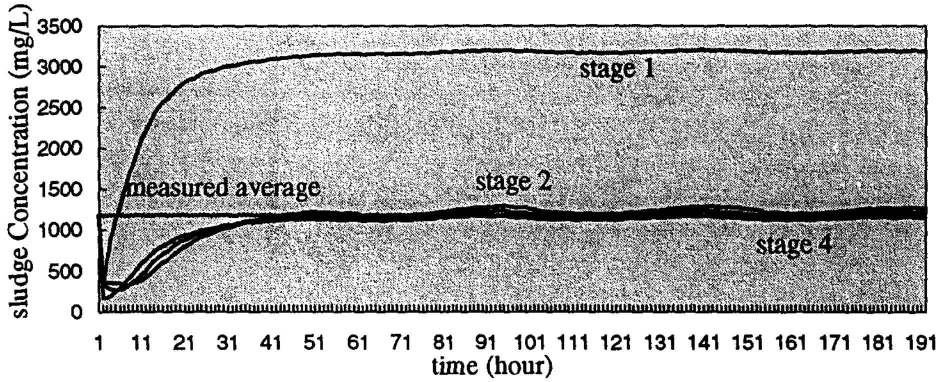


Figure 2.4.1 Estimated Sludge Concentrations Using State Estimator

The estimator is incorporated into the decision support system. With a proper initial transformation vector $\mathbf{Z}$, the convergence occurs much faster than the one shown in Figure 2.4.1. The operator can run the estimator either in simulation or in real-time mode. The estimated states provide a view of the on-going treatment process, which is a valuable assistance for the operator to assess the process state.

2.5 Knowledge Base

The knowledge base consists of two parts: problem diagnosis and fuzzy logic reasoning. The former is used to perform conventional problem diagnosis, and the later provides quantitative operation suggestions to the operator.

The knowledge base developed by Ozgur and Stenstrom (1992) contains about 300 hundred rules. The knowledge is coded for a refinery wastewater. The global knowledge and knowledge structure in the rule-base applicable to all activated sludge plants have been extracted. The local knowledge, which is site-specific, can be added to the main knowledge body for a particular treatment plant. The results of rule reasoning could be the cause of the problem, or a suggestion to solve the problem. Figure 2.5.1 shows a simple logic tree for temperature control. The global knowledge base is built into the decision support system using the G2 Diagnosis Assistant (GDA) where the rule structure is explicitly displayed by blocks and connections. The rule net is displayed graphically, and therefore the operator can observe the path of firing rules.

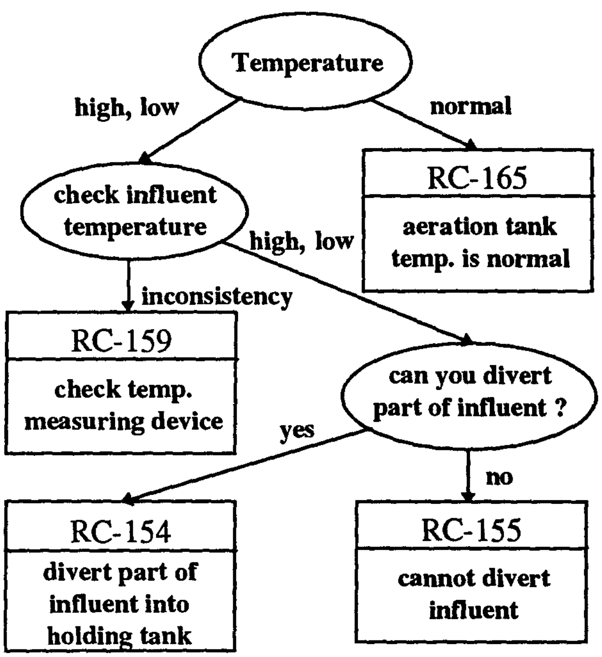
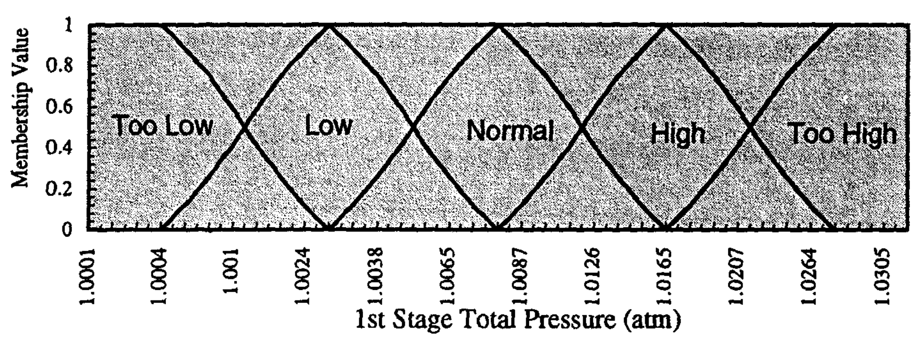


Figure 2.5.1 Logic Tree for Temperature Control

Fuzzy logic theory was first introduced by Zadeh (1965). Since then many successful applications of this theory have been achieved in Japan. Most of these applications are focused on the process control area. Tong *et al.* (1981) applied a fuzzy algorithm to control an activated sludge process. They concluded that the algorithm works rather well and a fuzzy controller would be a useful and practical way of regulating the activated sludge process. Another investigation was conducted by Zhou et al (1991), in which they built more than 100 fuzzy rules to control the sludge recycling rate, sludge conditioning time and air supply rate for a full scale treatment plant.

Fuzzy logic is a useful tool to handle processes that are characterized by uncertainties, such as biological treatment. We are designing a fuzzy logic controller (FLC) for the HPO-AS process. A group of membership functions for the stage 1 total pressure and the oxygen feeding valve openings is shown in Figure 2.5.2. The relationship



(a) Membership Function for Stage 1 Total Pressure

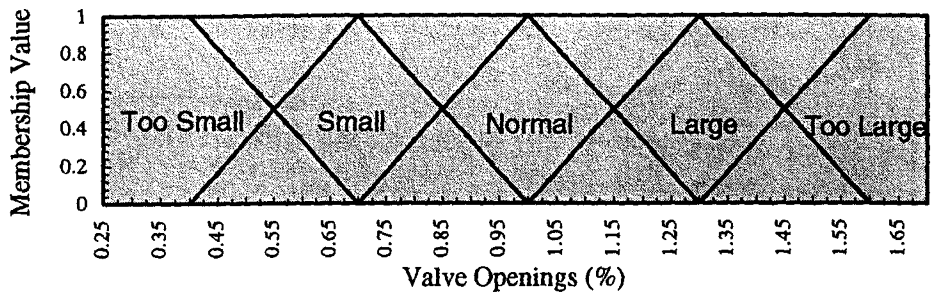


Figure 2.5.2 (b) Membership Function for Oxygen Feed Valve Openings

between the pressure and valve opening is generated by the process simulator. In this control scheme, the oxygen feeding valve is regulated based on the measurement of the stage 1 total pressure. The measurement is first fuzzed into a fuzzy set. This set is then mapped onto the membership discourse and a clipped set is obtained. Based on the fuzzy rules the clipped set of the membership values is projected onto the control output discourse (oxygen valve openings). Finally a deffuzzification is performed by calculating the center of the clipped sets so that a percentage opening is obtained.

Figure 2.5.3 shows a fuzzy rule relation matrix for the stage 1 total pressure, stage 4 oxygen gas purity and oxygen valve openings. This rule matrix is the backbone in the fuzzy reasoning process. In contrast to the conventional reasoning which results in a "black-and-white" conclusion, the fuzzy reasoning fires a group of

rules and produces several fuzzy sets. For example, if the input stage 1 total pressure is 1.0019 atm and the stage 4 oxygen purity is 40%, the total pressure is 78% of Low and 22% of Too Low, and the stage 4 oxygen purity is 86% of Low and 14% of Normal, when these inputs are mapped onto the membership functions. Thus, four rules in the matrix are fired as indicated in the shadowed area:

1. if the total pressure is Too Low and stage 4 purity is Low then the valve opening is Too Large;
2. if the total pressure is Low and stage 4 purity is Low then the valve opening is Large;
3. if the total pressure is Too Low and stage 4 purity is Normal then the valve opening is Large;
4. if the total pressure is Low and stage 4 purity is Normal then the valve opening is Large.

stage 1 total pressure (atm)

stage 4 O_2 purity (%)

	Too Low	**Low**	**Normal**	**High**	**Too High**
Too Low	**TL**	**TL**	**L**	**L**	**N**
Low	**TL**	**L**	**L**	**N**	**S**
Normal	**L**	**L**	**N**	**S**	**S**
High	**L**	**N**	**S**	**S**	**TS**
Too High	**N**	**S**	**S**	**TS**	**TS**

Figure 2.5.3 Fuzzy Rule Relation Matrix for HPO-AS Pressure Control

The controlled output is generated by the weighted average of these four fuzzy sets. The set points for this example are 1.008 for stage 1 total pressure and 60% for stage 4 oxygen purity, respectively.

Using the process simulator and common sense, more complicated fuzzy relations among the process states and controlled variables can be established. These relation matrices and their corresponding membership functions are being incorporated into the decision support system using GDA's built-in utilities, which will become an important part of the system.

2.6 Data Management

An expert system for a refinery wastewater treatment process was developed by Yuan *et al.* (1993). The data management utility of the system was implemented in the decision support system of this work. The data management utility includes data entry, retrieving, trending and an implausible data entry checking function. The utility is developed by making use of the built-in tools of the shell.

Data entry allows the operator to type in data collected from sensors and laboratories into a data file through a spreadsheet-like workspace. Certain typing errors can be detected by the utility rules and reported to the operator. The entered and processed data can be retrieved upon the request. The user can vary retrieving interval, such as monthly, weekly or hourly, so that the retrieved data are displayed in that interval. The utility can also display trend charts of major process variables.

2.7 Summary

A framework of a decision support system for wastewater treatment plant operation and control has been presented and discussed. The system is superior to a conventional expert system since it can perform the process diagnosis, and can also quantify the operation and control. With the assistance of the process simulator, estimator, data management and the knowledge base, the system can provide more information and better choices to the operator. This information can greatly facilitate process operation and provide the operator opportunities to make better decisions.

Implementation and integrating each module into the system are difficult tasks. Great care should be given to the interactions among the system modules. The information flow pathways between the components should be arranged logically and efficiently such that the system can act as a whole.

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3. A SIMULATOR-ENHANCED EXPERT SYSTEM FOR THE HIGH-PURITY OXYGEN ACTIVATED SLUDGE PROCESS

Abstract

Most of the expert systems developed to facilitate the operation of the activated sludge process are diagnosis-oriented systems. These systems have difficulties interpreting the linguistic recommendations into quantitative controls. This is especially true for the high-purity oxygen process (HPO), where more quantitative controls are required. In this investigation we incorporate a simulator, based on an HPO process model, into an expert system. The simulator provides the operator with more opportunities to make better decisions by allowing him to test his operational alternatives before they are implemented. The simulator is also a useful tool for training the new operator. The preliminary results have shown that the expert system's ability to produce more quantitative controls is greatly extended with the simulator.

3.1 Introduction

There are few available and reliable on-line measurements which require treatment plant operators to rely heavily on their experiences in operating the treatment plants (Patry and Chapman, 1989). This deficiency has stimulated the development of a number of "expert systems" for process control during the last decade (Beck *et al.*, (1979), Johnson (1985), Berthouex *et al.* (1989), Barnett *et al.* (1987), Gall and Patry (1988), Koskinen (1989), Parker *et al.* (1989) and Ozgur and Stenstrom (1994)). These expert systems encode the operator's knowledge or "know how" into a computer program in such a way that it can be used for process control. Most of the systems developed are process diagnosis-oriented, which usually produce a linguistic or semi-quantitative control recommendation to the operator. One of the major difficulties in developing such a system is to quantify these actions for process control. For more complicated treatment processes, such as the high-purity oxygen activated sludge (HPO) process, more quantitative control actions are required.

The HPO activated sludge process is more complicated than the conventional open-air process. The complexity of the HPO process is due to the use of the high purity oxygen, covered aeration tanks and multistage tanks in series. Appropriate operation and control of HPO process is of crucial importance to prevent process upset under the transit conditions and to avoid wasting energy. The series operation of the stages produces lags or process delays which further complicates control. This is especially true for the gas phase. In contrast to the conventional air process, the operator cannot observe the aeration tanks directly since the multiple stage tanks are covered up. This greatly limits the traditional use of the expert system which relies upon empirical observations, such as color of the sludge. The operation of the HPO process is further complicated by its configuration which provides more operational scenarios than a conventional air system does. Changing the step-feed mode of raw wastewater to each stage, regulating oxygen feed rate, adjusting the aeration rate, resetting the controller set-point for stage 1 total pressure or stage 4 oxygen purity, or the combination of these controls, are all possible operational alternatives for achieving a better process control. Conventional expert systems have difficulty in satisfying these operational needs.

To compensate for the shortcomings of the diagnosis-oriented expert system and quantify process control, one approach is to build a simulator based upon process models, which represents our partial knowledge of the process. A process simulator can simulate different control strategies before they are implemented. The simulated results are evaluated and compared by either the operator or the expert system. To improve performance these control actions can be modified and simulated again. Other control strategies can be developed in this fashion. Additionally, the process simulator can generate deeper knowledge, which is a part of the self-learning aspect of the expert system. The simulator also allows the operator to experience different operational scenarios, which is a cost-effective way for training the new operator. With the assistance of the simulator, the new operator is exposed to a wide spectrum of operational problems and can gain operating experience in a relatively short time.

A process simulator based on the HPO process models (Stenstrom *et al.*, 1989, 1991, Tzeng, 1992 and Yuan 1994) has been incorporated into the expert system in this investigation. Several cases based on HPO pilot plant data were used to test the simulator. The preliminary results have shown that with the assistance of the simulator, control actions can be evaluated and refined, thus achieving better process control. Alarms signaling potential process failure and abnormal states were delivered to the operator during the simulation. The process simulator, along with the dynamic display and user-friendly interface, provides the operator with an intuitive feeling of the process, and greatly extends the diagnosis-oriented expert system's abilities.

It should be noted that the process simulator presented herein is only one part (or one module) of the overall expert system (called decision support system) that is under development. Figure 2.2.1 shows the architecture of the overall system. For a more detailed explanations of the system integrity and the functions of each system module, the readers are referred to Yin *et al.*, (1994).

In the following sections, we first present the HPO process model which is the backbone of the simulator. The software tools for coupling this group of the ODE's into the expert system are also presented. The major features of the current version of the simulator are demonstrated next. Finally the summary and preliminary conclusions based on the work are presented.

3.2 Methodology

The simulator consists of four major parts: HPO model, process schematics and dynamic display, error detection and alarm system, and manual control panel. HPO process models are reviewed and a model is described in the following section. We will present the other three parts in the Results and Discussions section. More than 100 rules, 11 procedures and 32 ordinary differential equations are used in the current version of the simulator.

3.2.1 Process Model

Several dynamic models for the HPO process have been reported in the literature. The first person who systematically presented HPO model was Mueller *et al.* (1973). The model is a conventional activated sludge model based on Monod kinetics. In their steady-state, model the total pressure in each stage is assumed constant. A generalized mathematical model for describing the multi-component mass transfer in the HPO process was formulated by McWhirter and Vahldieck (1978). This model was developed primarily for the process design and is a steady-state model. Clifft and Andrews (1986) applied a structured activated sludge model to the HPO process. In their model the total pressure of each stage is no longer constant, which is much closer to reality. Stenstrom (1991) proposed a structured HPO model and tested the model using a pilot plant data. The model was further calibrated and verified by Tzeng (1992) and Yuan (1994) for a full-scale HPO treatment plant. The latest HPO process model was developed by Yuan (1994), who modified the IAWPRC activated sludge model (1989) and applied it to the HPO process. Yuan concluded that the modified IAWPRC model is compatible with Clifft and Andrews and Stenstrom HPO models.

In this investigation, the Monod-based model developed by Stenstrom *et al.*, (1989) was used as the basis of the simulator. Since the model is too complex to describe using conventional nomenclature, the model was rewritten in state-space format. For the liquid phase, it takes the following form:

$$\frac{d}{dt}\begin{bmatrix} DO \\ S \\ X \\ CO \\ NH \\ DN \end{bmatrix}_i = \begin{bmatrix} K_1 & K_2 \\ K_3 & K_4 \\ K_5 & K_6 \\ K_7 & K_8 \\ K_9 & K_{10} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mu_g \\ \mu_d \end{bmatrix}_i - \begin{bmatrix} DO \\ S \\ X \\ CO \\ NH \\ DN \end{bmatrix}_i D_i + \begin{bmatrix} DO_0 \\ S_0 \\ X_0 \\ CO_0 \\ NH_0 \\ DN_0 \end{bmatrix}_i D_{in} + \begin{bmatrix} OTR \\ 0 \\ 0 \\ CTR \\ 0 \\ NTR \end{bmatrix}_i \qquad 3.2.1$$

Equation 3.2.1 can be generalized as

$$\frac{d\xi_i}{dt} = K\mu_i(\xi_i) - D_i\xi_i + F_i + TR_i(\xi_i) \qquad 3.2.2$$

where i denotes the i-th stage of the aeration tank, ζ_L is the state vector, K is the stoichiometric and yield coefficient matrix, μ_i is the reaction rate vector which is a function of the state variables, D_i is the dilution rate, F_i is the mass input vector in the liquid phase and TR_i is mass transfer rate vector for O_2, CO_2 and N_2 between the gas phase and liquid phase, which is also a function of the state variables. Similarly, we can write the state-space equations for the gas phase as follows:

$$\frac{d}{dt}\begin{bmatrix} O_{2g} \\ CO_{2g} \\ N_{2g} \end{bmatrix}_i = 0 - \begin{bmatrix} O_{2g} \\ CO_{2g} \\ N_{2g} \end{bmatrix}_i D_{g_i} + \begin{bmatrix} O_{2g0} \\ CO_{2g0} \\ N_{2g0} \end{bmatrix}_i D_{g0_i} - \begin{bmatrix} \dfrac{OTR}{MW_{O_2}} \\ \dfrac{COTR}{MW_{CO_2}} \\ \dfrac{NTR}{MW_{N_2}} \end{bmatrix}_i R_i \qquad 3.2.3$$

where D_{g_i} is gas phase dilution rate, D_{g0_i} is dilution rate of the input gas flow at stage 1 and R_i is the liquid-gas volume ratio.

3.2.2 Developing Tool

The expert system shell used in this investigation is G2 (Gensym Corporation, Cambridge, Massachusetts, 1992), a real-time expert system shell. Equations 3.2.1 and 3.2.3 were incorporated into G2 using its built-in simulation capabilities. With the multi-tasking feature of G2, the expert system still controls the whole treatment process while the simulator is active. Under the G2 developing environment, the simulator is intrinsically related to the other system components. The relationship inside the simulator, such as the connections among the process schematics and icons, or the relationship between the simulator and the other system modules, is established through the rules, procedures and relations. These are the standard functions of G2. The implementation of the expert system and the process simulator have taken full advantage of these functions.

One of the major concerns in this research is the development of a more user-friendly and easy-to-use interface for the operator. Poor screen display, poorly organized menus and cumbersome simulation interface could jeopardize the operator's acceptance of the system. Under the G2 environment, the operator interface is designed as several menus for each system module under a root menu. The simulator has its own sub-menu system beneath the root menu, which is protected in the operator mode. The process schematic provides the operator a more intuitive and familiar interface. The operator can switch between the system modules shown in Figure 2.2.1, turn on-and-off simulator using the action button, test his operational alternatives by changing the slider of the valve openings in the control panel menu, and observe the predicted results by clicking on the process icons on the schematics. The initial conditions for equations 3.2.1 and 3.2.3 are provided by the estimator when it is active, or by data from the database when the estimator is inactive.

3.3 Results and Discussion

We present the process schematic and display, alarm system and control panel of the simulator in this section.

3.3.1 Process Schematic and Displays

Inclusion of the process schematic into the expert system and simulator helps the operator understand and accept the system. The operator can directly observe the process equipment layout and flow diagram. With the assistance of the dynamic display, such as trend charts, meters, dials and numerical tables, the operator gains an intuitive feeling of the process dynamics. The displays can be made to look like existing controller displays.

The HPO process schematic in this system was created based on a hypothetical and typical HPO process. Figure 3.3.1 shows the overall treatment plant layout. By clicking on the go-submenu button, the system displays the detailed primary or secondary treatment process diagram (Figure 3.3.2). Process equipment, such as pumps, tanks, meters and valves, are represented by the icons on the schematics. There is at least one display workspace beneath each process icon, which is displayed when the icon is clicked. For example, when the sludge recycling pump is clicked, the display workspace appears, which shows the current status (OK or BAD) and the current pumping rate. More detailed displays are imbedded in the icons of the key operation units, such as aeration tanks (4 stages), clarifier, etc. The displays for these equipment have several layers, including dials and meters, numerical tables and state variable trending charts shown process conditions. Figure 3.3.3 shows eight important state variables of stage 1 for both the gas and liquid phases. The total pressure of stage 1 can be seen by clicking on the pressure meter icon on the schematic (see Figure 3.3.2 for the total pressure meter icon). The operator can bring up the trend chart by clicking on the go-submenu button.

Two types of information can be shown in the displays: measured data obtained from the on-line sensors or manually entered laboratory results, and simulated "data" from the simulator or the estimator. The simulated values are displayed first if the simulator is active. The real process data is displayed if the simulator is inactive, or if the operator selects the process data. Due to the lack of on-line measurements in the wastewater treatment plants, the process simulator can be used to estimate state variables for process displays and control. In this way the simulator becomes a valuable tool to the operator in understanding the process dynamics.

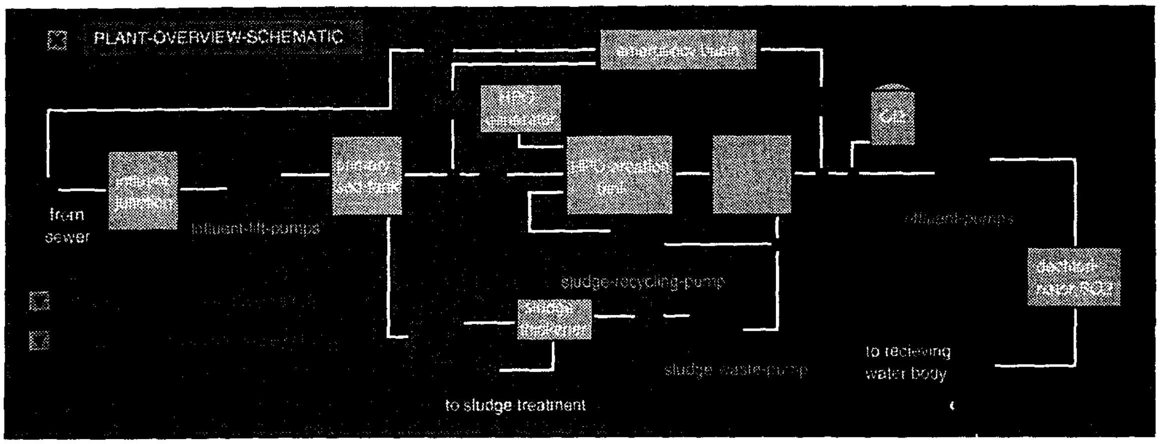

Figure 3.3.1 HPO Plant Overview Schematic

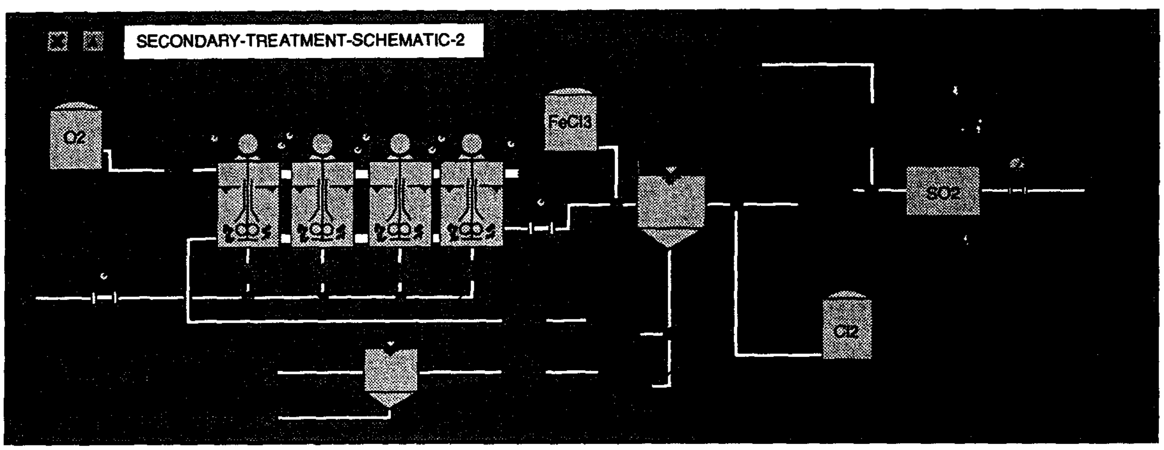

Figure 3.3.2 Secondary Treatment Schematic of HPO-AS Process

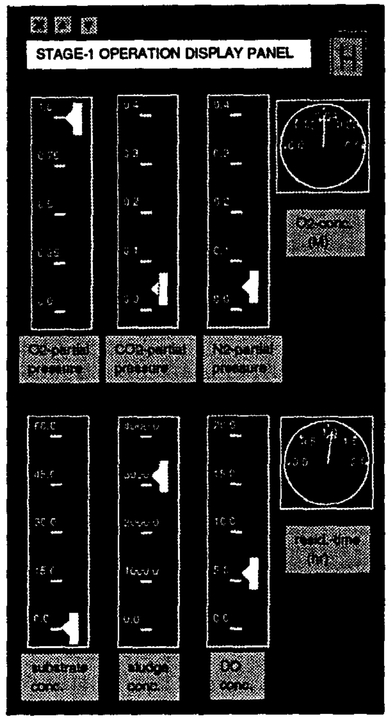

Figure 3.3.3 Meter and Dial Displays of Simulation Results for Stage 1

The simulator can be triggered by the operator or by the built-in rules and procedures. The operator can start the simulator whenever needed through an action button. For example, when evaluating changing to the step-feed mode, the operator may wish to turn on the simulator to observe the predicted process changes. The simulator can also be invoked through the diagnosis of a certain type of problem, or when an implausible measurement needs to be evaluated. The simulator is turned on and off automatically when involved in the later condition.

3.3.2 Alarm System

The alarm system is designed to alert the operator to the potential process failures and the status of process equipment. Early warning of the process upset can be vital to the biological treatment since it may take a long time to recover from the process failure. Many investigators have recognize this problem and built alarms in their systems (Patry and Chapman, 1989, Ozgur and Stenstrom, 1994). However, these systems do not include a process simulator.

Two types of alarm systems are provided. The first is error detection and alarm through the process diagnosis and real-time control, and the second is an alarm system that is built in the process simulator. The two alarm systems are intrinsically related through rules. Both the systems can invoke the alarm layer imbedded in the icons on the process schematics and flash the alarm color, indicating the status of the equipment and the location of the problem. The first type of alarm is conventional and is not discussed further; only the alarm system for the simulator will be discussed.

Two types of alarms are incorporated within the process simulator. The first relates to the simulation that the operator may perform in evaluating alternative control actions. When a simulation predicts a process state which is outside predefined limits, an alarm will flash. This alters the operator that his proposed control action produces conditions which are potentially harmful. The second relates to how well the simulation is tracking actual operation. If the deviation between simulated results and measured values is greater than predefined tolerances, an alarm will flash. Such an alarm may indicate that a probe is malfunctioning or needs recalibration. Figure 3.3.4 shows a typical alarm rule used in the system. When the rule is fired the alarming message will be delivered to the operator.

3.3.3 Control Panel

The control panel is designed so that the operator can test and evaluate operational alternatives. Different operational modes can be established by regulating the openings of the valves and the speed of the aerators. The changes of these modes are simulated and the results are dynamically displayed. The operator can evaluate and modify the strategies based on the predicted results. Under the G2 development environment, the simulator runs in parallel with the real-time system, and the simulated results can be used by the other operational units, or stored in a historical data file for later use.

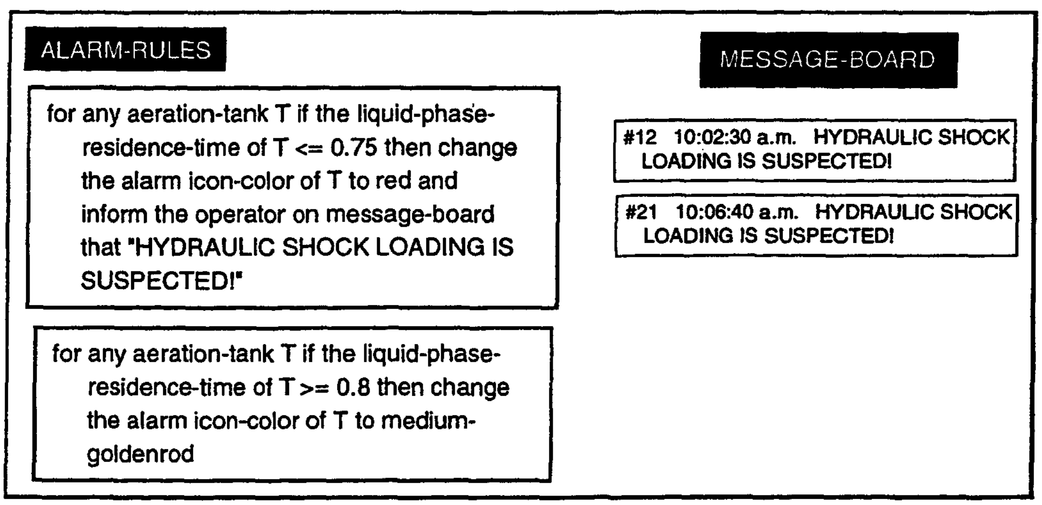

Figure 3.3.4 Rules and Message-Board Alarming Operator about Hydraulic Shock Loading

All the major control devices for a HPO activated sludge process are arranged as shown in Figure 3.3.5. The operator can change the operational modes by regulating the sliders of the different valve openings, or by inputting new values for the process parameters on the graph. On the upper-left corner, the combination of different valve openings of the wastewater feed forms various operational strategies. The primary effluent, for example, could be fed completely into the first stage by opening the first valve to 100% and closing the other valves to zero, or a reaeration mode could be established by opening the second valve to 100% and closing the other valves. The sludge age, which is a steady-state control variable, can also be regulated through the sludge wasting valve on the upper-right corner of the graph. Reduction of the opening of the sludge wasting valve increases sludge age and sludge concentration in the aeration tanks. This change can be observed in the display graphs shown in Figure 3.3.3. The aerator speed is controlled via the change of the $\mathbf{K_La}$ values of the four stages. For an existing treatment process with mechanical aerator, $\mathbf{K_La}$ is directly related to the motor speed of the aerator. For the other controls, such as oxygen feed rate, sludge recycle rate, and emergency diversion valves, the control provides the sub-menus at the lower-left corner of the graph. Clicking on the go-submenu action button will bring up these sub-control menus to the operator.

Operation of an HPO activated sludge process is more complicated than operating an equivalently sized air activated sludge process. It frequently provides the operator with more operational modes. The combination of these working modes results in additional and more flexible controls and operating scenarios. For example, if an increase of stage 1 dissolved oxygen (DO) concentration is desired, three alternatives are possible: 1) increasing the oxygen feed rate; 2) increasing the K_La of stage 1; and 3) decreasing the primary effluent feed to stage 1. All these are possible and will increase DO in stage 1; however, they also impact other parts of the process and may produce important impacts on process operation other than changing the DO in stage 1. The simulator can evaluate

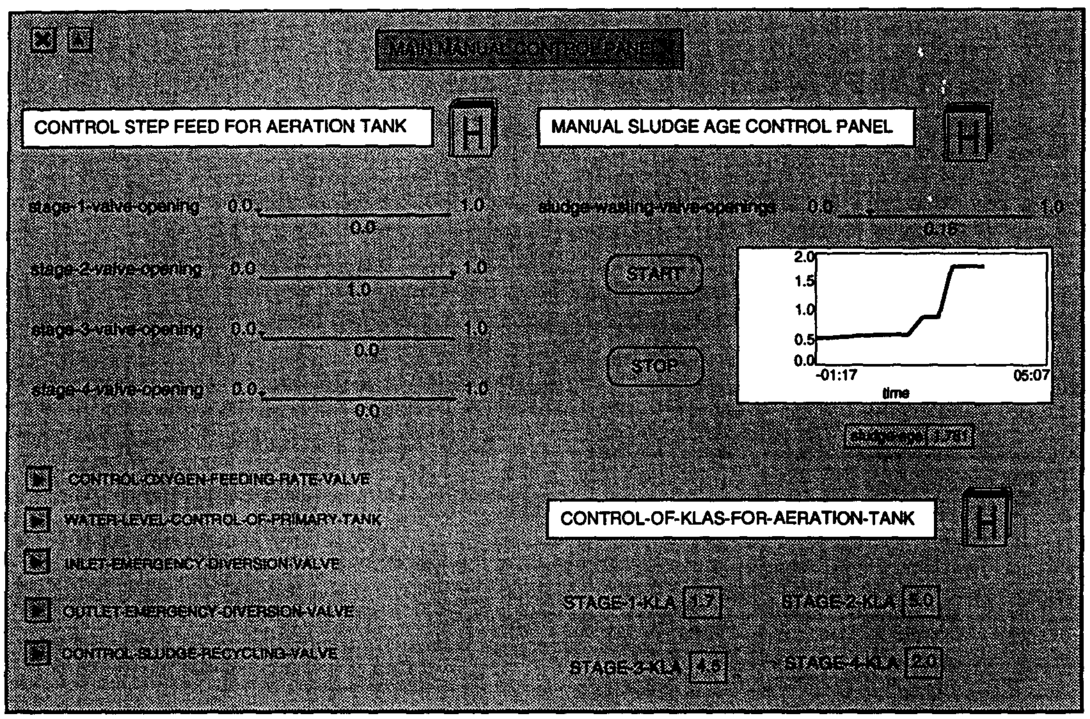

Figure 3.3.5 Control Panel for the Operator

all these alternatives, or combinations of alternatives, which allow the operator to pick the best strategy. If the same simulations are repeated many times and the results are analyzed, it may be possible to develop empirical rules for elevating stage 1 DO, which can update the existing knowledge base through the rule keeper.

3.4 Summary

A process simulator has been incorporated into the expert system shell for the high-purity oxygen activated sludge process. The preliminary results have shown that the simulator can greatly facilitate the operation of an HPO activated sludge process. With the assistance of the simulator, control actions can be evaluated and refined. The simulator can also provide the operator an inside view of the process. It can quantify the controls, which is important for operation and control of an HPO activated sludge process due to its complex nature. The simulator is a valuable tool for training the new operators.

It should be noted that the overall system is still under development. The current version of the simulator is subject to many changes. New features will be added and redundancies of the simulator will be eliminated as the research continues.

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4. DEVELOPING A FUZZY-SUPPORTED STATE AND PARAMETER ESTIMATOR FOR LIQUID PHASE OPERATION AND CONTROL OF THE HIGH-PURITY OXYGEN ACTIVATED SLUDGE PROCESS

Abstract

Lack of on-line measurements is a major problem in the operation and control of the high-purity oxygen activated sludge process. To overcome the problems, we developed an on-line estimator using dissolved oxygen measurements in each stage to estimate biomass and substrate concentrations, as well as biomass growth and decay rates. We employed a fuzzy algorithm to estimate unmeasured influent substrate and recycling biomass concentrations. The fuzzy rules also have the ability to adapt to process upsets and still make good predictions. The convergence of the algorithms used for the estimator is fast and stable, even with a large range of initial inputs and noisy dissolved oxygen measurements. The estimated results compare well with both plant and model simulated data. The estimator was also tested under certain types of process upsets, such as shock hydraulic loading and high diluted sludge volume index. The performance of the estimator is stable and satisfactory.

4.1 Introduction

One of the most challenging problems to operators in operation of the activated sludge process is the lack of on-line measurements. This leads to poor observability and poor system performance. The high-purity oxygen (HPO) activated sludge (AS) process, which is characterized by the high-purity oxygen feed and covered aeration tanks in series, is more complex to operate than conventional open-air activated sludge processes, and more quantitative controls are required. It is crucial for the operator to know the state of the on-going process when making operational decisions. The known states and parameters of the process can also be utilized for process control. An on-line estimator for the HPO-AS process is valuable because it can estimate many unmeasured states and parameters from the measured ones.

Constructing an on-line estimator (observer) is a common practice in the control engineering field (Aborhey and Williamson, 1978, and Ljung, 1979). A number of successful applications of this technique to the fermentation process has been reported in the literature (Stephanopoulos and San, 1984, Ramirez, 1987, Shimizu and Takamatsu, 1989, Dochain, 1992, and Dochain *et al.*, 1992). In the fermentation process, such as a fed-batch bioreactor, the input substrate is usually known, and biomass is not recycled. For the activated sludge process, the influent substrate concentration is highly stochastic and unknown, and biomass needs to be recycled to maintain biomass concentration in the aeration tank. The recycled biomass concentration is usually not measured on-line. This has greatly increased the complexity of applying on-line estimation techniques to the activated sludge process. Meditch and Hostetter (1974) developed an algorithm for systems with unknown inputs, but the algorithm can only be applied to constant-coefficient linear systems.

Previous application of on-line state and parameter estimation techniques for the activated sludge process can also be found in the literature. Holmberg and Olsson (1985) presented a simultaneous estimation scheme for K_La and oxygen uptake rate (OUR) based on a linear Kalman filter, taking advantage of the differing time scale of two variables. Marsili-Libelli (1990) constructed an on-line estimator to predict K_La and OUR using linear approximation. The estimator was coupled with a self-tuning PID regulator. Their results confirm that efficient estimates can be obtained in all cases. An on-line state and parameter estimation algorithm for identification of IAWPRC model was reported by Ayesa *et al.* (1991). They employed a recursive non-linear, extended Kalman filter to simulate the behavior of a specific activated sludge process under the steady and transients conditions. The results showed rapid convergence of the algorithm and accurate state estimation even with noisy data.

The purpose of this study is to develop a method to estimate important, unmeasurable variables using available on-line measurements, and process models. We employed an asymptotic algorithm (Dochain, *et al.*, 1992) to estimate biomass and substrate concentrations in each stage using the dissolved oxygen measurements. The maximum, specific growth and decay rate are simultaneously estimated based on the estimated biomass and substrate concentrations using a recursive least squares algorithm (Young, 1978, Bastin and Dochain, 1991). The oxygen uptake rates for each stage can also be obtained. A conventional HPO model was used for the on-line estimator (Stenstrom, 1989). To estimate the unmeasured influent substrate and recycling biomass concentrations, an on-line fuzzy logic algorithm (Pedrycz, 1993) was used. The recycling biomass concentration is estimated by first estimating the total effluent suspended solid

(TSS) using 30 fuzzy rules based upon the influent flow rate and diluted sludge volume index (DSVI). A mass balance is then made around the secondary clarifier to obtain the recycle biomass concentration. In this way, the off-line measurement (DSVI) is incorporated.

The estimated biomass and substrate concentrations in each stage were compared with the pilot HPO plant data (Stenstrom, 1990). The convergence of the state estimator is fast and stable even with a large range of initial inputs and noisy DO measurements. The estimated states reasonably agree with the plant data. Since there is very little dynamic field data available, the estimator was simulated and compared with an existing HPO process simulator, using a structured model developed by Stenstrom (1990). The estimated parameters were compared with both plant and simulated data, and very good agreement was achieved. The estimated OUR's closely track the simulated ones. With the assistance of fuzzy estimations of influent substrate and recycle biomass concentrations, the estimator exhibits a fast convergence and stable performance using dynamic inputs and transient conditions. The estimator was also tested under certain types of process upsets conditions, such as hydraulic shock loading or sludge bulking (high DSVI value). The results are reasonable and satisfactory.

It should be noted that the on-line estimator developed in this study is an integrated component of an overall decision support system for the operation of high-purity oxygen activated sludge process, which is still under development. The on-line estimator can provide data support to the operator, as well as to the other system components. For detailed description of the overall system, the interested readers are referred to Yin *et al.* (1994).

In the following section, we first describe the HPO-AS process, the process model and assumptions about the availability of on-line measurements. The asymptotic and recursive least squares algorithms are next described, followed by a description of the fuzzy rule base used for estimating influent substrate and effluent TSS concentration. The performance and simulated results of the estimator are next presented and discussed. Finally we conclude our study with some remarks.

4.2 HPO-AS Process and Process Model

4.2.1 High-Purity Activated Sludge Process and Process Measurements

The HPO process is different from the conventional open-air activated sludge process because of its use of high-purity oxygen (>97%) and the process configuration. Figure 4.2.1 shows a typical HPO process. The aeration tanks are covered and arranged in series (usually 3 to 6 stages) to increase treatment efficiency and oxygen utilization. The oxygen is normally fed to stage 1, which operates at slightly higher pressure than atmospheric, usually about 1.008 atm (5-15 cm water column). The mixed liquor DO concentrations in each stage are higher (6 - 10 mg/L) than commonly found in open-air activated sludge processes.

Primary effluent to the aeration tanks can be manipulated depending on operational needs. The primary effluent can be fed to the stage 1 in a conventional way, or can be fed to the second stage to establish a reaeration mode, or fed directly to stage 4 to protect sludge inventory when hydraulic shock loading is encountered (Clifft *et al.*, 1983). The estimator was operated in the reaeration mode to simulate the pilot plant operation. The estimator can work in any feed mode and we demonstrate this later by simulating a hydraulic shock load.

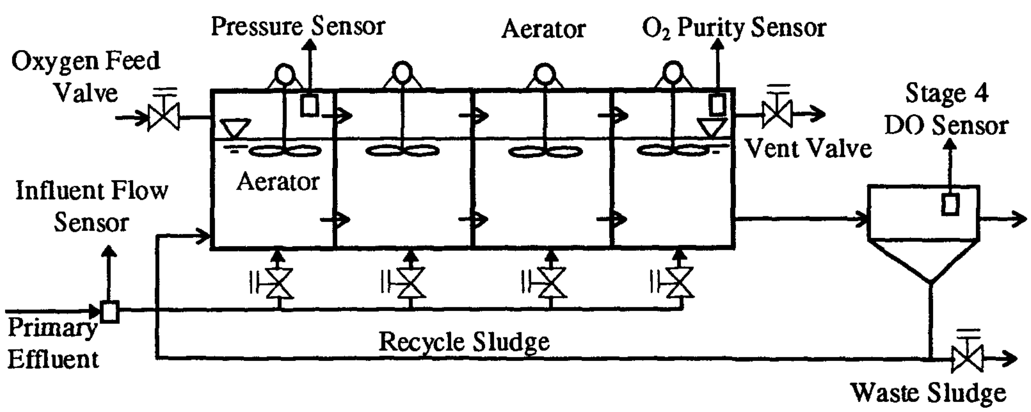

Figure 4.2.1 Flow Diagram for a Typical Four-stage HPO-AS Process

To construct an on-line estimator for liquid phase operation, it is necessary to examine the on- and off-line measurements used in the HPO process. Table 4.2.1 summarizes some of the possible measurements, which can be used in estimator design. Stage DO concentration is one of the major measurement required for the estimator. In most of the HPO plants, the stage DOs or oxygen partial pressures in each stage may be measured. In either cases, the DO concentrations can be known. The estimator also requires the on-line measurements of influent, recycling and sludge wasting flow rates.

Table 4.2.1 Summary of Some Measurements for HPO-AS Process

Variable Name (1)	**Measured On-Line** (2)	**Measured Off-Line** (3)	**Unmeasured** (4)
Influent Flow Rate	x		
Influent Substrate Concentration		x	x
Recycling Flow Rate	x		
Recycling Biomass Concentration		x	x
Oxygen Partial Pressure	x		
DO Concentration	x		
Sludge Wasting Flow Rate	x		
Effluent Total TSS		x	x
DSVI		x	
Effluent BOD_5 (or COD)		x	x

Note: x denotes the most likely method of measurement.

Another key parameter to run the estimator is the oxygen transfer coefficient (K_La). In most of the cases, K_La should directly proportional to the impeller speed (surface aerator) or gas recirculation rate (submerged turbine aerator). Various empirical equations may be used to estimate stage K_La and the following equation is used in this research.

$$K_L a = 0.11(P)^{0.9} \qquad 4.2.1$$

where P is the stage propeller horsepower. This equation is specific for this research, and shoud not be applied elsewhere. In this study we considered K_La as a known parameter.

4.2.2 HPO Process Model

A conventional Monod-type dynamic model developed by Stenstrom *et al.* (1989) was used as the governing equation for both state and parameter estimators. The liquid phase model takes the form

$$\frac{d}{dt}\begin{bmatrix} DO \\ S \\ X \\ CO \\ NH \\ DN \end{bmatrix}_i = \begin{bmatrix} K_1 & K_2 \\ K_3 & K_4 \\ K_5 & K_6 \\ K_7 & K_8 \\ K_9 & K_{10} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mu_g \\ \mu_d \end{bmatrix}_i - \begin{bmatrix} DO \\ S \\ X \\ CO \\ NH \\ DN \end{bmatrix}_i D_i + \begin{bmatrix} DO_0 \\ S_0 \\ X_0 \\ CO_0 \\ NH_0 \\ DN_0 \end{bmatrix}_i D_{in} + \begin{bmatrix} OTR \\ 0 \\ 0 \\ CTR \\ 0 \\ NTR \end{bmatrix}_i \qquad 3.2.1$$

Equation 3.2.1 can be generalized as

$$\frac{d\xi_i}{dt} = K\mu_i(\xi_i) - D_i\xi_i + F_i + TR_i(\xi_i) \qquad 3.2.2$$

where i denotes the i-th stage of the aeration tank; ξ_i is the state vector consisting of DO, substrate, biomass, CO_2, NH_4 and N_2 concentrations; K is the stoichiometric and yield coefficient matrix; μ_i is the biomass growth and decay rate vector, which is a function of the states; F_i is mass input vector in the liquid phase; Tr_i is mass transfer rate vector which is also a function of the process states; and D_i and D_{in} are the dilution ratios for influent flow rate plus recycle flow rate, and influent flow rate, respectively. Equation 3.2.1 (or 3.2.2) formulates the backbone of the on-line estimator.

The elements of K are defined and described in Table 4.2.2. Table 4.2.2 also shows the values of the stoichiometric and yield coefficients used in the estimator. It should be noted that the K matrix is known and constant.

Table 4.2.2 Definition and Values for K Matrix

Element (1)	**Formula** (2)	**Explanation** (3)	**Value** (4)
K_1	$-(1-Y)Y_{O21}/Y$	Y, cell yield, mass X/mass S	Y=0.55
		Y_{O21}, mass O_2/mass S	Y_{O21}=1.42
K_2	$-Y_{O22}$	Y_{O22} , mass O_2/mass X	Y_{O22}=1.42
K_3	-1/Y		
K_4	0		1
K_5	1		
K_6	-1		-1
K_7	$(1-Y)Y_{CO21}/Y$	Y_{CO21}, mass CO_2 produced/mass S converted	Y_{CO21}=1.37
K_8	Y_{CO22}	Y_{CO22}, mass CO_2 produced/mass X oxidized	Y_{CO22}=1.95

4.3 Estimation Methodologies

4.3.1 On-Line Estimator Schematic

The on-line estimator consists of three major parts: fuzzy estimation for the influent substrate and effluent total suspended solid (TSS) concentrations, estimation of the process states and parameter estimations. Since influent substrate and TSS are usually not measured on-line, this estimation is an important function for the estimator. An asymptotic algorithm was employed for state estimation, and recursive least squares algorithm was applied for parameter estimation.

Figure 4.3.1 shows the overall structure of the estimator. The estimator was

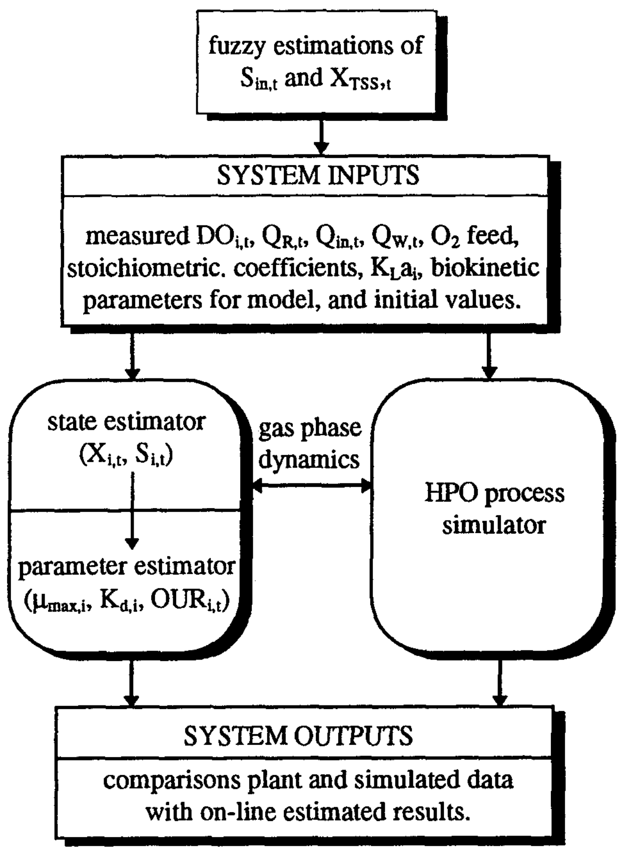

Figure 4.3.1 On-Line Estimator Schematic

incorporated into an existing HPO simulation program and; runs in parallel with the simulator. The estimator and simulator share the same gas phase (O_2 feed, pressure, etc). The estimation starts with the fuzzy estimation of influent substrate and effluent TSS. These estimates along with the DO measurements, initial conditions and other measurements, initiate both the estimator and simulator. The estimated substrate and biomass concentrations are used for estimating biomass growth and decay rates. Finally, the estimated states and parameters are graphically displayed to the operator. To illustrate the success of the estimator, we compare these estimates with both plant data and simulated results.

4.3.2 Asymptotic and Recursive Least Squares Algorithms

An asymptotic observer algorithm (Dochain *et al.*, 1992) was employed to estimate biomass and substrate concentrations in each aeration stage using DO measurement only. It partitions the equation 3.2.1 into two parts (a, b), which correspond to the measured and unmeasured states, respectively. The partitioned states are then linearly combined to eliminate the non-linear vector μ_i by introducing an auxiliary state vector Z_i.

$$\frac{d\hat{Z}_i}{dt} = -D_i\hat{Z}_i + A_0(F_{i,a} + TR_{i,a}) + (F_{i,b} + TR_{i,b}) \qquad 4.3.1$$

$$\hat{\xi}_{i,b} = A_2^{-1}(\hat{Z}_i - A_1\xi_{i,a}) \qquad 4.3.2$$

where A_1, A_2, and A_0 are coefficient matrices and can be obtained from the K matrix; $\xi_{i,a}$, $\hat{\xi}_{i,b}$ are the measured and estimated states, respectively.

This algorithm allows the partial use of equation 3.2.1 to perform the estimation. In this case the first three states in equation 3.2.1 were used and partitioned. Since only the DO state is measured, A_2 matrix is not inversable. To overcome this problem, we used the estimated $\hat{\mu}_d$ in the parameter estimator at time t-1 to approximate μ_d in the μ_i vector of equation 3.2.1. Therefore, the coefficient matrices in equations 4.3.1 and 4.3.2 have the following formats:

$$A_0 = A_1 = -\frac{1}{K_1}\begin{bmatrix} K_3 \\ K_5 \end{bmatrix} \quad \text{and} \quad A_2 = 1 \qquad 4.3.3$$

$$\xi_{i,a} = DO_i \qquad \text{and} \qquad \hat{\xi}_{i,b} = [S \quad X]_i^T \qquad 4.3.4$$

We used a recursive least squares algorithm (Young, 1984, and Bastin, 1991) for biomass growth and decay rate estimation. This algorithm is a recursive least squares algorithm obtained by applying a linear regression technique. Based on equation 3.2.1 the algorithm can be written as

$$\hat{\mu}^m_{i,t+1} = \hat{\mu}^m_{i,t} + T\Gamma_{i,t}KH_{i,t}(\xi_t)\{\xi_{t+1} - \xi_t - T[KH_{i,t}(\xi_t)\hat{\mu}^m_{i,t} - D\xi_t + TR_i + F_i]\} \qquad 4.3.5$$

$$\Gamma_{i,t+1} = \frac{\Gamma_{i,t}}{\lambda}\{I - T^2H^T_{i,t}(\xi_t)K^T[\lambda I + T^2KH_{i,t}(\xi_t)\Gamma_{i,t}H^T_{i,t}(\xi_t)K^T]^{-1}KH_{i,t}(\xi_t)\Gamma_{i,t}\} \qquad 4.3.6$$

where $\mu_{max\,i}$ and K_{d_i} are the i-th stage biomass maximum growth and decay rates, respectively; K_{S_i} and K_{DO_i} are the half-saturation coefficients for substrate and dissolved oxygen concentrations, respectively. Incorporating Monod kinetics into $H_{i,t}$ is very important to obtain good performance of the estimator. The biomass growth is subject to the limitation of biomass, substrate and DO concentrations. The endogenous respiration is limited by the DO concentration. This is especially true in stage 1 when the process is operated in the reaeration mode, where less substrate is present and endogenous respiration becomes significant.

4.3.3 Fuzzy Logic

Since influent substrate and recycle biomass concentrations are not measured on-line, estimating these two variables becomes crucially important to support the estimator. We used a fuzzy logic algorithm to make these predictions. Three sets of fuzzy rules have been developed and implemented into the estimator.

The first set consists of 14 fuzzy rules used for estimating the influent substrate concentration. For municipal wastewater, the substrate loading pattern is strongly correlated to living habits and the characteristics of the sewer system in the service area, such as the length of the sewer and travel time of flow. The peak substrate loading at treatment plant usually lags the peak substrate discharge since there is a traveling time between the plant and the resident area. The 14 rules were formulated based upon the observed loading pattern corresponded to the time. For example, rule 4 is "If time is between 3 to 5 in the morning, then the influent dissolved BOD_5 is extremely high".

The other set of 30 fuzzy rules estimates the total effluent suspended solid (TSS). We considered the two operational parameters that may have significant influence on effluent TSS: influent flow rate and diluted sludge volume index (DSVI). Olsson and Stephenson (1985) have correlated high influent flow rate and high effluent TSS concentration. DSVI represents the sludge settling characteristics (Koopman and Cadee, 1983, and Hultman *et al.*, 1991) where high DSVI value usually indicates poor sludge settling rates. Such conditions also result in high effluent TSS concentration.

Figure 4.3.2 shows the fuzzy rule relations among influent flow rate, DSVI and effluent TSS. The horizontal axis is the influent flow rate which changes from very low to extremely high. Similarly, DSVI changes from very low to very high on the vertical axis. Each box inside the matrix represents the predicted effluent TSS. For example, rule 18 reads as:

> "If the influent flow rate is high (H) and DSVI is normal (N), then the TSS in the effluent is high (H)."

Influent Flow Rate

DSVI	VL	L	N	H	VH	EH
VL	1 **VL**	6 **VL**	11 **L**	16 **N**	21 **H**	26 **H**
L	2 **VL**	7 **L**	12 **L**	17 **N**	22 **H**	27 **VH**
N	3 **L**	8 **N**	13 **N**	18 **H**	23 **VH**	28 **VH**
H	4 **N**	9 **H**	14 **H**	19 **VH**	24 **VH**	29 **EH**
VH	5 **H**	10 **H**	15 **VH**	20 **VH**	25 **EH**	30 **EH**

Interpretation of Variable:
VL --- very low L --- low N --- normal
H --- high VH --- very high EH --- extremely high

Figure 4.3.2 Fuzzy Rule Relation Matrix for Flow Rate and DSVI vs. Effluent TSS

This matrix reflects the empirical knowledge among the three parameters: higher values of flow rate and DSVI correspond to higher effluent TSS concentration. It should be noted that the estimator only works on each horizontal axis for certain period of time, since DSVI is not measured on-line. Whenever the estimator receives a new DSVI value, the estimator can function along the vertical axis corresponding to the current DSVI value. In this way, we utilize the off-line measurement for on-line estimation.

After obtaining the effluent TSS, the recycle biomass concentration can be obtained by making a mass balance around the clarifier as follows:

$$X_{R,t} = \frac{(Q_{in,t} + Q_{R,t})X_{4,t} - (Q_{in,t} - Q_{W,t})X_{TSS,t}}{Q_{R,t} + Q_{W,t}} \qquad 4.3.10$$

where $Q_{in,t}$, $Q_{R,t}$ and $Q_{W,t}$ are the influent, recycle and sludge waste flow rates at time t, respectively; $X_{4,t}$ is the stage 4 biomass concentration, estimated from the state estimator; and $X_{TSS,t}$ is the effluent TSS concentration obtained using the fuzzy logic algorithm described previously.

To deal with the abnormal operations, such as sludge bulking or wet weather flow, fuzzy TSS estimation is needed for the abnormal state. To do this, we developed the third set of rules (10 rules) which allows the fuzzy estimate to adapt to abnormal conditions. When predefined flow rates or DSVI limits are exceeded, the rule set is invoked and the scaling factors are obtained. These scaling factors are then applied to the support sets for flow rate, DSVI and effluent TSS concentration. In this way, the scale and shape of the membership functions are changed, so that a new working estimation state is established. We present the estimation results in detail in the Results and Discussion section.

4.4 Results and Discussions

4.4.1 Plant Data and Model, Estimator Inputs

In order to confirm and evaluate the performance of the estimator, pilot plant data were, as shown in Table 4.4.1. These data are averaged values and do not represent the process dynamics, especially when the process is under transit conditions. An alternative way to mimic these conditions is to use a simulator to simulate the process, and then compare the simulated results with the estimator's predictions.

Table 4.4.1 Pilot Plant Data

Parameter (1)	**Value** (2)	**Parameter** (3)	**Value** (4)
Liquid Phase Volume	7.84 m^3	Stage 1 OUR	63 mg O_2/L-hr
Gas Phase Volume	1.13 m^3	Stage 2 OUR	96 mg O_2/L-hr
Gas Phase Pressure	3 cm w.c.	Stage 3 OUR	48 mg O_2/L-hr
Average Flow Rate	6 m^3/hr	Stage 4 OUR	41 mg O_2/L-hr
Recycling Ratio	52 %	Average Stage 1 DO	7.6 mg/L
Sludge Waste Rate	0.48 m^3/hr	Average Stage 2 DO	5.2 mg/L
Net Yield	0.6-0.85	Average Stage 3 DO	5.5 mg/L
MLSS	1346 mg/L	Average Stage 4 DO	5.0 mg/L
MLVSS	1171 mg/L	Stage 1 O_2 Purity	93.7 %
Recycle Sludge Conc.	3577 mg/L	Stage 2 O_2 Purity	82.8 %
Recycle Sludge Conc. (VSS)	3112 mg/L	Stage 3 O_2 Purity	71.0 %
Influent Total BOD_5	88 mg/L	Stage 4 O_2 Purity	65.6 %
Influent Soluble BOD_5	39 mg/L	O_2 Flow In	0.62 m^3/hr
Influent Total COD	217 mg/L	O_2 Flow Out	0.07 m^3/hr

A structured dynamic HPO process model developed by Stenstrom (1990) was used for this purpose. The model was well calibrated and validated by Tzeng (1992) and

Yuan (1994) based upon this pilot plant data and another full scale HPO plant data. Good agreement between model prediction and plant data were obtained. Table 4.4.2 summarizes the biokinetic parameters used in the model. The stoichiometric and yield coefficients used in the estimator are shown in Table 4.2.2.

Table 4.4.2 Biokinetic Parameters Used in Model (After Tzeng, 1992)

Parameter (1)	**Value** (2)	**Description** (3)	**Parameter** (1)	**Value** (2)	**Description** (3)
bci	0.012	decay coeff. (hr^{-1})	K_{O2str}	1.10	O_2 stoich. coeff. (m/m)
bsstor	0.405	transfer coeff.	K_{SO2}	2.0	O_2 saturation coeff. (mg/L)
bstor	0.5	transfer coeff.	m_{sol}	0.006	max. growth rate (hr^{-1})
f_{cstrm}	0.6	max. fraction (m/m)	m_{stor}	0.75	max. growth rate (hr^{-1})
K_{cstor}	0.05	saturation coeff. (m/m)	Y_{1sol}	0.4	active mass yield (m/m)
K_{oex}	1.42	O_2 stoich. coeff. (m/m)	Y_{1str}	0.4	active mass yield (m/m)
K_{O2sol}	1.10	O_2 stoich. coeff. (m/m)	Y_2	0.15	inert mass yield (m/m)

Note: all time units are in hours.

The same input data were used as both simulator and estimator inputs. The pilot plant had four stages in series and operated in reaeration mode, and the primary effluent was fed to the second stage. The plant used surface aerators. A diurnally varying flow rate was observed in the plant which was approximated by a sinusroid. The DO measurements in each stage were assumed in a sinusoidal pattern due to the flow rate pattern, with a mean equaling to the measured average plant data (Table 3), and were corrupted with a white noise.

4.4.2 Fuzzy Estimation of Influent Substrate and Effluent TSS

We used 14 fuzzy rules to estimate the influent substrate pattern. All the rules use time as the rule antecedent. Figure 4.4.1 shows the estimated soluble BOD_5 for a typical

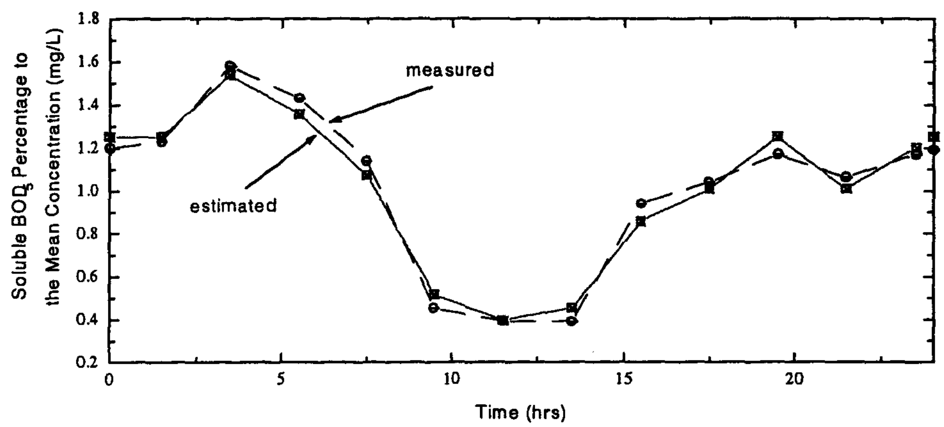

Figure 4.4.1 Comparison of Fuzzy Estimated and Measured Soluble BOD5 for A Typical Day

day. Very good agreement between the observed and predicted soluble BOD_5 was obtained. The number and defined ranges (support sets) of rules will vary from plant to plant, depending upon the characteristics of the sewer system and the service area. One should create these rules based on the observed substrate loading pattern to obtain estimates for different sites.

Figure 4.4.2 shows the estimated effluent TSS using the fuzzy rules described in the Fuzzy Logic section. As the influent flow rate undergoes a periodic change during 24 hours period, the TSS changes accordingly: more TSS is lost through the effluent when flow rate is high, and less TSS is present in the effluent when flow rate is low. Another important parameter that greatly influences effluent TSS is the DSVI value. Two DSVI conditions were simulated, as showed in the graph. Both DSVIs are partially within the "normal (N)" range, but one is partially in the "high (H)" range (DSVI=125) and another is in the "low (L)" range (DSVI=75). As expected, the results show increased TSS with increased DSVI. This is exactly the knowledge that implemented in the rule matrix (Figure 4.3.2).

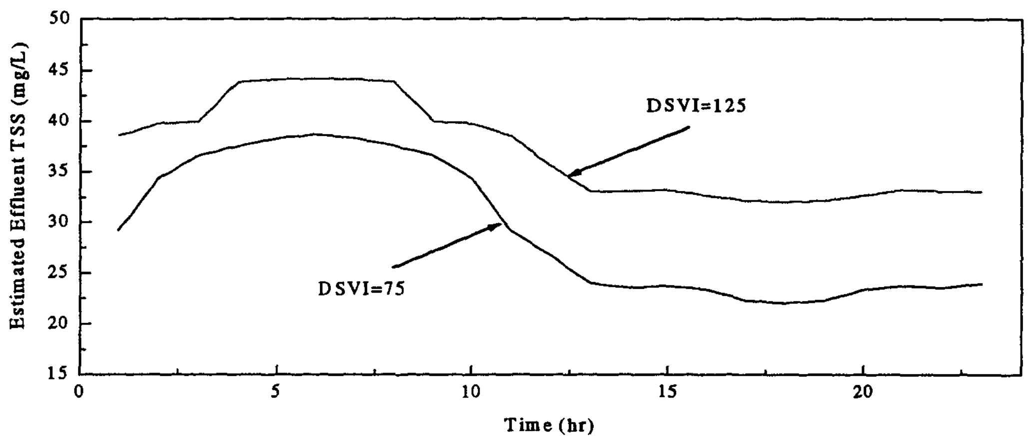

Figure 4.4.2 Fuzzy Estimation of Effluent TSS with Different DSVIs

A crucial step in making this estimation is design of the fuzzy relation matrix (Figure 4.3.2), which should represent the best empirical knowledge among the three parameters. Correctness of the rules determines the overall trend of the estimates (the shape of the curves showed in Figure 4.4.2). The shape of the curve could be completely different if the relation matrix is defined differently than in Figure 4.3.2. The number of the rules and appropriately defined ranges of the linguistic variables, such as high, low, normal, are responsible for making an accurate prediction. In principle, increasing the number of rules can make the prediction more accurate (smoother curves), but also greatly increases the complexity of the estimation. To properly define the range of each linguistic variable, one should use trial-and-error to fine-tune the fuzzy estimator based upon specific plant data.

To make the TSS estimation adaptive to the process upsets, we designed another set of rules to obtain scaling factors, which can change the estimation state. We will present these in the State Estimation under Abnormal Operation section.

4.4.3 State Estimation

To validate the asymptotic state estimator, we first use the exact pilot plant data (recycle and waste sludge flow rates and concentrations) in the estimator to observe the convergence and stability of the estimator with a large range of initial values of the auxiliary states (Z's). To simulate realistic inputs to the estimator for DO measurements, influent flow rate and substrate concentration, etc., we used sinusoidally varying functions with means equal to the plant data and with an amplitude equal to the expected variations in the plant data, while noises was added. Due to the absence of measured effluent substrate data, we ran the estimator in parallel with the process simulator, and compare the simulated and the estimated results.

Figure 4.4.3 shows the estimated biomass and substrate concentrations for stage 2 using the plant data during a 24 hours period. We used initial values of the Z_2 vector (auxiliary state vector) from 500 to -500 for both biomass and substrate. Even with this large range of initial estimates, the convergence is fast and stable for both states. The same convergence patterns were also observed in stages 1, 3 and 4.

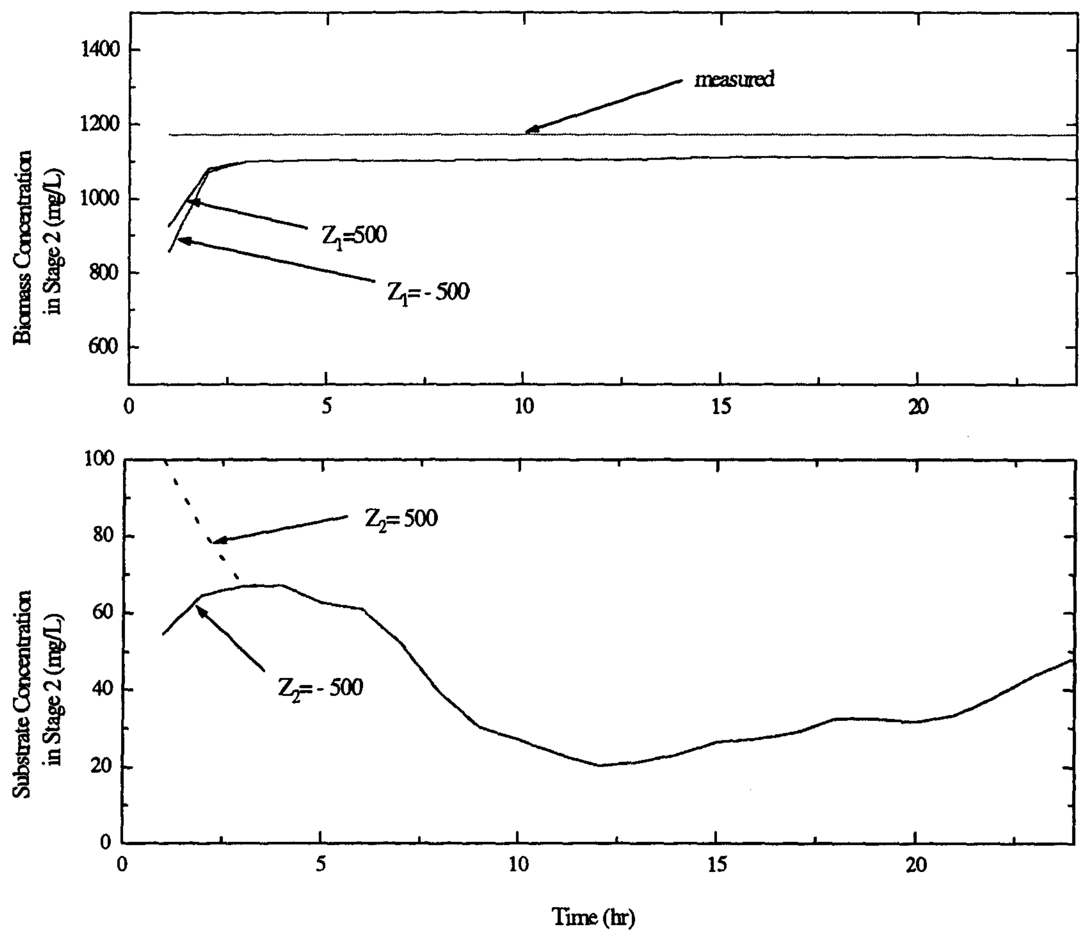

Figure 4.4.3 Estimated Biomass and Substrate Concentrations for Stage 2

The convergence for biomass estimation is faster than for that of substrate (about 2 hours). The relative error between the plant measured and estimated biomass concentration is 6%. The substrate estimation converged within 3 hours. Similar results are obtained when larger initial values of Z vector were tested.

Figure 4.4.4 shows comparisons of biomass and substrate concentrations between the estimated and simulated results. The simulation inputs are the estimated influent

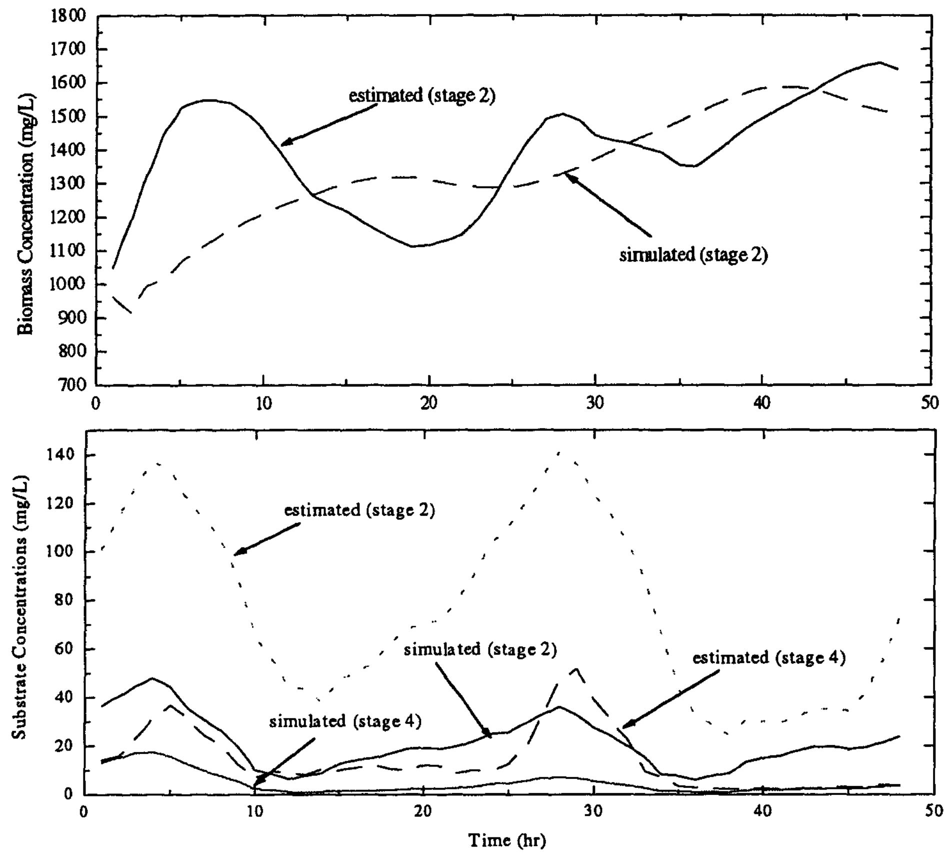

Figure 4.4.4 Comparison of Estimated and Simulated Biomass and Substrate Concentrations

substrate and recycling sludge concentration obtained via fuzzy estimation of effluent TSS. In order to fine-tune the TSS estimation, the ranges of the support sets for influent flow rate and DSVI were redefined. The estimated biomass concentration in stage 2 can track the simulated biomass well, except the initial period of simulation (first 10 hours). The same pattern of biomass concentration changes can be observed for the rest of the stages. Since we assumed influent flow rate and substrate loading are in phase, the oscillation of biomass concentration may be caused by the sinusoidally changed loading pattern.

Significant differences between the simulated and estimated substrate concentrations in stage 2 are presented in Figure 4.4.4. The reason for this is the difference between the structured and conventional models. The simulator uses the concept of stored substrate and mass where the particular substrate are first stored (or may be entrapped in bioflocs) as stored substrate that is slowly biodegradable, and then the stored substrate is converted into stored mass that is readily biodegradable. This accounts for a rapid and large amount of substrate removal after substrate mixed with mixed liquor. This also causes the maximum oxygen demand lagging the maximum loading. The conventional Monod kinetics have difficulty in presenting this phenomenon. However, constructing a structure model based estimator could greatly increase the complexity of the algorithm, and very time consuming for calculation.

4.4.4 Parameter Estimation

Based on equations 4.3.5 through 4.3.9, the parameter estimation is performed using the estimated biomass and substrate concentrations in each stage along with the measured DOs and fuzzy estimated influent flow rate and recycling sludge concentrations. The estimated parameters include maximum and specific growth rates, decay rate and oxygen uptake rate (OUR). As mentioned before, the estimator was running in parallel with the simulator and the results are then compared.

Figure 4.4.5 shows the estimated specific growth rates, OURs, and comparison between the estimated and simulated results in stage 2 in a 48 hour simulation period. As evidenced in the upper graph of Figure 4.4.5, the dynamics of biomass specific growth rates in stages 2 and 4 are in phase with the organic loading (dotted line): the higher the organic loading is, the larger the growth rate. The average growth rate of stage 2 is higher than that of stage 4 due to more substrate entering stage 2 (primary effluent is fed into stage 2). The higher growth rate usually results in higher oxygen uptake rate. The lower graph shows the relationship between specific growth rate and OURs for all four stages. For stages 2, 3 and 4, since less food is fed into the sub-sequence stages, the specific growth rates decrease from stage 2 to 4, and therefore the OURs of stages are reduced, respectively. The high OUR occurrring in stage 1 is caused by endogenous respiration of biomass due to the presence of very low substrate.

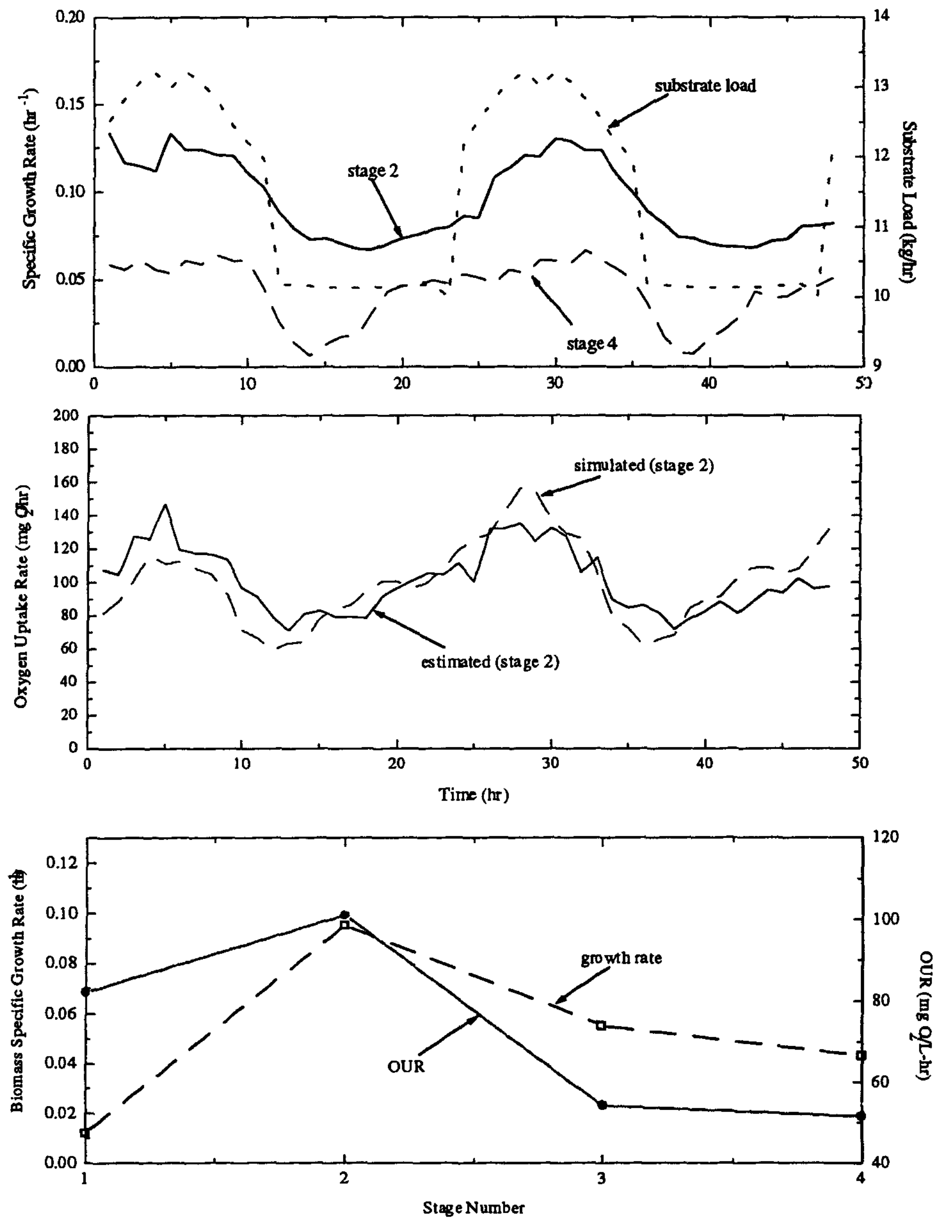

Figure 4.4.5 Estimated Results for Biomass Specific Growth Rate and OURs in Stages 2 and 4

The estimated OUR in stage 2 tracks the simulated OUR (middle graph) well and the organic loading pattern (comparing middle with upper graph). This good tracking ability is particularly due to the correctly estimated specific growth rate. However, a time lag (2-3 hours) between the estimated and simulated OURs were observed in stages 2, 3 and 4. This is caused by using different models in constructing the simulator and estimator. The simulator used a structured model in which the substrate is divided into several pools: soluble and particulate biodegradable BOD_5, soluble and particulate inert substrate, etc. The particulate BOD_5 is slowly biodegraded. This portion of BOD_5 can account for 60 to 85% of total BOD (Tzeng, 1992 and Yuan, 1994). The conventional model based estimator can not represent this delay. One alternative method to overcome this problem is to use a delay time ($t-\tau$, where τ is the delay time) in equations 4.3.5 and 4.3.6.

Table 4.4.3 summarizes the simulation results. The negative values of biomass decay rates in stages 2 and 3 indicates large biomass growth, where the growth dominates the degradation process. This occurs because the feed point is stage 2. The simulated and plant measured data for OUR and biomass concentration are reasonably agree. The high simulated and estimated OURs in stage 1 may be caused by high biomass concentrations.

Table 4.4.3 Summarized Simulation Results and Comparison Among Estimated, Simulated and Measured Data

Parameter (1)	Stage 1 (2)	Stage 2 (3)	Stage 3 (4)	Stage 4 (5)
K_La Used (hr^{-1})	2.0	5.0	3.0	3.0
K_S Used (mg/L)	1.0	20.0	20.0	20.0
K_{DO} Used (mg/L)	0.5	0.5	0.5	0.5
Average Biomass Maximum Growth Rate (hr^{-1})	0.013	0.133	0.091	0.081
Average Biomass Decay Rate (hr^{-1})	0.010	-0.005	-0.003	0.006
Average Biomass Specific Growth Rate (hr^{-1})	0.012	0.095	0.055	0.043
Average Estimated Oxygen Uptake Rate (OUR) (mg O_2/L-hr)	82.1	100.9	54.2	51.5
Average Simulated Oxygen Uptake Rate (OUR) (mg O_2/L-hr)	80.6	100.2	63.4	45.7
Average Measured Oxygen Uptake Rate (OUR) (mg O_2/L-hr)	63.0	96.0	48.0	41.0
Average Estimated Biomass Concentration (MLVSS, mg/L)	3447	1042	1055	1070
Average Simulated Biomass Concentration (MLSS, mg/L)	3597	1334	1333	1327
Average Measured Biomass Concentration (MLVSS, mg/L)	3112	1171	1171	1171

4.4.5 State Estimation Under Abnormal Operation

Process upsets, such as sludge bulking and high flow due to storm water, are usually experienced in wastewater treatment plants. Under these abnormal operational conditions, it is very important for the operator be aware of the key process states, in order to change the operation mode to accommodate the upsets. A process estimator may be useful in these circumstances. In this section we present two abnormal cases (high hydraulic loading and high DSVI value) using the on-line estimator to predict biomass concentrations in each stage. All the simulation inputs are as same as those previously presented in the state and parameter estimation sections, except influent flow rate and DSVI, which are changed to simulate the process upsets.

The upper graph of Figure 4.4.6 shows the estimated biomass concentrations of stages 1 and 4 when a high influent flow rate occurs at time 36 hour. Because of the higher flow rate, the biomass in the clarifier (caused by high TSS in effluent) washes out, increasing effluent TSS and reducing recycle sludge concentration. The average biomass concentrations before and after high flow rate occurring for stage 4 are 1033 and 803 (mg/L), respectively. A 22% reduction of biomass concentration is estimated. Similar reductions are observed for the other stages. If an even higher flow rate were used, further reductions of biomass would be expected in each stage. This may cause treatment process failure.

An alternative strategy dealing with hydraulic shock loading is to directly feed primary effluent to the last stage of the process. In this way the biomass in stages 1, 2 and 3 can be preserved. The lower graph of Figure 4.4.6 shows the results of applying this strategy. When the feed point is changed from stage 2 to stage 4, the fuzzy logic sets the biomass concentrations in stages 2 and 3 equal to the stage 1 biomass concentration. As compared with the reaeration mode (upper graph), this strategy can increase the total sludge mass from 8.0 kg to 11.7 kg in all four stages, which is a 46% increase over reaeration operation. This change allows the plant to retain its sludge inventory, and greatly helps the plant recover after the high hydraulic loading ends.

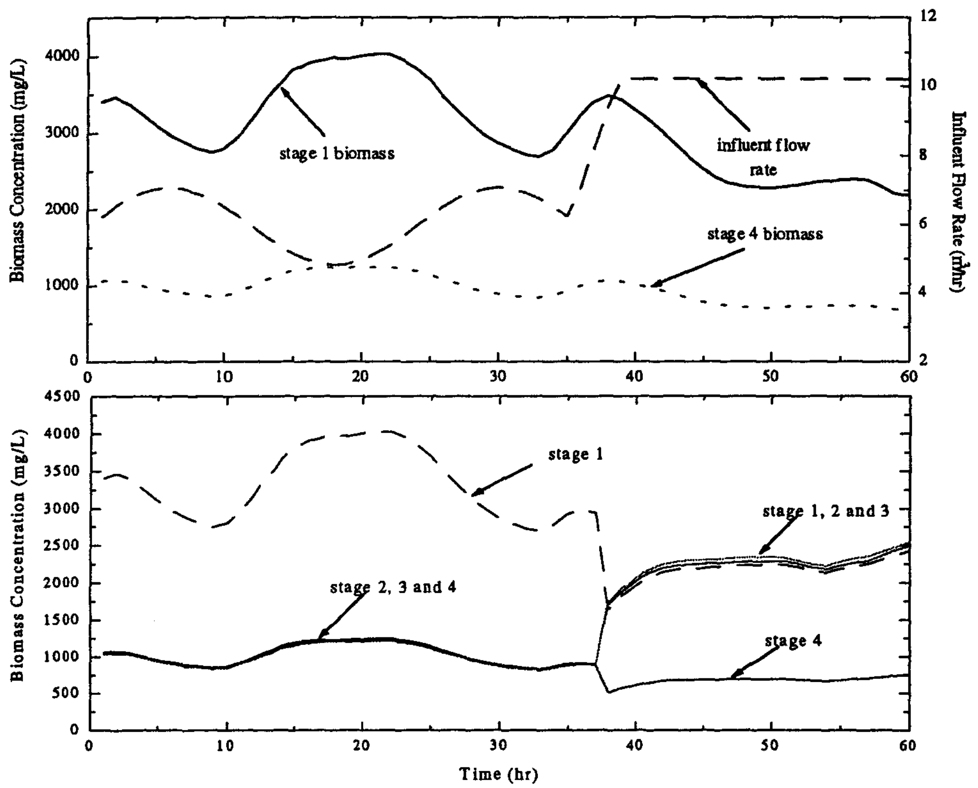

Figure 4.4.6 Estimated Biomass Concentrations Under Hydraulic Shock Loading

High DSVI usually implies poor biomass settling ability and large quantity of biomass may be lost through the effluent. To properly apply the estimator in this situation, the estimation of effluent TSS becomes critical important. As discussed in the Fuzzy Estimation of Influent Substrate and Effluent TSS section, we use a separate set of rules to readjust the rule sets that are used in normal operation. Figure 4.4.7 shows the performance of the adaptive rules for the estimation of TSS (dotted line) when high DSVI occurs at time 24 hour. The effluent TSS is increases from 13.5 to 58 mg/L. This results in reduction of biomass concentration for all stages. As evidenced in Figure 4.4.7, the average reduction of biomass concentration for each stage is 40%, which may jeopardize the treatment process and cause process failure. Effluent permit violations will almost certainly occur.

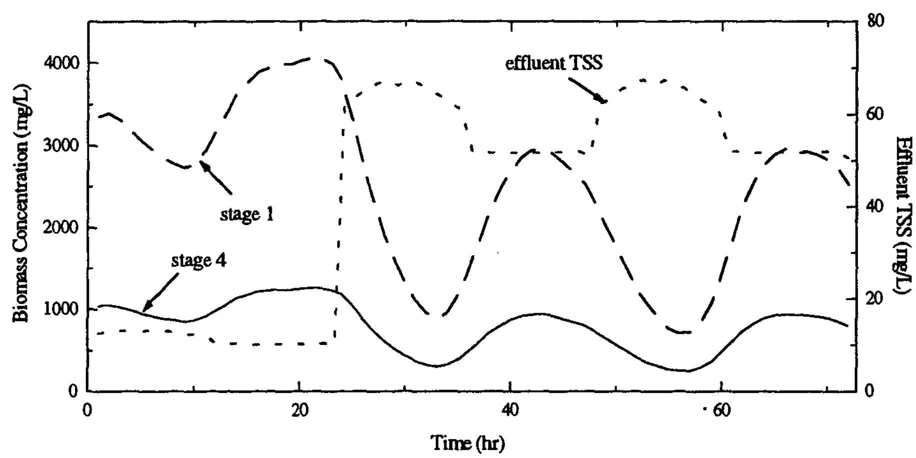

Figure 4.4.7 Estimated Biomass Concentrations for Stages 1 and 4 with High DSVI

Conclusions

A fuzzy logic supported on-line state and parameter estimator was developed for the high-purity oxygen activated sludge process. For state estimation, an asymptotic algorithm was employed. A recursive least squares method was used for parameter estimation. To compensate for unknown influent substrate and recycle biomass concentrations, a fuzzy logic algorithm was applied to predict these unmeasured process inputs. The estimator can predict the unmeasured substrate and biomass concentrations in each stage using DO measurements alone. It can also estimate other important parameters, such as maximum, specific growth and decay rates, and oxygen uptake rates (OURs). Knowledge of these estimated states and parameters can greatly help the operator in making decision, as well as providing quantitative supports for advanced process control.

The convergence of the algorithms is fast and stable even with a large range of initial values and noisy dissolved oxygen (DO) measurements. The estimated process parameters are agree reasonably well with both plant and simulated data. The estimator can closely track the simulated OURs under transients conditions. It can also be used for state and parameter estimation when certain types of process upsets occur. The overall performance of the estimator is stable and satisfactory.

A crucial step in developing such an estimator is fuzzy estimation of effluent total suspended solids (TSS), since TSS has great influence on the biomass inventory. Correctness of the rules is the key for the whole estimation. Influent flow rate and diluted sludge volume index (DSVI) are the two major parameters influencing TSS. The fuzzy rules developed for the estimator also have self-tuning ability to accommodate the process upsets, such as high hydraulic loading and high DSVI. The estimator utilizes the off-line measurement (DSVI) for on-line estimation purposes.

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5. APPLICATION OF FUZZY LOGIC ALGORITHM TO GAS PHASE CONTROLFOR HIGH-PURITY OXYGEN ACTIVATED SLUDGE PROCESS

Abstract

Conventional Proportional Integral Derivative (PID) controller and control strategies usually cannot control process disturbances, and have difficulty in handling extreme upsets such as stormwater flows. Four fuzzy logic control systems were developed for normal weather flow in this study. The simulated results show that the fuzzy systems are superior to conventional control systems in reducing DO variations, stabilizing oxygen feed and exit gas venting, and consuming energy. A direct control strategy, using feedforward aerator speed control and feedback stage 4 DO control, is the best among the four systems. For plants without variable speed aerators, a feedforward control based on influent flow rate to adjust the stage 1 pressure set point, with feedback stage 4 DO control, is the best. To address the extremes in wastewater flow due to stormwater, an adaptive fuzzy logic control system was developed. The control system can immediately shift to a new state to adapt to large changes in influent flow rate. The system can prevent DO depletion under wet weather conditions, and avoid oxygen wastage while providing energy conservation during dry weather flow.

5.1 Introduction

Operation and control of the high-purity oxygen (HPO) activated sludge (AS) process is more difficult than conventional air activated sludge process control. The major difficulties are 1) the complex nature of the process, with its use of high-purity oxygen, covered aeration tanks and tanks in series; 2) highly stochastic inputs to the process, such as influent flow rate (including wet weather and dry weather flows) and organic loading; 3) lags or process delays due to series operation of the stages. Lags can be especially significant for the gas phase. The hydraulic shock loading caused by fixed-speed influent pumps or diurnal variations in flow rate further complicate process control. The goal for the gas phase control is to keep dissolved oxygen (DO) concentrations in the aeration tanks as constant as possible, even with dynamic inputs, to obtain stable process operation, and to conserve energy. Conventional PID controller and control schemes have difficulty in meeting these goals.

Conventional PID controllers based upon stage 1 pressure have difficulty in controlling gas phase of HPO-AS process, and can be upset by process disturbances. An example was documented by Norman *et al.* (1985). When a hydraulic shock loading occurs, the liquid level of the aeration tank increases and compresses the head space volume, which results in a pressure increase. When the pressure sensor detects this increase, the controller reduces the oxygen feed rate attempting to return to the set point, which is the exact opposite of the desired control action. Conventional PID controllers also have difficulty in tracking the oxygen demand caused by bacteria activity. The maximum oxygen demand usually lags the peak influent flow rate (Olsson and Andrews, 1978 and 1981, Clifft and Andrews, 1986, Tzeng, 1992). This causes oxygen depletion when the oxygen demand is large, and oxygen wasting when the oxygen demand is small. It is difficult to implement this knowledge into a conventional PID controller.

Conventional feedback control strategies also have difficulty in tracking the oxygen demand, which can cause large variations of DO concentration in the aeration tanks. Most commonly used control strategies include control of stage 1 total pressure (McWhirter, 1978), and control of both stage 1 pressure and vent gas flow rate or vent gas oxygen purity (Tzeng, 1992). One shortcoming of these control schemes is the oxygen losses through the cracks and pin holes in the aeration tank covers, since the pressure in each stage must be higher than atmospheric pressure. A second shortcoming is regulating vent gas flow rate, since only very limited pressure drop is available at the vent valve. All these effects can produce significant DO variations in the aeration tank with diurnal changes in loading. A new approach proposed by Clifft (1991) suggests using lower than atmospheric pressure be applied in each stage of the reactor. An exhaust apparatus is used in the last stage to vent exit gas. Since this produces a negative pressure (< 1 atm.) in the head spaces, oxygen losses can be reduced. Clifft simulated this strategy for both the wet and dry weather conditions. Less variable oxygen feed and improved control over the conventional strategies were obtained.

To overcome the shortcomings of the conventional PID controller and control strategies, we developed a fuzzy logic controller with proportion-like (P-like) properties, to perform regulating control, and modified conventional strategies by introducing a feedforward loop in the control schemes. PI-, PD- and PID-like fuzzy controllers were also tested. We found that these controllers have no significant improvement over the P-like fuzzy controller, but have the disadvantages of increased complexity. Therefore a P-like fuzzy logic controller was adopted for set point control throughout this investigation. A feedforward loop was implemented in the control system based on the influent wastewater flow rate, which is or can be frequently and reliably monitored at most treatment plants. The feedforward loop consists of a group of fuzzy rules that represent our partial knowledge of HPO-AS process. The simulation results show that feedforword control along with the feedback control, such as stage 1 total pressure control, stage 4 DO control, vent gas regulation, stage 4 oxygen purity control, or a combination of all forms, can more closely track the oxygen demand with dynamic influent flow and substrate. The diurnal fluctuation of DO concentration is greatly reduced. The fuzzy control system also provides a stable oxygen feed and high oxygen utilization rate. The set point of stage 1 total pressure can be reduced from 1.008 atm to 1.004 atm or even lower, which can reduce the oxygen losses from leaks.

To handle the extreme weather flows, such as storm and extreme dry season flows, an adaptive fuzzy control system has been developed. This system can immediately change the fuzzy logic controller to a new working state whenever extreme flows are encountered. It can prevent DO depletion and oxygen wasting. If a three speed or variable speed aerator drives (high, media and low speeds which correspond to wet, normal and dry weather flows) are installed, the system is further enhanced and an even better performance can be achieved.

A dynamic, structured high-purity oxygen activated sludge process model developed by Stenstrom (1990) was used to simulate the fuzzy control systems. The process model was calibrated by Tzeng (1992) based on a pilot plant data and data from a full scale plant. The calibrated model is in good agreement with both data sets. The fuzzy logic algorithm was incorporated into the model and simulated using the pilot plant data to observe the fuzzy control systems performance. Since the purpose of this study is to provide a qualitative or semi-quantitative aid for design of control system for HPO-AS process, sinusoidal inputs to the system were used to simulate the diurnal variations in wastewater influent flows and substrate concentration.

In the following sections we first present the high-purity oxygen activated sludge process and conventional control strategies. A fuzzy logic algorithm and the structure of fuzzy logic controller (FLC) are discussed next. Several conventional control strategies, modified with feedforward control, and the major rule bases are presented next, followed by the simulation results of the control strategies and discussion. Conclusions and recommendations for future work are presented last.

5.2 HPO Process and Conventional Controls

5.2.1 High-Purity Oxygen Activated Sludge Process

The high-purity oxygen activated sludge process is characterized by high-purity oxygen feed, closed aeration tanks, and several tanks in series. Figure 5.2.1 shows a typical HPO process. Several aeration tanks are covered and arranged in series (usually 4) to increase treatment efficiency. Ninety-seven percent or higher oxygen purity is normally used in the feed for large plants. This feed purity results in a high oxygen partial pressure in each stage, which greatly increases the oxygen transfer capacity (3-6 times higher than open-air system) to the liquid phase. It is common to use higher mixed liquor DO concentrations (6-10 mg/L) than normally found in air activated sludge processes.

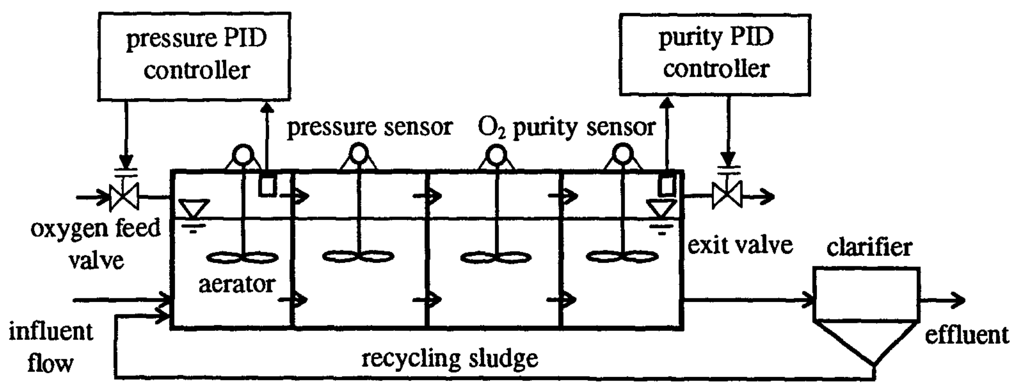

Figure 5.2.1 Flow Diagram for A HPO-AS Process

Conventional control systems maintain a total pressure in stage 1 a little higher than atmospheric, usually about 1.008 atm or 5 to 15 cm (2 - 6 inches) water column. This creates gas concurrent flow from one stage to another. The exit gas pressure at stage 4 is almost equal to atmospheric pressure. Oxygen absorption and efficient oxygen utilization produce longer gas residence times, which causes large process delays in the gas phase.

Typical gas phase residence time in stage 1 may be 2 hours and may increase to 12 hours in stage 4. The problem is further complicated by oxygen demand lags in the liquid phase. When substrate loading occurs the oxygen demand does not immediately increase to the maximum, since a finite length of time is needed to assimilate the substrate. This time accounts for the time lags in oxygen demand. Conventional controllers have difficulty in tracking this oxygen demand, which may result in DO oscillation.

5.2.2 Conventional Control Strategies

Figure 5.2.1 shows the measurements used in the HPO gas phase control. Stage 1 total pressure and exit gas purity are commonly used measurements in the conventional gas phase control. Conventional control variables include oxygen feed valve opening and exit gas flow rate. The available pressure drop is too low for conventional meters, which can create large errors in exit gas measurement. This is one of the major problems for conventional stage 4 control.

Two basic control loops are used in conventional gas phase control. The first is stage 1 total pressure control to regulate the oxygen feed valve around a set point (McWhirter, 1978). The main purpose of this control is to provide certain marginal pressure in each adjacent stage and to prevent backflow. The advantage is fast response and effectiveness. The second loop is the vent oxygen gas purity control by manipulating the exit gas flow rate (Tzeng, 1992). This control loop can increase oxygen utilization rate and ensure sufficient oxygen supply. The major problems associated with these control loops are 1) the constant set points which can not address the dynamic inputs (influent flow and substrate) to the process where oxygen depletion or over supply occurs; 2) the exit gas flow and available pressure drop are too small to perform accurate control (Clifft, 1991).

To enhance stage 4 control, Clifft (1991) and Tzeng (1992) suggest installing venting equipment at the last stage. Placing a DO sensor in the clarifier or exit channel can provide an additional closed loop for stage 4 DO control. This loop, however, cannot co-exist with the vent gas purity loop since both controller outputs are vent gas flow rate.

5.3 Fuzzy Logic

A fuzzy logic algorithm (FLA) is a useful tool to handle processes where the mechanism is not well understood, but where empirical knowledge about the process exists, such as biological treatment. A fuzzy logic controller (FLC) that uses a fuzzy logic algorithm as its control law can perform the same task as a PID controller, such as P-, PI-, PD-, or PID-like FLC. In addition, our partial knowledge of the process can be implemented into a FLC such that better performance of the system is obtained. A fuzzy logic algorithm is also robust and tolerates the disturbances produced from both measurement and process. The advantages of FLC over conventional PID controllers are well documented by Driankov *et al.* (1993).

Fuzzy logic theory was first introduced by Zadeh (1965). Since then many successful applications of this theory have been achieved. The applications are mainly focused in the process control area. The first application of fuzzy logic algorithm to control the activated sludge process was reported by Tong *et al.* (1981). They concluded that the algorithm works well and a fuzzy controller would be a useful and practical way of regulating the activated sludge process. Another investigation was conducted by Chen *et al.* (1990). They built more than 100 fuzzy rules to control the sludge recycling rate, sludge conditioning time and air supply rate for a full scale treatment plant. Significant improvement in process performance was achieved as compared with the conventional control method.

In general, a fuzzy logic algorithm works in three steps: input signal fuzzification, fuzzy reasoning and defuzzification. To avoid confusion to readers who are not familiar with the fuzzy logic method we will not use fuzzy mathematics to define these steps. Instead, we use the fuzzy relations between the oxygen feed valve openings and the error of the pressure to illustrate how the FLA works (Figure 5.3.1).

Figure 5.3.1 shows the fuzzy rule relations between the error of stage 1 total pressure and oxygen feed valve opening for stage 1 total pressure control. Each triangle in Figure 1 represents a fuzzy membership function or a fuzzy set, and each set has a linguistic meaning, such as "Large", "negative large", etc. Different shapes of membership functions other than triangles are possible, such as a bell function (Yamakawa, 1992). However, the effects of different membership functions on the performance of FLC are not well documented (Driankov and Hellendoom, 1993). The triangle shape function is most frequently used for process control due to its simplicity and computational ease. In this study a triangle membership function and Mamdani composition method were adopted

(Terano *et al.*, 1992). Both input and output universe discourses are normalized between -1 and 1.

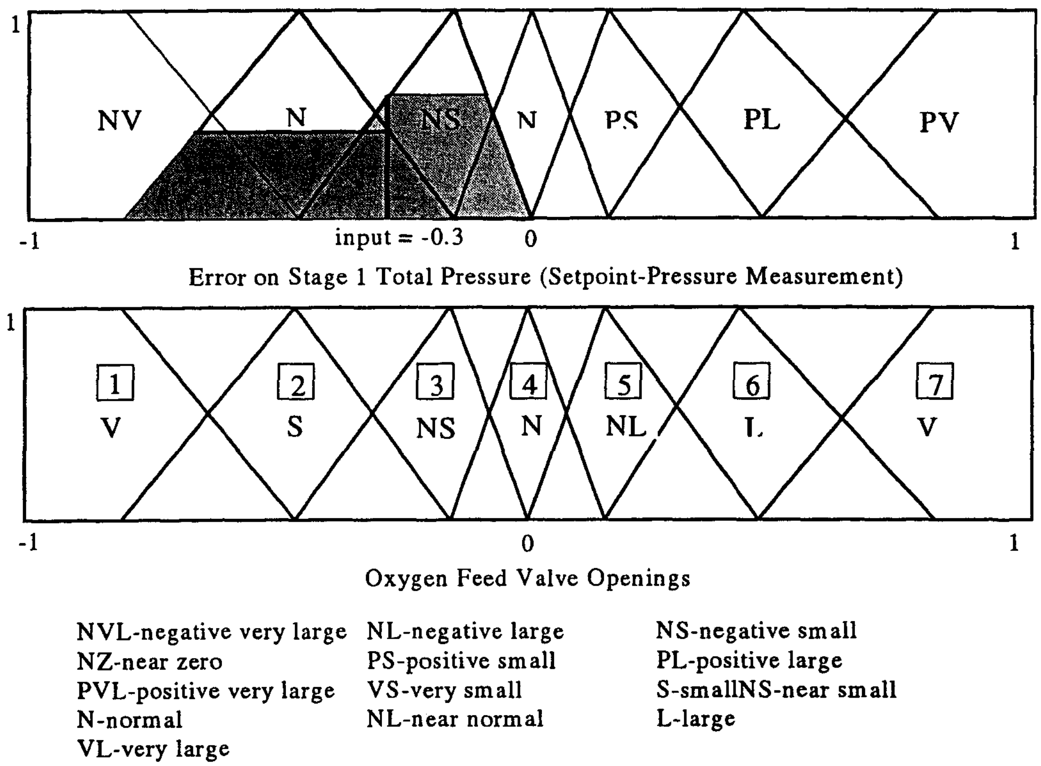

Figure 5.3.1 Membership Function for Stage 1 Total Pressure Setpoint Control

Fuzzification is the process in which a crisp controller input signal is mapped into the fuzzy membership functions such that fuzzy sets are obtained. For example, if the pressure error is -0.3 after normalization, it intersects with both negative small and negative large in the input discourse. Therefore two sets are obtained by this mapping as indicated in the shadowed areas in Figure 5.3.1.

There are 7 rules in the stage 1 pressure controller as shown in Figure 5.3.1. The following are the examples of the rules:

if the error is negative very large then the oxygen feed valve opening is very small;

....

if the error is positive very large then the oxygen feed valve opening is very large.

Obviously, the error being negative very large (NVL) implies that the total pressure in stage 1 is much higher than the set point. Therefore the oxygen feed valve opening should be reduced in order to bring the pressure to the set point. These rules, obtained by common sense or by experience, are the heart of the fuzzy reasoning process. Fuzzy reasoning fires the rule based on the match up of the rule antecedence, and projects the fuzzified sets on the corresponding output membership functions on the output discourse. In the above example two rule antecedence are matched: error is negative large (NL) and negative small (NS), therefore, rules 2 and 3 are fired. The two cut sets obtained in the fuzzification process are projected on the small and near small functions of the oxygen feed valve opening.

After fuzzy reasoning, deffuzzification is needed to convert the projected fuzzy sets into a crisp control output. This is performed by taking weighted average of the projected membership values in the output discourses. We employed the Center of Area method (Lee, 1990) to perform the defuzzification in this study.

A fuzzy logic controller consists of three major parts: rule base, data support for the rule base, and fuzzy logic algorithm. Figure 5.3.2 shows a typical FLC structure. The measured, on-line process states are first normalized between 1 and -1. The normalized inputs are then fuzzified into fuzzy sets. The rule antecedence are searched and matching rules are invoked, so that the membership functions on the output discourse are located. The fuzzified sets are then projected on these output functions. Defuzzification is performed to convert these output sets into crisp values. Finally, denormalization is used to obtain the controlled outputs.

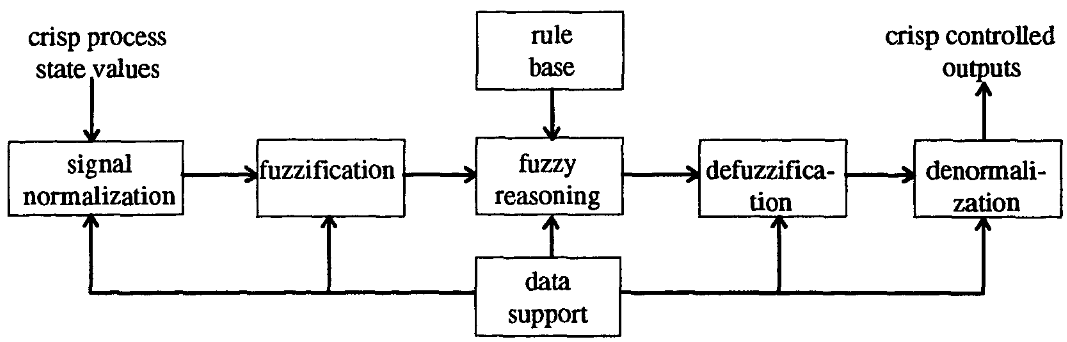

Figure 5.3.2 A Typical FLC Structure

A FLC setpoint controller can perform the same tasks as a PID controller, but has other advantages over a PID controller. A conventional PID controller has difficulty in controlling a process which involves phase changes (process lags or delays) or requires changing from one working state to another. For example, when wet weather flow occurs, the oxygen feed valve opening is increased to a very large value to prevent the DO depletion. The HPO-AS process is characterized by these unwanted lags in both the gas and liquid phases, and can experience stormwater wash out. To accommodate these process disturbances, two feedforward loops were added to the conventional FLC to increase the adaptability of the controller, which will be discussed in Control Strategies section in great detail.

5.4 Control Strategies

The control strategies being presented in this section are based on the conventional control schemes, which were described previously in the Conventional Control Strategies section, and modified by introducing influent flow rate as a feedforward control. Installation of venting equipment and placement of DO sensor in the clarifier or exit channel are also assumed.

5.4.1 Modified Fuzzy Logic Controller Structure

Figure 5.4.1 shows the modified FLC structure. The feedforward loops are based on the measurement of influent flow rate. The first feedforward loop is used for adjusting controller set points, such as stage 1 total pressure, exit gas oxygen purity, stage 4 DO, or for regulating K_La's which are directly related to the aerator motor speed. Set point adjustment is made through a rule base which consists of 18 rules. For example, if the influent flow rate increases, and is large, a large value of the set point of stage 1 pressure is assigned, which results in an increase in oxygen feed. In this way the controller is more robust to the gas phase volume disturbance and can trace the oxygen demand. A detailed explanation will be given in the Feedforward Control section.

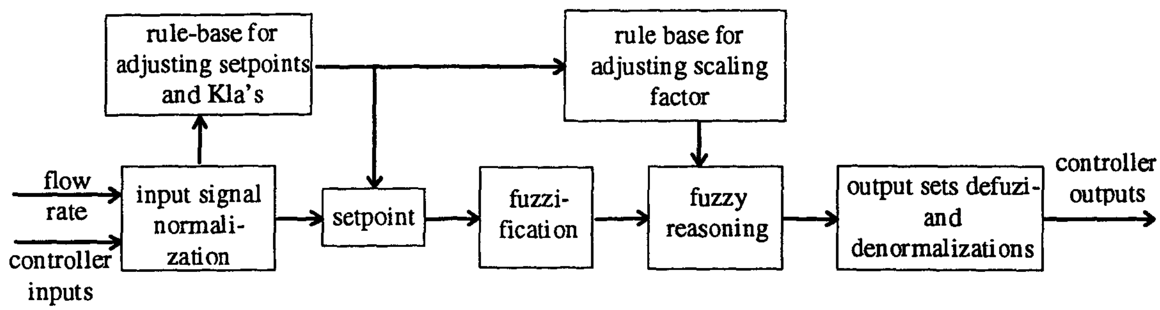

Figure 5.4.1 Modified FLC Structure

An adaptive FLC can be designed in several ways. The first is to use scaling factors. Determination of the factors can be made through a rule set. This rule set is activated when certain predefined controller input thresholds are reached or the constraints are violated. These factors are then applied to both the input and output discourses. The second method is to modify the current rule base as a function of the controller inputs. In this way the controller self-tunes itself to adapt to the changing conditions of the process states. Other methods can be found in the literature (Bare *et al.*, 1988, Batur and Kasparian, 1989). In this study we applied the scaling factor method in the second feedforward loop to address wet and extremely dry weather flows. A group of

7 rules (in each rule set) is designed for this purpose. When influent flow exceeds the predefined threshold, the rule set is invoked and the scaling factors are obtained. The factors are then multiplied by both the input and output discourses so that the shape of triangle membership function and their support set values are changed to adapt to the process change. In this way a new operational state is established. The performance of the adaptive FLC will be presented and discussed in the Results and Discussion section.

5.4.2 Feedforward Control

One of the major purposes of performing gas phase control is to maintain relatively constant DO concentrations in each stage under the dynamically varying input conditions. This goal can be realized by tracking the oxygen demand with oxygen supply. The conventional methods have difficulty in making this match. Both the stage 1 pressure and vent gas purity control cannot instantaneously change DO concentration due to the large delays and long gas residence time in the gas phase. The phase change between the substrate load and oxygen demand also deteriorates the efficiency of conventional control strategies. However, these gas and liquid phase delays can be modeled via a fuzzy rule set. The rules are inferenced-based on the influent flow measurement.

A feedforward loop based on the measurement of influent flow was used in this study. It is assumed that the flow rate and substrate concentration are in phase. In fact substrate loading may have smaller lag time than hydraulic loading as observed in the plants. The feedforward loop contains 18 rules. Figure 5.4.2 shows the fuzzy rule relation matrix

trend of flow ↑ / flow rate →	ES	VS	S	NS	N	NL	L	VL	EL
IN	**VS** 1	**ES** 2	**VS** 3	**S** 4	**NS** 5	**N** 6	**NL** 7	**L** 8	**VL** 9
DE	**VS** 18	**S** 17	**NS** 16	**N** 15	**NL** 14	**L** 13	**VL** 12	**EL** 11	**VL** 10

IN-flow increase DE-flow decrease ES-extremely small VS-very small
S -small NS-near small N -normal NL-near large
L -large VL-very large EL-extremely large

Figure 5.4.2 Fuzzy Rule Relation Matrix for Stage K_La Control

for K_La control of the 4 stages. The horizontal axis represents the magnitude of the flow rate, such as extremely small, very small, etc. The vertical axis shows the trend of flow, which is determined by two adjacent flow rate samples. The linguistic variables inside the matrix represent the controller output. Rule number 9, for example, can be interpreted as

If the influent flow is Extremely Large and flow rate is Increasing then the K_La's for each stage are Very Large.

Stage K_La is directly related to the aerator impeller speed. Increasing K_La results in an increasing oxygen transfer rate which increases the DO concentration. Under the normal conditions (no delays between the peak flow and oxygen demand), rule 9 could be written as follows:

> if the influent flow is Extremely Large and flow rate is Increasing then the K_La's for each stage are Extremely Large.

In this way, when flow rate reaches its maximum, stage K_La is also increased to the maximum. More oxygen is dissolved into the liquid phase to prevent DO depletion. However, the maximum oxygen demand usually occurs shortly after the peak flow, which is not addressed by this rule. To correctly address this phenomena, an extremely large value of K_La is given when the flow is very large and flow rate is decrease (rule 11), instead of flow rate being extremely large (rules 9 or 10). The shift from rules 9 to 11, for delaying assigning the extremely large K_La value while the influent flow rate being extremely large, addresses the fact that the maximum oxygen demand lags the maximum loading. The same rule shift is arranged when flow is extremely small.

A similar arrangement of rule sets for adjusting controller set points in the feedforward loops was used. Since there is large delay in operation of stages in the gas phase, further shift in rules is required.

5.4.3 K_La Control

The mass transfer coefficient K_La can be affected by many factors. In most situations, K_La should be directly proportional to the impeller speed (surface aerator) or gas recirculation rate (submerged turbine aerator). Unfortunately, fixed speed drives are commonly installed in HPO plants; however, control of K_La's (impeller speed) could be a potential control technique, and could significantly improve process performance. Changing motor speed to match the oxygen demand can save energy and reduce DO variation. Operating surface aerators at reduced speed also extends motor and gear box life, while reducing maintenance. The use of K_La control by adjusting motor speed was simulated in this work. The results are useful for the design of new HPO-AS control system, or for retrofitting or expanding existing plants.

5.4.4 Control Strategies

As discussed earlier, three closed control loops can be formulated: stage pressure control, vent gas purity and stage 4 DO control. In addition to these closed loops, the feedforward loops for predicting K_La and modifying controller set points are also discussed. The control alternatives were combined and formulated as shown in Table 5.4.1.

In strategy 1 the K_La of each stage is adjusted based on the measurement of the influent flow. The rule base in this loop is described earlier in this section (Figure 5.4.2). To ensure sufficient oxygen supply, the oxygen feed is regulated based on stage 4 DO error, and the exit vent gas flow is constant. Nine rules were implemented in the stage 4 DO control loop, which act like a P-controller. If the DO error is negative large, for example, it implies that the DO concentration is higher than the set point and the valve opening is reduced.

Table 5.4.1 Control Strategies for Gas Phase Control

Strategy No. (1)	Strategy Description (2)	Controller Inputs (3)	Controller Outputs (4)
1	set point (SP) control for stage 4 DO combined with K_La regulation for each stage based on influent flow measurement	stage 4 DO concentration; influent flow rate.	O_2 feed valve opening; K_La's of each stage.
2	SP control for stage 1 total pressure with SP adjusted based upon influent flow rate, SP control for stage 4 O_2 purity and with SP is adjusted based upon stage 4 DO error	stage 4 O_2 purity; stage 4 DO; influent flow rate.	O_2 feed valve opening, motor speed of exit vent device.
3	stage 1 total pressure SP control with SP adjusted based upon influent flow rate, adjusting vent O2 purity SP based upon influent flow rate, and maintaining SP by regulating vent flow rate	stage 1 total pressure; stage 4 O_2 purity; influent flow rate.	O_2 feed valve opening; motor speed of exit vent device.
4	stage 1 pressure SP control with SP adjusted based upon influent flow rate, and regulating vent flow rate based upon stage 4 DO error	stage 1 total pressure; stage 4 DO; influent flow rate.	O_2 feed valve opening; motor speed of exit vent
5*	stage 1 pressure SP control based upon stage 1 total pressure, and stage 4 O_2 purity SP control by regulating vent flow rate	stage 1 total pressure; stage 4 O_2 purity.	O_2 feed valve opening; motor speed of exit vent

* This strategy is most similar to conventional strategies and is provided for comparison.

Strategy 2 consists of two control loops: stage 1 pressure control and vent gas oxygen purity control. The set point of the pressure controller is adjusted based on the influent flow rate, and the adjusted set point is maintained by regulating the oxygen feed valve. This feedforward loop has 18 rules, but the arrangement of the rules is different from the K_La control in strategy 1. In the K_La control loop the rule is shifted from left to right (Figure 5.4.2) because the oxygen demand lags the flow rate. The maximum oxygen supply should be provided after the peak flow. If the reaeration mode (influent feed to stage 2) is used, the oxygen gas flow requires time to reach the second stage, which has the greatest demand. This delay compensates for the oxygen demand delay. Therefore, no rule shift is made in this feedforward loop. A typical rule in this rule base may written as follows:

> if the influent flow is Extremely Large and flow rate is Increasing then the pressure set point is Extremely Large.

The second loop is used to control the vent gas purity. The purity set point is adjusted by the stage 4 DO error and the adjusted set point is maintained by regulating vent gas flow rate. Figure 5.4.3 shows this control strategy.

The same stage 1 pressure control scheme is applied to strategies 3 and 4 to ensure oxygen supply, and addresses the delays in gas phase. The difference between strategies 3 and 4 is the schemes for last stage purity and DO controls, respectively.

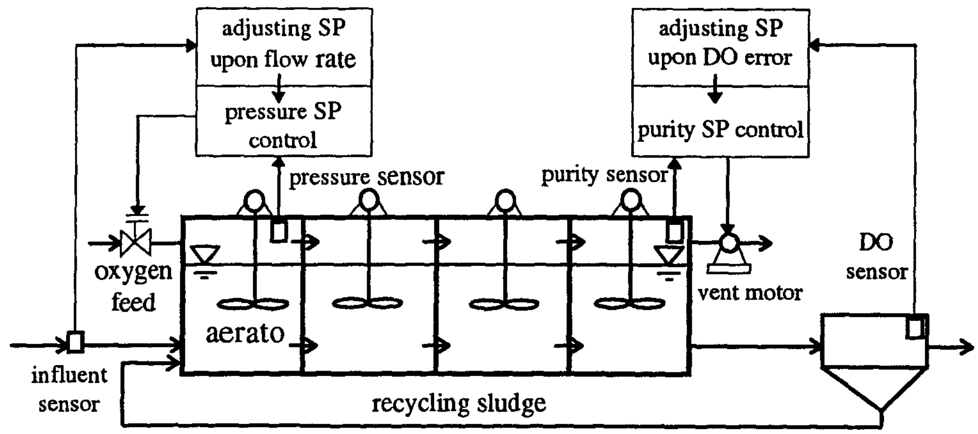

Figure 5.4.3 Control Diagram for Strategy No. 2

In strategy 3 we introduce another feedforward loop to dynamically adjust the purity set point based on the flow rate. The set point is then traced by manipulating vent gas flow rate. The rules in this loop are different from those in stage 1 pressure control loop. In general, when flow is large a high oxygen purity set point is assigned to ensure large oxygen transfer rate. A rule shift between the peak flow and the highest set point is arranged in the rule set. This is to account for the delay in the oxygen demand. A closed loop stage 4 DO control is arranged for strategy 4. Strategy 5 is a conventional control scheme without feedforward control, and using conventional PID controllers. It is used for comparison to the first four strategies.

5.5 Results and Discussions

5.5.1 Model Inputs and Plant Data

A structured dynamic HPO process model developed by Stenstrom (1990) was used to simulate the performance of the control system. The model was calibrated and validated by Tzeng (1992) based on a pilot and a full scale HPO plant data. Good agreement between model prediction and plant data has been achieved. For detailed model structure and bio-kenitic parameters, the readers can refer to Tzeng (1992) and Yuan (1994).

We used the pilot plant data as the simulation inputs. Table 5.5.1 summarizes the pilot plant data for the simulation. The plant had four stages in series and a surface aerator was used for each stage. The plant is operated in reaeration mode. The primary treated wastewater was fed to the second stage. A daily sinusoidally varying flow and substrate loading was observed in the plant. To mimic this pattern, we employed a sinusoidal influent pattern with a mean equaling the average flow rate.

5.5.2 Normal Weather Simulation

The ultimate goal in performing gas phase control is to increase treatment efficiency and avoid wasting energy. The treatment efficiency is affected by many factors, such as DO concentration, oxygen uptake rate, food to organism ratio and mean cell residence time. For gas phase control of the HPO process, maintaining a relative constant DO concentration at a suitable set point is required to conserve energy and avoid sludge bulking. Energy savings can be evaluated by the total amount of oxygen feed, oxygen utilization rate and aerator power. To evaluate the fuzzy control system performance we chose DO concentrations in each stage, amount of oxygen feed, oxygen utilization rate and aerator power, as well as system stability, as the performance indices of the control systems.

Table 5.5.1 Pilot Plant Data for Simulation

Parameter (1)	**Value** (2)	**Parameter** (3)	**Value** (4)
Liquid Volume	7.84 m^3	Stage 1 O_2 Uptake Rate	63 mg O_2/L-hr
Gas Volume	1.13 m^3	Stage 2 O_2 Uptake Rate	96 mg O_2/L-hr
Gas Pressure	3 cm w.c.	Stage 3 O_2 Uptake Rate	48 mg O_2/L-hr
O_2 Consumption	0.16-0.29 kg O_2/kg BOD_5	Stage 4 O_2 Uptake Rate	41 mg O_2/L-hr
Average Flow rate	6 m^3/hr	Average Stage 1 DO	7.6 mg/L
Recycle Ratio	52 %	Average Stage 2 DO	5.2 mg/L
O_2 Flow In	0.62 SCMH (Standard m^3/hr)	Average Stage 3 DO	5.5 mg/L
O_2 Flow Out	0.07 SCMH (Standard m^3/hr)	Average Stage 4 DO	5.0 mg/L
O_2 Purity (feed)	97 %	Stage 1 O_2 Purity	93.7 %
Waste Sludge	0.48 m^3/hr	Stage 2 O_2 Purity	82.8 %
O_2 Utilization Rate	92.5 %	Stage 3 O_2 Purity	71.0 %
Influent Total BOD_5	88 mg/L	Stage 4 O_2 Purity	65.6 %
Average MLSS	1346 mg/L	Average Temperature	19.5 C

Four fuzzy control systems were simulated and compared with the conventional strategy. The simulation results are summarized in Table 5.5.2. Figure 5.5.1 shows the DO profiles of 5 strategies and their corresponding oxygen feed during 48 hours simulation. The DO profiles show that the fuzzy control systems with the feedforward loop to control stage 1 pressure are superior to the conventional control strategy. The average stage 1 total pressure is reduced to 1.004 atm, which can reduce oxygen leakage. Among the 4 fuzzy control strategies, set point control of stage 4 DO and feedforward control of stage K_La's (strategy 1) is the best in maintaining constant DO.

The superiority of strategy 1 is partly due to its ability to manipulate stage K_La by regulating motor speed or gas recirculation rate. Manipulating stage K_La implies directly adjusting oxygen transfer rate. This control is not affected by the gas phase delays. Moreover, the measurement of the influent flow rate used in the feedforward loop provides additional information to the fuzzy rule base, which results in a relatively constant DO, reduced oxygen feed, higher oxygen utilization rate and energy conservation. As long as the fuzzy rules match the oxygen demand pattern, a constant DO can be maintained. The improved DO control is most significant in stage 2, where the variations of the influent flow and concentration have the most profound effects.

Table 5.5.2 Simulation Results for Normal Weather

Parameter (1)	Strategy 1 (2)	Strategy 2 (3)	Strategy 3 (4)	Strategy 4 (5)	Strategy 5 (Conventional) (6)
Stage 1 K_la (hr^{-1})	2.5 (avg)	2.5	2.5	2.5	2.5
Stage 2 K_la (hr^{-1})	5.12 (avg)	5.0	5.0	5.0	5.0
Stage 3 K_la (hr^{-1})	3.55 (avg)	3.5	3.5	3.5	3.5
Stage 4 K_la (hr^{-1})	3.49 (avg)	3.0	3.0	3.0	3.0
O_2 Utilization Rate (%)	85	83	84	82	81
Total O2 Feed (kg/d)	40.4	42.8	43.1	43.5	43.2
Average Stage 1 Total Pressure (atm)	1.0032	1.0042	1.0042	1.0042	1.004
Average Stage 4 O2 Purity (%)	46.6	47.6	46.3	47.8	47.8
Max. percent of DO off the Average in Stage 2 (%)	5.3	13.8	10.9	13.5	32.1
Max. percent of DO off the Average in Stage 4 (%)	4.6	2.7	7.5	2.2	46.3
DO Range for Stage 2 (mg/L)	4.8-5.1	4.3-5.6	4.3-5.3	4.3-5.6	3.6-6.6
DO Range for Stage 4 (mg/L)	5.5-6.1	5.5-6.0	5.1-5.9	5.6-6.0	3.6-8.8
Average Pressure Controller Set-point (atm)	N/A	1.0042	1.0042	1.0042	1.004
Average Vent Gas O2 Purity Set-point (%)	N/A	47.41	43.37	N/A	40
Stage 2 Average O2 Uptake Rate (mg/L-hr)	79.3	79.0	79.0	79.1	78.2
Stage 4 Average O2 Uptake Rate (mg/L-hr)	44.1	44.1	43.9	44.1	44.2

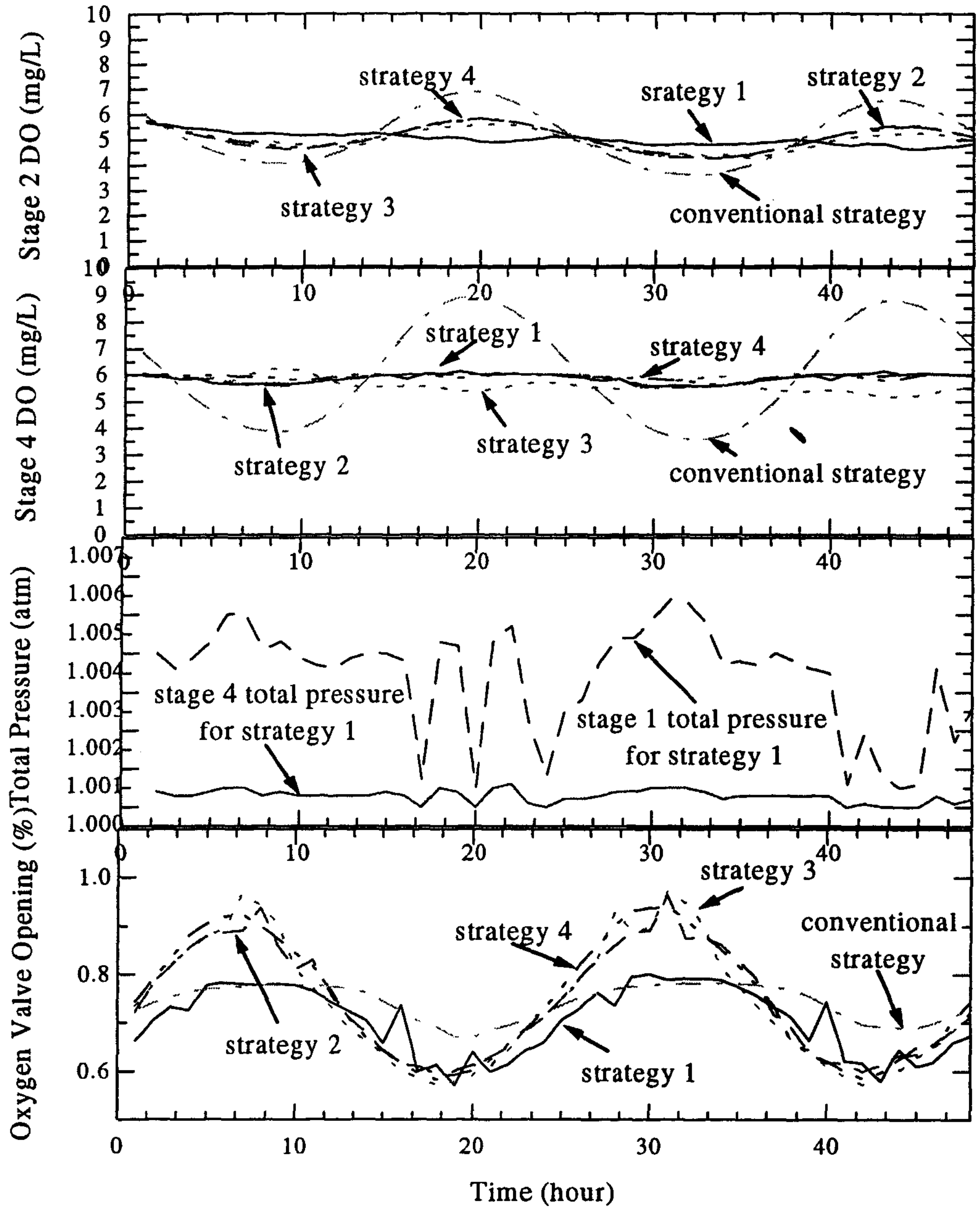

Figure 5.5.1 DO Profiles and Oxygen Feed for Normal Weather Simulation

For strategies 2, 3 and 4 we assumed the aerator speed is not adjustable. The feedforward loop is used to adjust the stage 1 pressure set point. Matching oxygen demand occurs by regulating the oxygen feed. These strategies are all affected by gas phase delays; a large change in the oxygen feed to stage 1 cannot simultaneously change DO concentration. Furthermore, a higher oxygen partial pressure can create large driving force, but the increased driving force may still be inadequate to offset a large oxygen demand due to the limitation of K_La. Strategies 2, 3 and 4, which use gas phase control to manipulate DO concentration, are inferior to the controlling K_La in each stage.

Another characteristic of strategy 1 is smaller oxygen feed and larger K_La requirement as compared with the other strategies. The oxygen feed is 7% less than in strategy 4, while the K_La's for stage 2, 3, and 4 are 2.4, 1.4 and 16% greater, respectively (Table 5.5.2). Reducing oxygen feed usually requires increasing in K_La's, if a specified DO concentration is to be maintained, or vice versa (McWhirter, 1978). There is a trade off between oxygen feed and K_La in design and control of HPO process. As discussed earlier, K_La control is more effective than the other indirect controls. Increasing the K_La can also increase oxygen utilization rate with a corresponding reduction of oxygen purity in stage 4 and oxygen feed rate. This results in reduced oxygen costs. The disadvantage is the need for variable speed aerators and increased aerator power at peak loading.

Another disadvantage of strategy 1 is the rapid manipulation in oxygen feed rate. As compared with strategy 4 and conventional control, sharp changes in oxygen supply are required at times 16 to 20, and 38 to 40 hours. The same phenomenon are also observed in strategies 2 and 3 at time periods of 6 to 11, and 26 to 33 hours. The sharp change may be caused by inaccuracies in the fuzzy membership function in the feedforward loop. One method to solve this problem is to fine tune the membership functions using trial-and-error as a optimization technique. These fluctuations are small and would not cause instability of the system.

Significant improvement in DO control is achieved in stage 4 for all four fuzzy control systems. A 40% reduction in DO variation is achieved as compared to the conventional control scheme. Varying oxygen purity in stage 4 (40-60%) usually causes larger DO fluctuations in the liquid phase, which results in wasting oxygen when DO is high and oxygen depletion when DO is low. The DO concentration in stage 4 is also affected by the DO fluctuation in the upstream stages. Large fluctuations of DO in the stages prior to stage 4 create difficulty for stage 4 DO control in the conventional control scheme (strategy 5). For all 4 fuzzy control systems, less DO variations in stages 2 and 3 help to achieve a constant DO concentration, as evidenced in Figure 5.5.1.

In the conventional control scheme the exit gas flow is too small to regulate with a single valve. With the installation of venting equipment, stage 4 DO and oxygen purity controls are greatly enhanced. When the stage 4 DO error or oxygen purity error is positive large, a large exit flow is required to build up higher oxygen partial pressure and increase oxygen transfer rate. If the errors are negative, the exit gas flow must be reduced. This knowledge is implemented in the feedback loops in all four fuzzy control strategies. The simulation has confirmed the correctness of the knowledge and the effectiveness of the control strategies.

Among the fixed- K_La control strategies (2, 3, and 4), strategy 4 may be the best choice in terms of overall performance. All three strategies have the same stage 1 pressure control scheme and same rule base in the feedforward loop. The stage 4 feedback loop of strategy 4 is more simple than in strategies 2 and 3, since only a DO error control is used. Adjusting the FLC set point in the feedback loop is not required. This simplification greatly reduces the number of rules, and a more stable oxygen feed is presented by this strategy. In the next section we developed an adaptive system based on strategy 4 for extreme weather flow simulation. Strategy 4 is also serves as a comparison basis for the adaptive control system.

5.5.3 Extreme Weather Condition Simulations

Storm and extremely dry weather flows are usually experienced in wastewater treatment plants. The DO concentration in the aeration tank is low when storm flow occurs and the aeration tank may be near wash-out. In dry weather, DO concentration may be high due to the small influent flow. This may result in oxygen wastage. To control these extreme cases, the control system is required to self-adjust to different working states. Conventional PID controller and control strategies have difficulty in satisfying this requirement.

To accommodate the extreme weather flows, a fuzzy adaptive control system was designed and simulated. The adaptation of the fuzzy control system was made through adjusting the input and output membership function discourses by applying scaling factors.

These scaling factors are obtained by firing sets of rules when certain predefined influent flow rates are reached. There are two sets of rules that are responsible for obtaining the scaling factors: wet-weather and dry-weather rule sets. The general knowledge in the rule sets is simple : if the storm flow rate is large, then the scaling factor is larger; if the dry-weather flow is small, then the scaling factor is smaller. The adaptive system was implemented with control strategy 4 (Table 5.5.1).

The wet-weather mean flow was simulated by doubling the normal average flow rate. A sinusoidal flow pattern was then superimposed to the mean storm flow rate. The same procedure was applied to simulate the dry-weather flow, but the average normal flow rate was only one-half of the mean dry-weather flow rate. A 10% reduction in gas phase volume, caused by the higher flow rate through the tanks, was used to simulate the gas volume disturbance for the wet weather condition. The other operating conditions are the same as for normal weather.

Figure 5.5.2 shows DO concentration and oxygen feed in stage 4 under the wet weather condition. The storm event occurs at time 12. DO concentration immediately drops to less than 1 mg/L for control strategy 4 due to the stormwater dilution. The average DO concentrations of Stage 2 and 4 for strategy 4 are 1.6 and 0.6 mg/L, respectively. Although 10% reduction in head space volume was simulated, the control system did not reduce the oxygen feed in response to the pressure increase. This is an improvement over conventional PID system (Clifft, 1991). This is because the fuzzy rules in the feedforward loop provide higher pressure set point. However, the oxygen feed is not elevated to address the stormwater, which results in DO depletion in each stage.

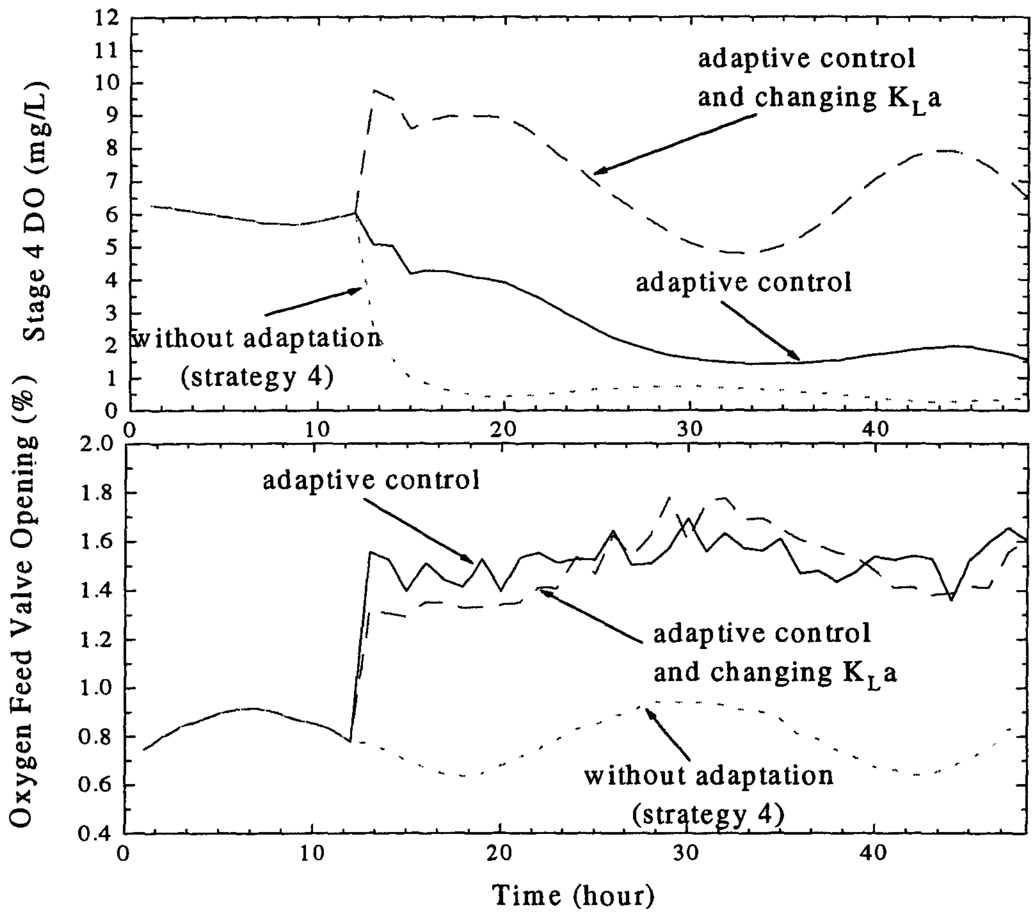

Figure 5.5.2 Stage 4 DO and Oxygen Feed for Wet Weather Simulation

Figure 5.5.2 also shows the DO profile and oxygen feed produced by the adaptive control system. The average DO concentrations for stages 2 and 4 are 2.53 and 2.47 mg/L, respectively, which are 1 mg/L closer to the designed value than obtained by strategy 4 (without adaptation). Table 5.5.3 summarizes these quantitative indications of the improved performance of the adaptive control systems. When the storm event is detected by monitoring the large change in influent flow, the system immediately shifts the control to the storm operation condition. Both the membership function discourses of oxygen feed and venting motor speed in the FLCs are elevated. This results in increased oxygen feed and oxygen partial pressure in stage 4. The average oxygen feed valve opening is 152.7% as compared with 77.7% for strategy 4, which results in a 49% increase in oxygen feed. Since the motor speed of the aerator is fixed (K_La's are the same as the normal weather) an average 62.9% oxygen purity occurs in stage 4. This high oxygen purity causes oxygen wasting through the venting apparatus and lowers the oxygen utilization rate to 60%.

To determine the impact of variable speed aerators for extreme flow conditions with the adaptive control system, we assumed that the plant installed three speed aerator drives: high, low and medium, which correspond to wet, dry and normal weather operations. Figure 8 shows the simulated results with K_La increased by 50%.

The average oxygen feeds for adaptive and adaptive plus changing in K_La control systems are almost the same. The DO concentrations in stages 2 and 4 are elevated to 5.98 and 7.08 mg/L, respectively, for the adaptive system with higher K_La. This is very close to the 6.0 mg/L set point for each stage. The DO peaks immediately after the storm occurs (between time 12 to 16 hours) because of the increase in oxygen feed and K_La. This could be avoided by gradually enlarging the scaling factors in the first few hours of the storm.

The oxygen utilization rate is increased from 60 to 70% using this control strategy because of the higher K_La. We used the same rules to obtain the scaling factors for both the adaptive and adaptive plus changing K_La. The higher oxygen utilization rate could be obtained if different scaling factors were used for the two adaptive control strategies. In comparing with strategy 4 and the adaptive control system, the adaptive system with control of aerator motor speed provides the best overall system performance in the storm condition.

Extremely dry weather flow can also be experienced at treatment plants. In this case the major goal of the control system is to reduce the oxygen feed and conserve energy. Figure 5.5.3 shows stage 4 DO profiles and oxygen feed for three control strategies: strategy 4, the adaptive control system and the adaptive system with lower K_La's. The simulated quantitative results of the three strategies are presented in Table 5.5.3.

For extremely dry weather the DO concentrations of stages are very high for the control system with little or no adaptability (strategy 4). The average DOs in stages 2 and 4 are 12.5 and 14.9 mg/L, respectively. For the adaptive control system the DO concentrations of stages 2 and 4 are reduced to 9.5 and 7.8 mg/L. The adaptive control system with fixed K_La's reduces the total oxygen feed by 10%. This results from a 12% lower oxygen feed valve opening than in strategy 4.

Table 5.5.3 Simulation Results for Extreme Weather Flows

Parameter	Wet Weather			Dry Weather		
	Adaptive Control	Adaptive and Changing K_La	Strategy 4	Adaptive Control	Adaptive and Changing K_La	Strategy 4
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stage 1 K_La (hr^{-1})	2.5	3.75	2.5	2.5	1.75	2.5
Stage 2 K_La (hr^{-1})	5.0	7.5	5.0	5.0	3.5	5.0
Stage 3 K_La (hr^{-1})	3.5	5.25	3.5	3.5	2.75	3.5
Stage 4 K_La (hr^{-1})	3.0	4.5	3.0	3.0	2.1	3.0
O_2 Utilization Rate (%)	60	70	86	93	91	75
Total O_2 Feed (kg/d)	67.0	66.1	44.9	33.0	33.2	36.6
Average Stage 1 Total Pressure (atm)	1.0153	1.0153	1.004	1.0027	1.0027	1.004
Average Stage 4 O_2 Purity (%)	62.9	57.2	40.6	36.7	40.7	52.8
Average DO in Stage 2 (mg/L)	2.5	6.0	1.6	9.5	5.9	12.5
Average DO in Stage 4 (mg/L)	2.5	7.1	0.6	7.8	6.0	14.9
Average Oxygen Feed Valve Opening (%)	152.7	149.5	77.7	37.5	38.0	49.5

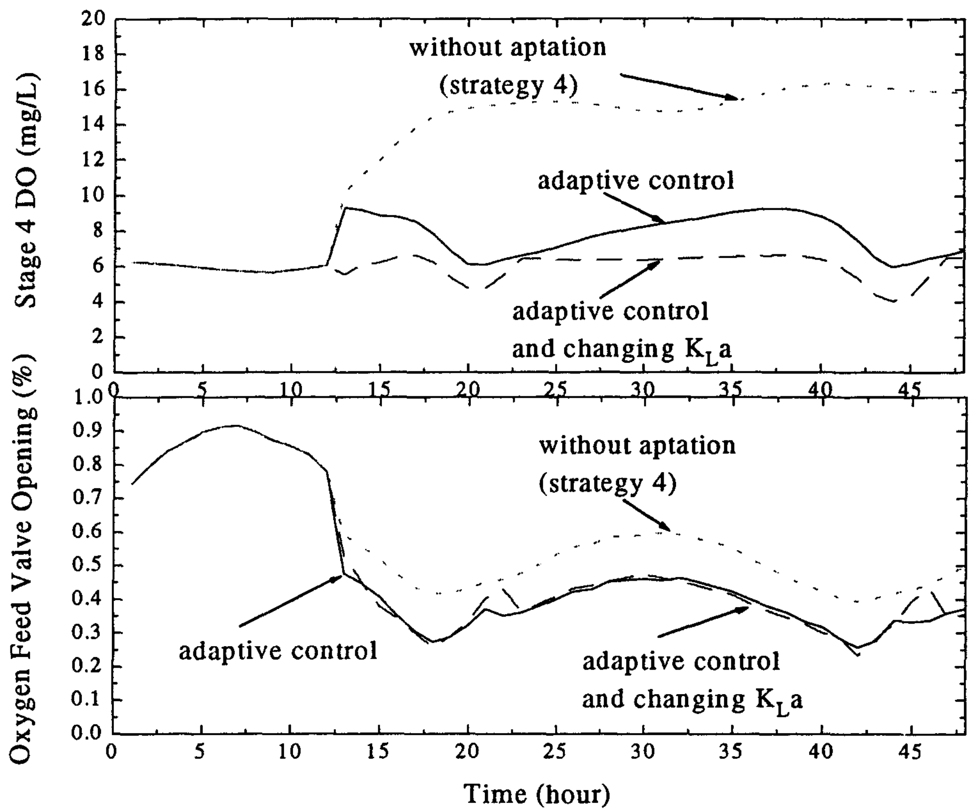

Figure 5.5.3 Simulation Results for Extremely Dry Weather Flows

The adaptive control system plus changing K_La has a better performance than the adaptive system with a fixed K_La. The two systems have the same oxygen feed, but a 30% reduction in K_la was achieved by changing K_La. The DO concentrations of stages 2 and 4 are controlled at 5.88 and 6.01 mg/L by applying the reduced K_La, and are more closer to the DO set points (6.0 mg/L).

5.6 Conclusions

Four fuzzy control systems have been developed for performing gas phase control of the high purity oxygen activated sludge process for normal weather condition. All the four systems have shown improved controls over the conventional PID control systems in terms of reducing diurnal DO variations, stable oxygen feed and energy savings. Among the four fuzzy systems the direct control method (control of aerator motor speed) based on the influent flow rate in the feedforward loop, and in conjugation with the stage 4 DO control (strategy 1), provides the best overall performance. For plants where a fixed speed drive is installed, the stage 1 pressure control using the feedforward loop to adjust FLC set point, along with the stage 4 DO feedback regulating (strategy 4), is the most attractive choice.

Using influent flow measurement as a feedforward control method can greatly reduce the process disturbances caused by hydraulic shock loading and increase the robustness of the system. The knowledge for tracking oxygen demand can be implemented through the fuzzy rules in the feedforward loop and fuzzy logic controller. These fuzzy rules are more resistant to the gas volume disturbances and reduce DO variations in each stage.

Aerator motor speed control is the most effective method for maintaining a constant DO and conserving energy. This is especially true for the extreme weather flows. Increasing K_La's allows operation at reduced total head space pressure so that the oxygen leakage is also reduced. Another advantage of aerator speed control is to elevate oxygen utilization rate by reducing the wastage of oxygen through the exit gas flow.

The adaptive fuzzy control system developed based on strategy 4 showed better performance in reducing disturbances from extreme weather flows than the initial fuzzy system without adaptability. The adaptive control can shift operation to a completely different state when the extreme flows are detected. An even better performance is achieved if three speed variable frequency aerator drives are installed. The fuzzy adaptive control system can operate the plant at high, medium and low aerator speeds to adapt to the wet, normal and dry weather conditions.

Fuzzy rules are the backbone of the fuzzy control system. The correctness of the rules is of crucial importance to the system performance. Further research will focus on using neural network techniques to develop better rules.

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6. DEVELOPING A KNOWLEDGE-BASE TO FACILITATE THE OPERATION OFTHE HIGH-PURITY OXYGEN ACTIVATED SLUDGE PROCESS

Abstract

In this paper we present a global, real time knowledge base (KB) developed specifically for the operation of the high-purity oxygen activated sludge process (HPO-AS). The KB consists of two types of logic trees: elementary and symptom-oriented. The logic trees are arranged in block format. More than 20 commonly used parameters in operation of HPO-AS are selected for building the logic trees. The architecture of the KB allows the operator to efficiently perform on- and off-line diagnosis. The KB can also be easily updated and maintained under the G2 and GDA expert system shell environment. With minor modifications, the KB can be applied to HPO plants to accommodate site specific conditions.

6.1 Introduction

The high-purity oxygen activated sludge process (HPO-AS) has become one of the major choices for building or updating treatment plants where the infrastructure of the mature city is well developed and land is limited. Numerous HPO-AS treatment plants have been built since their introduction in the late 1960's. Unfortunately, using high purity oxygen (usually higher than 96%), high food to biomass ratio (F/M) and short hydraulic retention times can potentially waste energy and violate discharge permits if the plant is not operated properly. Operation and control of HPO-AS process have become an important research topic, especially for very large facilities.

High-purity oxygen activated sludge processes are more complex than the conventional air systems due to high purity oxygen feed, covered and multi-stage tanks, and series operation of these tanks. The complexities require a higher level of operational expertise by skillful operators. However, experienced operators are scare and new operators require a long time to obtain needed experience. The operation is further complicated by the fact that there are few reliable on-line measurements (Patry and Chapman, 1989). Operators must rely heavily on their personal experience to operate the process. To overcome these aforementioned difficulties, a number of "expert systems" have been developed during the last decade (Beck *et al.*, 1978, Johnston, 1985, Barnett *et al.*, 1987, Berthouex *et al.*, 1988, Gall and Patry, 1988, Parker *et al.*, 1989, Koskinen, 1989, and Ozgur and Stenstrom, 1994). These expert system applications were developed specifically for the conventional air activated sludge process, anaerobic digester, nitrification for refinery wastewater, or diagnosis of the presence of the toxic compounds. They dealt with a verity of operational and control problems. However, most of the systems function as off-line diagnosis or training tools, and few posses real time features. An expert system designed specifically for the HPO-AS process has not been reported in the literature.

A global and real time knowledge base (KB) is developed specifically for operation of HPO-AS process in this study. Two kinds of knowledge are included in the KB:

conventional diagnosis-oriented knowledge, and fuzzy logic. The fuzzy logic part is applied only to the gas phase control. The fuzzy logic converts real time gas phase data and operator experience into control actions. In this paper we focus our discussion on the development of the conventional diagnosis-oriented knowledge base. We briefly introduce how the conventional knowledge base interacts with the fuzzy logic control. These interactions are good examples of interaction at large treatment plants.

The KB is structured in logic tree format. The logic trees are formulated based upon the most commonly used operational parameters in an HPO-AS plant, such as sludge age, pH, stage 1 total pressure, vent gas purity, etc. The knowledge is organized in two categories: elementary logic trees (ELT) and symptom-oriented logic trees (SLT). The ELTs are constructed based upon some very important operational parameters, and are invoked in a real-time fashion. The SLTs serve as an off-line diagnosis tool to help the operator identify the cause and solutions of the problems. These logic trees are fired based upon the detection of abnormal parameters or upon the operators' observations. The primary simulation results have shown that the knowledge base can provide the operator with more information which results in improved operation. Site specific conditions can be included in the KB with only slight modifications.

The knowledge base presented herein is one part (or called one module) of a decision support system which is still under development. For more detailed explanations of the system structure and the functions of each system module, the readers are referred to Yin *et al.*, (1994).

The knowledge base is developed using G2, a real time expert system shell (Gensym Corporation, 1992), and G2 Diagnosis Assistant (GDA), which is a separate product of G2. The development of the knowledge base makes full use of the GDA's features: user friendly interactions, easy updating and maintaining existing logic trees, graphical display of logic trees and data, etc. With these functions of GDA, the knowledge base can be easily modified and updated, and then applied to the specific treatment plant.

In the following sections, we first briefly present a typical HPO-AS process. The development of the knowledge base and the results are discussed next. Finally we summarize our research in progress and suggest topics for future research.

6.2 High-Purity Oxygen Activated Sludge Process (HPO-AS)

The HPO-AS process is characterized by its use of high-purity oxygen feed, covered aeration tanks, and parallel trains of four or more tanks-in-series. Figure 6.2.1 shows the process flow diagram for a typical HPO-AS process. The oxygen (usually purity more than 96%, depending what kind of oxygen generation processes is used: cryogenic or pressure swing adsorption) is fed to stage 1. The oxygen feed rate is controlled by the position of the oxygen feed valve (OFV). The oxygen production rate can also regulated by the position of the compressor suction or compressor discharge

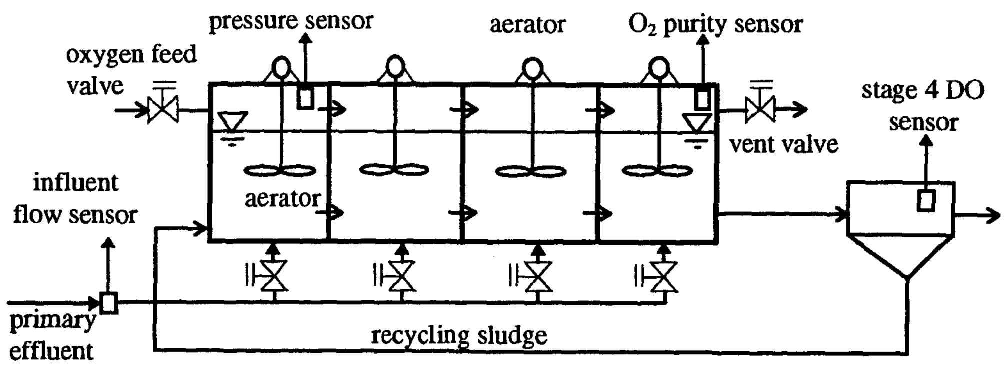

Figure 6.2.1 Process Flow Diagram For A Typical HPO-AS Process

valves located in the oxygen generation processes. A pressure which is slightly higher than atmospheric (about 1.008 atm.), is produced in stage 1, and drives the gas flow from one stage to another. The vent gas pressure is almost equal to the atmospheric pressure. The primary effluent is usually fed to stage 1. However, it can also be fed to stage 2, 3 and 4 to create different operational modes (e.g. step feed), depending upon operational needs. When storm flow occurs, for example, the wastewater may be fed directly to stage 4 to prevent the sludge wash out and process failure.

In general, the technology of the HPO-AS process can be classified into two parts: gas and liquid phases. The two phases are coupled by mass transfer of oxygen, nitrogen and carbon dioxide. The purpose of gas phase control is to provide sufficient dissolved oxygen concentrations (DO) for each stage. The major operational parameters for the gas phase include stage 1 total pressure, vent gas oxygen purity, DO concentrations in each stage, aerator impeller speed (if variable drives are used) and air recirculate rate (for diffused or submerged turbine aerators only). In the liquid phase, the most commonly used measurements are flow rate, pH and DO concentrations of each stage. The placement of the DO probe may be varied from plant to plant (at stage 1, or stage 4, or at every stage). In developing this knowledge base we assume that DO probe is located at stage 4. For treatment plants with DO probes placed other than stage 4, some minor modifications are needed to use the KB.

One of the major differences between the open-air and HPO-AS processes is that the operator can not directly observe the aeration tanks, since the tanks are covered. This makes it difficult to apply the expert system to the process, as compared with the open-air activated sludge process, since many of the operators' observations are visual. This disadvantage is somewhat compensated by the on-line measurements, such as total pressures and purities of stage 1 and 4, vent gas purity, etc., and by the observations of the aeration tank effluent in the clarifier. To perform the gas phase control, the knowledge base outputs are connected to fuzzy logic sets (Yin and Stenstrom, 1994), which produce quantitative outputs to the process actuators. We will discuss this in detail in the next section.

6.3 Knowledge Base Development and Results

6.3.1 Global Knowledge

The operators' experiences for activated sludge process can be classified into global and local knowledge (Barnett and Andrews, 1987). Global knowledge is the knowledge that is universally applicable to any activated sludge processes. A good example is pH control. Local knowledge may be changed from plant to plant, depending upon the characteristics of the influent, and the site-specific conditions. The purpose of this investigation is to develop such a global knowledge base for the HPO-AS process, so that it can be applied to most HPO plants with only minor modifications.

A key step to develop such a KB is to properly select globally used and representative parameters. Table 1 shows the parameters used in the knowledge base. These parameters formulate the backbone of the logic trees. The control measures displayed in Table 1 represent the manipulating devices used to perform the process controls.

To make the knowledge base applicable to different treatment plants, the ranges of the operational parameters shown in Table 6.3.1 are defined using fuzzy terms, such as high, normal and low. These fuzzy terms can be obtained using histogram charts (Berthouex *et al.*, 1988) or Bayesian statistics analysis (Duda *et al.*, 1976, Ozgur and Stenstrom, 1994) based on plant data. Berthouex *et al.*, found that 5% of plant data typically fall outside of the frequency distribution curve and should be considered abnormal operation or indicating a process upset. For HPO-AS processes we have yet to define a cutoff to define process upsets.

Table 6.3.1 Parameters and Control Measures Used in the Knowledge Base

No.	Liquid Phase	Gas Phase	Measures
1	Influent Flow Rate (IFR)	O_2 Feed Purity (OFP)	Number of Trains
2	Sludge Age (SA)	O_2 Feed Rate (OFR)	PE Step Feed Mode
3	Food to Biomass Ratio (F/M)	O_2 Production Rate (OPR)	Equalization Basin (EB)
4	$MLSS_i$	Stage 1 Total Pressure (TP_{S1})	Sludge Recycle Valve (SRV)
5	Dissolved O_2 Conc. (DO_i)	Vent Gas Purity (VGP)	Sludge Wasting Valve (DWV)
6	O_2 Uptake Rate (OUR_i)	Vent Gas Flow Rate (VGFR)	Base Addition Pump (BAP)
7	Sludge Recycle Rate (SRR)	O_2 Partial Pressure (P^i_{O2})	O_2 Feed Valve (OFV)
8	Sludge Recycle Conc.(X_R=X_W)	Air Recirculate Rate (ARR_i)	Vent Gas Valve (VGV)
9	Sludge Volume Index (SVI)		Compressor Suction Valve (CSV_{O2})
10	Sludge Blanket Height (SBH)		
11	Base Addition Rate (BAR)		Air Recirculate Valve (ARV_i)
12	pH_i		
13	Temperature (T)		
14	Influent BOD_5 (IN_{BOD5})		
15	Effluent BOD_5 (IN_{BOD5})		
16	Influent pH (pH_{in})		
17	Influent TSS (TSS_{in})		
18	Effluent TSS (TSS_{out})		
19	Influent Ammonia (IN_{NH4})		
20	Effluent Ammonia (EF_{NH4})		
21	Nitrification Rate (NR)		
22	Nutrient (N-P)		
23	BOD_5/NH_4 Ratio (B/N)		

Note: i denotes the i-th stage of the aeration tanks

The definition of abnormal conditions and process upsets may vary from plant to plant. One approach to detect process upsets or abnormal conditions is to differentiate the frequency distribution curve into very high, high, normal, low and very low regions, which correspond to problem, potential problem, normal operation, etc. The disadvantage of this method is that it makes the knowledge base more complex, requiring more computing time.

To overcome this problem, we used the fuzzy terms (high, normal and low) in the logic trees for both the gas and liquid phases. The fuzzy logic sets for gas phase control (pressures, vent gas purity, stage 4 DO, oxygen feed valve and vent gas valve positions) can be formulated based on the process simulator (Yin *et al.*, 1994) or can be based upon plant data. These fuzzy sets are invoked only when an increase or decrease of a certain control action is suggested by the KB. In this way, the fuzzy logic sets produce a quantitative control output to the process actuators, and serve as a bridge that connects the continuously monitored signals to the expert reasoning, and then to the controlled output. This approach greatly simplifies the knowledge base, reduces the reasoning process and computing time (as compared with fuzzy logic reasoning), and makes the knowledge base more globally applicable. For a detail explanation of how the gas phase is controlled using the fuzzy logic algorithm and the simulation results, the readers are referred to Yin and Stenstrom (1994).

6.3.2 Knowledge Base Structure

To efficiently perform diagnosis and organize the knowledge base, it is arranged in logic tree format. Two separate logic trees are developed: elementary logic trees (ELTs), and diagnosis-oriented logic trees (SLTs). The logic trees are arranged in the block format in GDA. These two types of logic trees are differentiated based upon their functions and the ways that the logic trees are invoked. Figure 6.3.1 shows the structure of the KB.

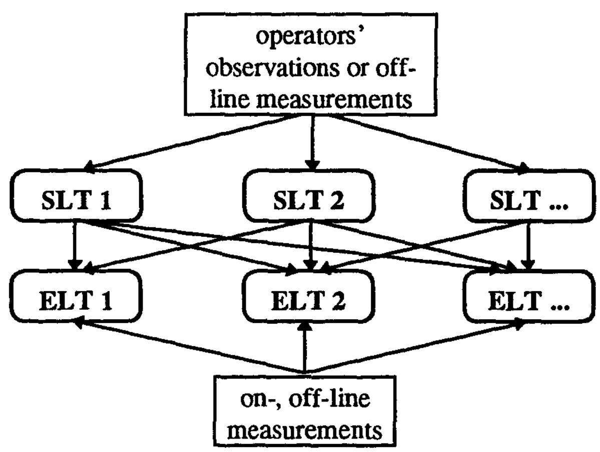

Figure 6.3.1 The KB Structure

The ELTs are the basic elements in the KB. They can individually perform process diagnosis in a real time fashion based upon the results of on- or off-line measurements, and can also provide off-line diagnosis support to the SLTs, which are fired upon the operators' inquiries. Under the GDA development environment, all the rules associated with the ELTs can be executed in a predefined time period. This time period can be the sampling interval, or any regular time intervals depending on operational needs. The ELT is "led" by a prime parameter, such as pH, temperature (T), vent gas purity, influent flow rate (IFR, see Figure 6.3.2) etc. When a measurement is obtained, the ELT is fired and the condition of the prime parameter (low, high or normal) is checked. Whenever abnormal operation is detected, the logic tree is searched and the recommendations are presented to the operator.

The SLTs are on top of ELT and are invoked based upon the operators' observations or laboratory's analysis results. The SLTs are executed in an off-line mode. They are led by certain process symptoms, such as high SVI, effluent BOD_5 violation, loss of nitrification, floating sludge in the clarifier, etc. These symptoms may be caused by several prime parameters (ELTs). When the operator detects and enters a symptom, the SLT is first triggered. The SLT then invokes the ELTs that may have the potential to cause that symptom. After all possible ELTs are fired, the final results are presented to the operator.

One of the advantages of strengthening the knowledge in ELTs and SLTs blocks is increased flexibility. When the knowledge and rules in the KB are updated, the new knowledge can be easily added to the KB as a new ELT. This newly established ELT can be connected to the SLT through rules or a connecting line on the workspace in GDA. The maintenance of the KB can also be easier since both the ELT and SLT are arranged in the separate workspaces, act as the individual units, and graphically display the tree structures.

Two kinds of reasoning processes are arranged in the logic trees: regular and in-depth. For the real time reasoning mode (for ELTs), only regular diagnosis is used. This can greatly reduce the required computer time. An in-depth diagnosis can be performed off-line, or in the background, or by the operator.

6.3.3 Elementary Logic Trees (ELTs)

Among the parameters listed in Table 6.3.1, 11 parameters are selected as prime parameters which create 11 ELTs. We believe these parameters are the most important, problem-causing parameters. These parameters can be either measured or calculated based upon on-, off-line measurements. Table 6.3.2 shows the selected parameters.

The ELT starts with a prime parameter which is always monitored. When an abnormal value is detected, the ELT is fired and the reasoning process begins. Figure 6.3.2 shows an example of the ELT for influent flow rate (IFR). Table 6.3.3 provides the explanations and the possible actions caused by invoking this ELT.

The influent flow rate measurement (IFR) is first matched with the 4 fuzzy sets: low, normal, high and extremely high. If the IFR is within the normal range, no actions will be taken. When the IFR is low, it is concluded that reducing oxygen feed and production are required. These conclusions trigger the fuzzy logic algorithm developed in the KB. The quantitative reduction of oxygen feed valve position is calculated. When the

IFR is high, the oxygen feed and production can be increased in a similar way. The operator can also be asked to put more trains into service. If storm flows occur, diversion of part of the influent to an equalization basin (EQ) can be concluded. For treatment plants without off-line equalization basin, part of influent can be directly fed into the last stage of the aeration tank to protect the biomass from being washed out.

Table 6.3.2 Prime Parameters Used for ELTs

No.	Liquid Phase	Gas Phase
1	Influent flow rate (IFR)	Stage 1 total pressure (TP_{S1})
2	Sludge age (SA)	Stage 4 DO concentration (DO_4)
3	Food to biomass ratio (F/M)	(used for control of stage 4 O_2 purity)
4	Oxygen uptake rate (OUR)	
5	Effluent ammonia (EF_{NH4})	
6	pH	
7	Temperature (T)	
8	Nutrient (N-P)	
9	Effluent Total Suspended Solids (TSS)	

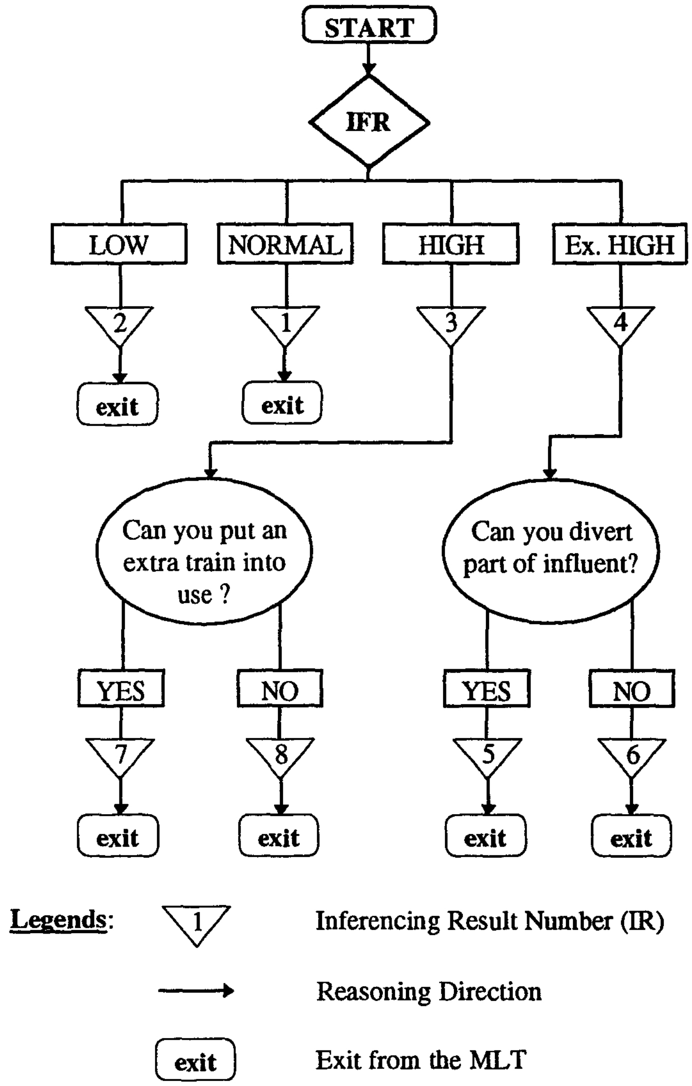

Figure 6.3.2 Influent Flow Rate ELT

Table 6.3.3 Explanations and Actions of Inferencing Results

IR	Explanation (Exp) and Action (Act)	IR	Explanation (Exp) and Action (Act)
1	Exp: The parameter checked is normal. Act: a) Confirm that parameter; b) If faulty, correct & run KB again.	**5**	Exp: Yes, we can divert part of the influent. Act: Divert X% of the influent to the equalization basin.
2	Exp: Influent flow rate is low. Act: a) Confirm IFR value; if correct, do: b) Reducing CSV_{O2} position; c) Reducing OFV position.	**6**	Exp: No, we can not divert part of the influent. Act: Change step feed mode (STP): feed X% of primary effluent to the last stage.
3	Exp: Influent flow rate is high. Act: a) Confirm IFR value; if correct, do: b) Increasing CSV_{O2} position; c) Increasing OFV position.	**7**	Exp: Yes, we have an extra train available. Act: Put that train into use.
4	Exp: Influent flow rate is extremely high, and storm water may occur. Act: a) Confirm IFR value; b) Set CSV_{O2} & OFV to max. posi.	**8**	Exp: No, we do not have an extra train available. Act: We have nothing to do about it.

6.3.4 Symptom-Oriented Logic Trees (SLTs)

Symptom-oriented logic trees (SLTs) are problem-oriented and are used for off-line process diagnosis. An SLT addresses a specific process problem. It is triggered by operator inquiry about the causes and measures of the observed problem. Table 6.3.4 lists some of the commonly observed problems and their potential causes. It should be noted that the observations are not limited to those shown in Table 6.3.4. Since the SLTs and ELTs are arranged in block format, new observations can be easily added to the knowledge base under the GDA shell environment.

Table 6.3.4 Observed Problems and Their Possible Causes

No	Observations	Possible Causes
1	High SVI	Filamentous: low DO, insufficient N-P, low F/M, low pH Non-filamentous: high or low F/M, high organic or hydraulic loading
2	BOD violation in effluent	Low DO, low SA, low OUR, high organic or hydraulic loading
3	NH_4 violation in effluent	Low DO, low SA, low NR
4	High SS in effluent	High SVI, high SA
5	Pinpoint floc	High DO, high SA, over aeration
6	Straggle floc	Low SA, or high F/M
7	White foam	Low SA, or high F/M

Figure 6.3.3 shows an SLT used for diagnosis of nitrification loss in an HPO-AS process. When the operator detects high effluent NH_4 concentration, the inference engine first searches for DO elementary logic tree to check if the DO concentration is low. If true, the DO ELT is searched to find out the causes of the low DO and corresponding measures. After searching the DO ELT, the sludge age ELT is then checked, as shown in dashed line in Figure 6.3.3. If the DO is adequate, the inference engine directly checks the sludge age. In this way all three prime parameters are sequentially checked.

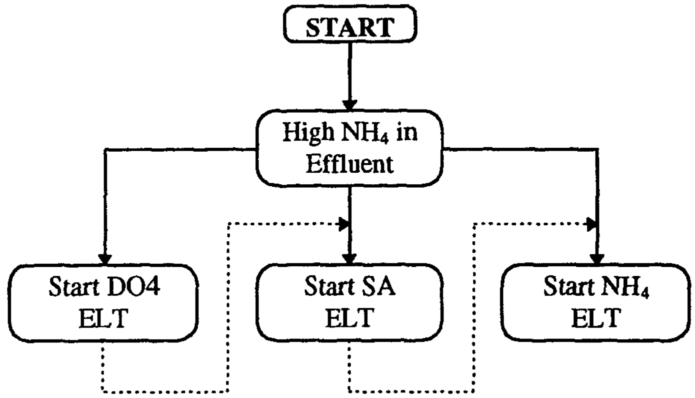

Figure 6.3.3 A SLT Used for Diagnosing Loss of Nitrification

6.4 Summary and Future Work

A global and real time knowledge base for facilitating the operation of high-purity oxygen activated sludge process is developed in this investigation. The knowledge base is an integrated part of an overall decision support system for operation of the activated sludge process, which is still under development. To construct the knowledge base, some of the commonly used parameters for a typical HPO-AS process are selected to develop the KB. The knowledge is organized in the elementary and symptom-oriented logic tree formats, and graphically displayed using the G2 and GDA real time expert system shell. This knowledge structure allows the operator to efficiently perform on- and off-line process diagnosis. The KB also has the advantage of easy maintenance and extendibility. The quantitative control of the gas phase is through a fuzzy logic algorithm, which converts the linguistic knowledge into quantitative actions. With minor modifications, the KB can be readily applied to other HPO plants.

One major future task is to further test the knowledge base. Conflicting and ill-defined knowledge are usually encountered in the knowledge acquisition and knowledge base developing processes. A pilot scale test is needed to verify the knowledge base.

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7. CONCLUSIONS

The main objective of this research is to develop a decision support system (DSS) to facilitate the operation and control of the high-purity activated sludge (HPO-AS) process, to provide the operator with more information when he or she is making a decision, and to provide quantitative support for advanced controls. A framework of such a decision support system has been developed for this purpose.

The DSS consists of 5 major components: operators' interface, data managing utilities, process simulator, on-line state and parameter estimator, and knowledge base. All the components are arranged in a module format and integrated via a menu system. The system was partially implemented into a computer software package - G2 and GDA, a real-time expert system shell. The algorithms involved in the components (simulator, estimator and knowledge base) have been developed and thoroughly tested.

The results of the investigation show that the system is superior to a conventional expert system since it can perform process diagnosis, and can also quantify the operation and control. With the assistance of the process simulator, on-line estimator, data management and knowledge base, the system can provide more information and better choices to the operator. This information can greatly facilitate process operation and correct decisions are more likely to be made.

A process simulator has been incorporated into the expert system shell for the high-purity oxygen activated sludge process. The results have shown that the simulator can greatly facilitate the operation of an HPO activated sludge process. With the assistance of the simulator, control actions can be evaluated and refined. The simulator can also provide the operator with an inside view of the process. It can quantify the process states, which is important for operation and control of an HPO activated sludge process due to its complex nature. The simulator is a valuable tool for training the new operators.

An on-line estimator using the asymptotic and recursive least squares algorithms, as well as fuzzy predictions of influent substrate and total effluent suspended solids (TSS), was constructed. The estimator can estimate the substrate and biomass concentrations, and the maximum, specific growth and decay rates for each stage using the dissolved oxygen (DO) measurements. The convergence of the algorithms is fast and stable even with a large range of initial inputs and noisy DO data.

The estimated states and parameters are reasonably agreed with both the plant measured and model simulated data. The estimated states and parameters can be plotted and provide the operator an intuitive feeling of the on-going process. These estimated states and parameters can also be referenced by the other system components to perform diagnosis, simulation and fuzzy logic control. The simulator was also tested under abnormal operation, such as hydraulic shock loading and sludge bulking. The performance of the estimator in these circumstances is stable and satisfactory. This is primarily due to the adaptability of fuzzy estimation of the effluent TSS.

Four fuzzy logic control strategies were developed to perform the gas phase control for HPO-AS process. For normal weather flow, all four strategies are superior to the conventional PID control systems in terms of reducing DO variations, stabilizing performance, and conserving energy. The fuzzy knowledge built into the feedforward loops and fuzzy logic controllers are mainly responsible for the improved performance.

To handle the extreme weather flows, an adaptive fuzzy logic control system was developed. This system can adapt to extreme flow rates by changing the control system to a new working state. In this way, both the DO depletion and over aeration can be avoided. If a variable speed motor drive of the mixer is installed, even better system performance can be achieved.

A process diagnosis knowledge base (KB) for the high-purity oxygen activated sludge process is developed in this study. The knowledge base is arranged in logic tree format. Two kinds of logic trees are used: elementary and sympton-oriented. The elementary logic tree (ELT) is executed in a real time fashion, while the sympton-oriented logic tree (SLT) is invoked based on the operator's request for certain process problems and executed off-line. More than 200 rules were developed in the knowledge base. The KB also has the advantage of easy maintenance and extendibility. The KB will be implemented into the system using the GDA.

8. FUTURE WORK

As stated in the Introduction section, the work documented in this dissertation is the completion of phase 1 for development of the decision support system. Much work needs to conducted in phase 2, and includes:

- further testing the knowledge base described in Chapter 6, and a pilot scale test is needed to verify the knowledge base;
- using a neural network to train the fuzzy rules developed in this study for both the fuzzy controllers and the prediction of the influent substrate and effluent TSS concentrations;
- implementing the conventional and fuzzy knowledge into the system via the GDA, and performing β-testing;
- integrating all the system components (modeles) together; special attention should be given to the interactions among the system modules.

Appendix A COMPLETE LOGIC TREES OF THE KNOWLEDGE BASE FOR THE HIGH-PURITY OXYGEN ACTIVATED SLUDGE PROCESS

This appendix contains the elementary and symptom-oriented logic trees for the high-purity oxygen activated sludge (HPO-AS) process. The elementary logic tree (ELT) is led by a prime parameter as showed in Table 6.3.2, and the symptom-oriented logic tree is led by a process symptom (Table 6.3.4). For ELTs, the explanations of the inferencing results are provided immediately after the logic tree graph. For detailed explanations of how the ELTs and SLTs working, the readers are referred to Chapter 6 of this dissertation.

It should be noted that the ELTs for pH, effluent ammonia (EF_{NH4}) and temperature (T) are adopted from Ozgur's work (Ozgur, 1991). These ELTs will not present in this appendix.

Figure A-1 Elementary Logic Tree for Influent Flow Rate (IFR)

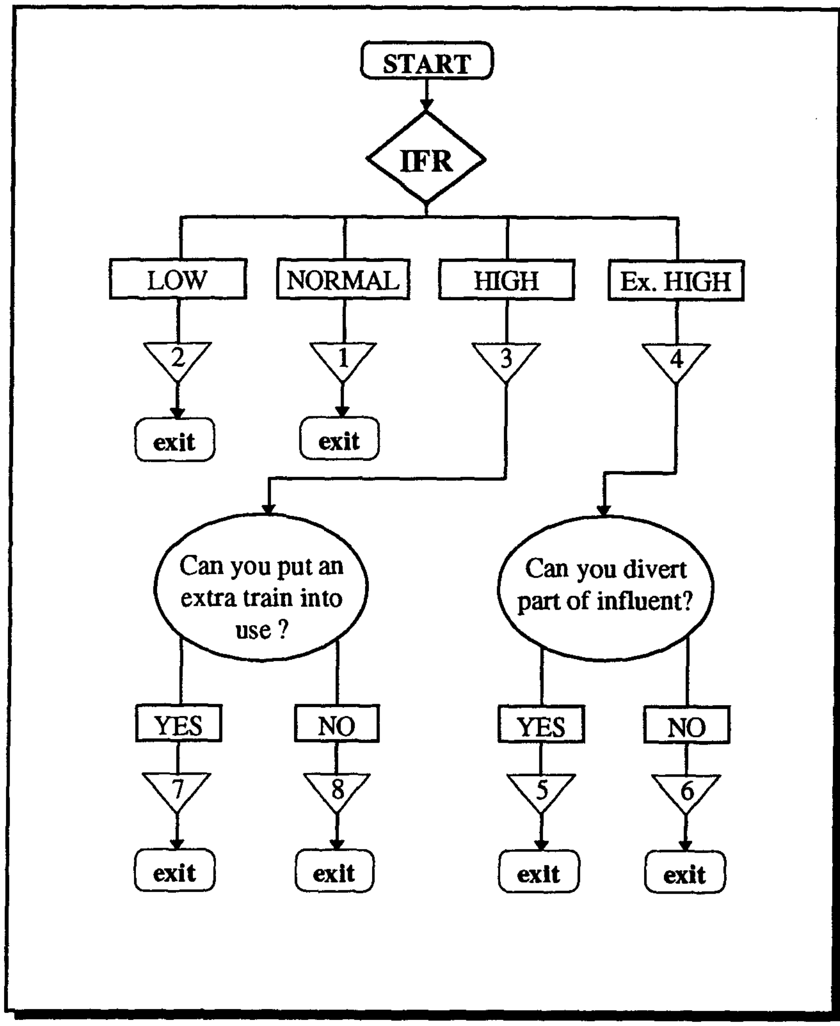
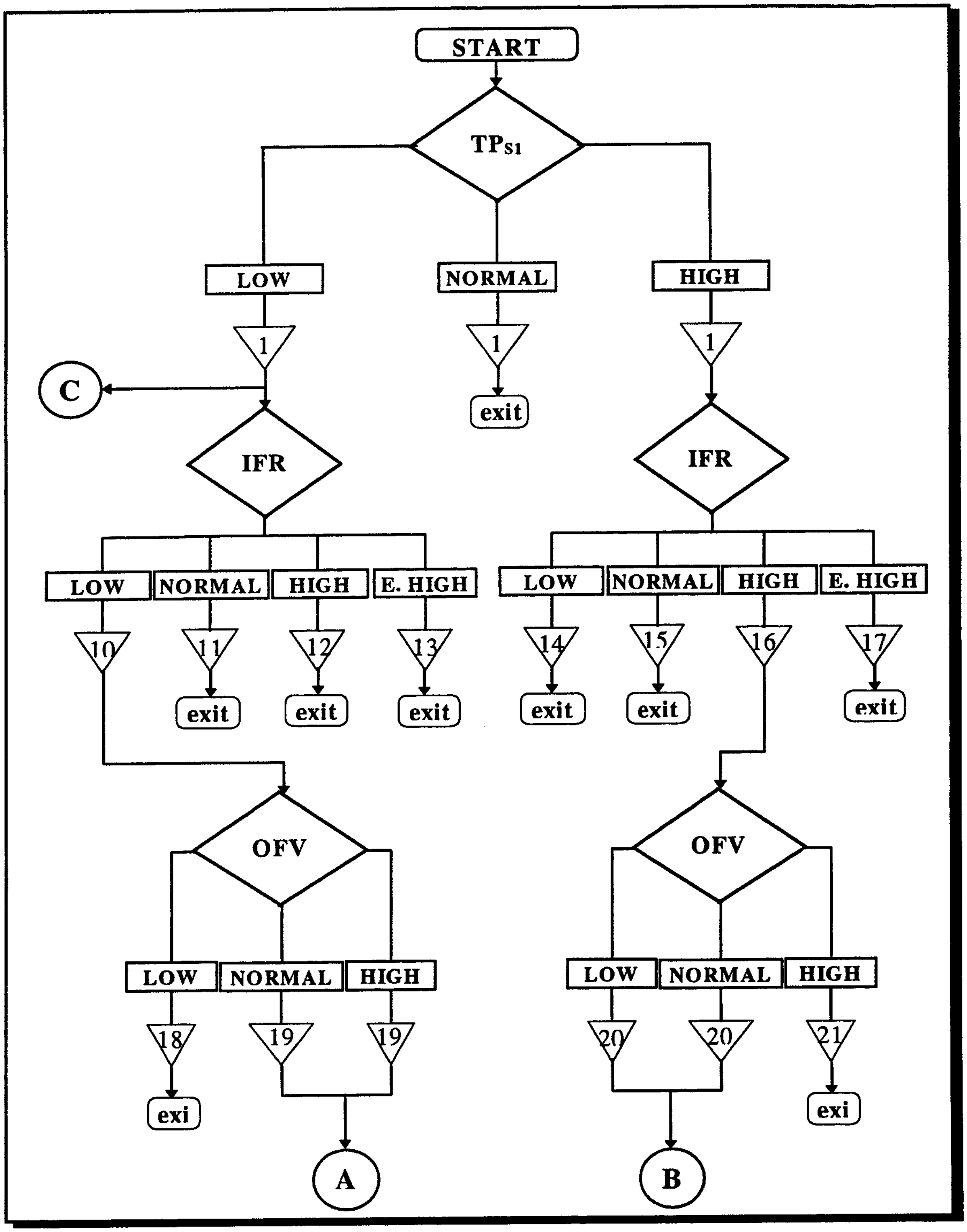


Table A-1 Inferencing Results for Flow Rate Diagnosis

IR	Explanation (Exp) and Action (Act)	CF
1	Exp: The parameter checked is checked and normal. Act: a) Confirm that parameter; b) If faulty, correct and run KB again.	**90**
2	Exp: Influent flow rate is low. Act: a) Confirm IFR value; if correct, do: b) Reducing CSV_{O2} position; c) Reducing OFV position.	**90**
3	Exp: Influent flow rate is high. Act: a) Confirm IFR value; if correct, do: b) Increasing CSV_{O2} position; c) Increasing OFV position.	**90**
4	Exp: Influent flow rate is extremely high, and storm water may occur. Act: Confirm IFR value; if faulty, correct and run the KB again.	**95**
5	Exp: Yes, we can divert part of the influent. Act: Divert X% of the influent to the equalization basin.	**100**
6	Exp: No, we can not divert part of the influent. Act: Change step feed mode (STP): feed X% of primary influent to the last stage.	**100**
7	Exp: Yes, we have an extra train available. Act: Put that train into use.	**100**
8	Exp: No, we do not have an extra train available. Act: We have nothing to do about it.	**100**

Figure A-2 Elementary Logic Tree for Stage 1 Total Pressure (TP_{S1})



Continued from Figure A-2

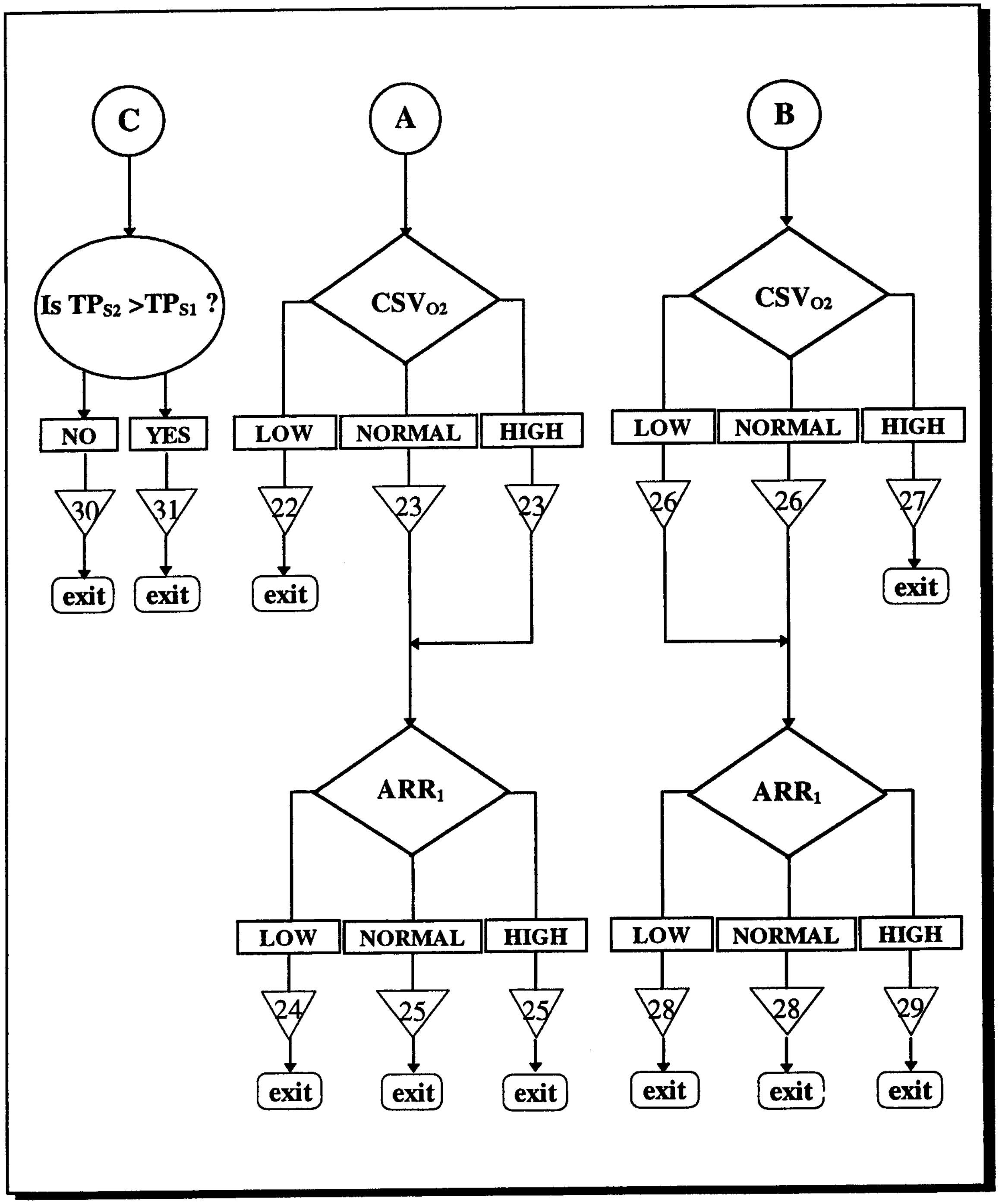


Table A-2 Inferencing Results for Stage 1 Total Pressure (TP_{S1}) Diagnosis

IR	Explanation (Exp) and Action (Act)	CF
1	Exp: That parameter is checked. Act: a) Confirm that parameter value; b) If faulty, correct and run the system again.	95
10	Exp: The influent flow rate (IFR) is low. Act: a) There might be measurement errors on Tp_{S1} & IFR; confirm them; b) If they are correct, increasing OFV & CSV_{O2} may be needed.	95
11	Exp: The influent flow rate is normal. Act: a) Confirm IFR measurement; if faulty, correct and run the system again; b) A X% increase of OFV may be needed.	95
12	Exp: The influent flow rate is high. Act: a) Confirm IFR measurement; if faulty, correct and run the system again; b) Increasing both OFV & CSV_{O2} positions by X%.	95
13	Exp: The influent flow rate is extremely high. Act; Set OFV & CSV_{O2} positions to maximum for storm water.	95
14	Exp: The influent flow rate (IFR) is low. Act: Reducing OFV & CSV_{O2} positions by X%.	95
15	Exp: The influent flow rate is normal. Act: a) Confirm IFR measurement; if faulty, correct and run the system again; b) Reducing OFV & CSV_{O2} positions may be needed.	95
16	Exp: The influent flow rate is high. Act: a) Confirm IFR measurement; if faulty, correct and run the system again; b) If correct, compressing head space volume may occur due to high flow rate; c) If b) is true, keep current OFV & CSV_{O2} positions.	95
17	Exp: The influent flow rate is extremely high. Act: a) Confirm IFR, Tp_{S1} measurements; b) If correct, compressing head space volume occurs; c) Increasing OFV & CSV_{O2} positions by X%.	95
18	Exp: The O_2 feed valve position (OFV) is low. Act; a) Verify OFV measurement; b) If correct, increasing OFV by X%.	95
19	Exp: The O_2 feed valve position (OFV) is normal or high. Act: There might be errors on OFV, IFR and TPS1 measurements; confirm them and run the system again.	95
20	Exp: The O_2 feed valve position (OFV) is low and normal. Act: There might be errors on OFV, IFR and TPS1 measurements; confirm them and run the system again; If correct, increase OFV by X%.	95

Continued from Table A-2

IR	Explanation (Exp) and Action (Act)	CF
21	Exp: The O_2 feed valve position (OFV) is high. Act: a) Confirm OFV measurement; b) If correct, keep current position.	95
22	Exp: The compressor suction valve position (CSV_{O2}) is low. Act: a) Confirm the CSV_{O2} measurement; b) If correct, increasing CSV_{O2} by X%.	95
23	Exp: The compressor suction valve position (CSV_{O2}) is normal or high. Act: a) Confirm CSV_{O2} measurement; b) If correct, O_2 leaks in stage 1 are suspected.	95
24	Exp: The air recirculating rate (ARR_1) of stage 1 is low (for aerator with diffuser only). Act: a) Verify TP_{S1}, IFR and ARR_1 measurements; b) O_2 leaks in stage 1 are suspected.	95
25	Exp: The air recirculating rate (ARR_1) of stage 1 is normal or high (for aerator with diffuser only). Act: a) Check TP_{S1}, IFR and ARR_1 measurements; b) If correct, suggest reducing ARR_1 rate.	95
26	Exp: The compressor suction valve position (CSV_{O2}) is low or normal. Act: a) Confirm CSV_{O2}, IFR, OFV and TP_{S1} measurements; b) If correct, increasing CSV_{O2} position by X%.	95
27	Exp: The compressor suction valve position (CSV_{O2}) is high. Act: Confirm CSV_{O2} measurement; If correct, keep current high CSV_{O2} position.	95
28	Exp: The air recirculating rate (ARR_1) of stage 1 is low or normal (for aerator with diffuser only). Act: a) Confirm CSV_{O2}, IFR, OFV and TP_{S1} measurements; b) If correct, increasing ARR_1 rate	95
29	Exp: The air recirculating rate (ARR_1) of stage 1 is high (for aerator with diffuser only). Act: Confirm ARR_1 measurement; If correct, keep current high ARR_1 rate.	95
30	Exp: Stage 2 pressure (TP_{S2}) is not higher that stage 1 pressure (TP_{S1}). Act: Confirm the pressure measurements; if faulty, correct and run the system again.	95
31	Exp: Stage 2 pressure (TP_{S2}) is higher that stage 1 pressure (TP_{S1}), backflow occurs. Act: Increasing OFV and CSV_{O2} positions by X%.	95

Figure A-3 Elementary Logic Tree for Stage 4 DO (DO_4)

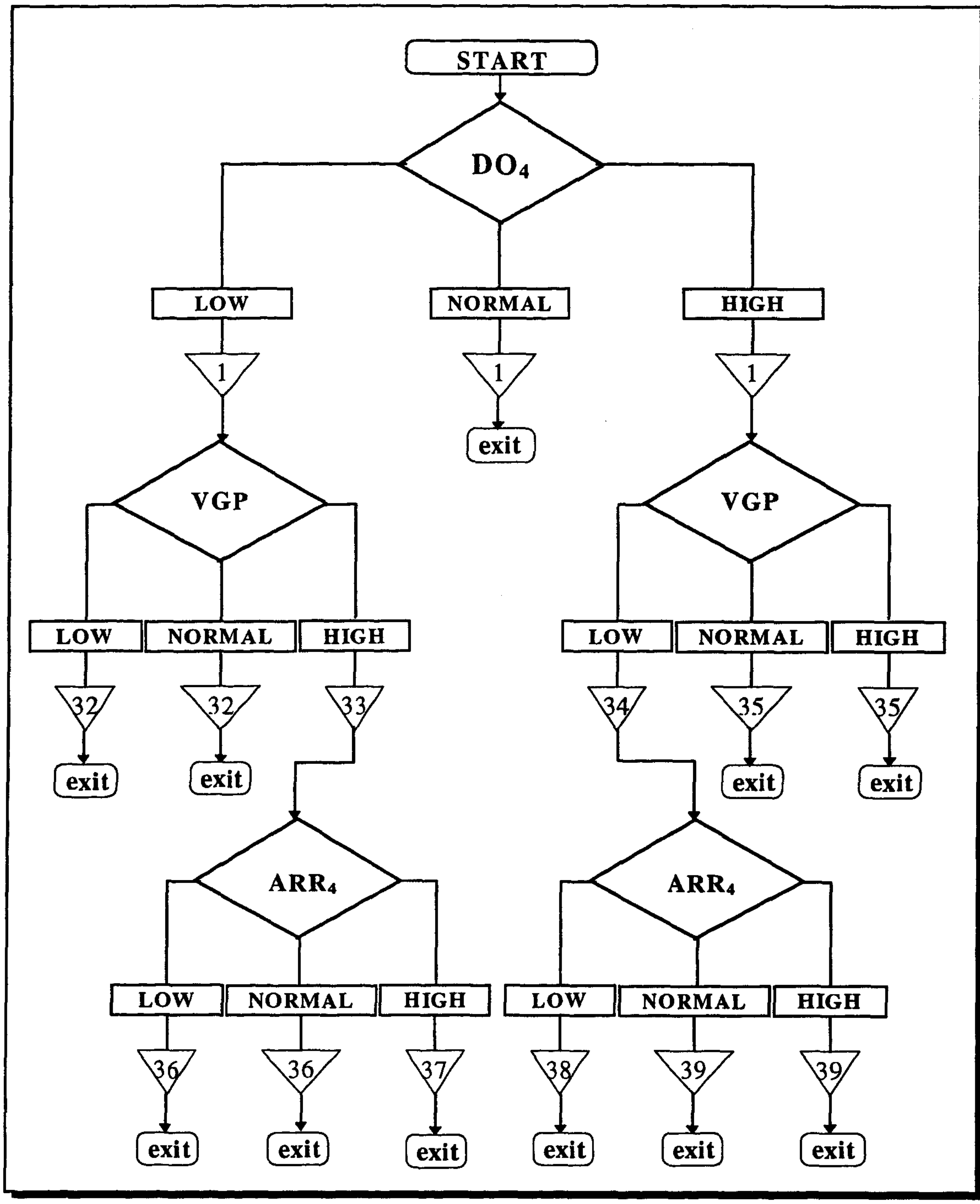


Table A-3 Inferencing Results for Stage 4 DO Diagnosis

IR	Explanation (Exp) and Action (Act)	CF
1	Exp: The parameter is checked. Act: a) Confirm that parameter value; b) If faulty, correct and run the system again.	95
32	Exp: Vent gas purity (VGP) is low or normal. Act: a) Confirm VGP measurement; b) If correct, increase vent gas valve (VGV) by X%.	90
33	Exp: Vent gas purity (VGP) is high. Act: There might be errors on DO concentration and VGP measurements; re-measure DO using potable DO meter, and run the system again.	90
34	Exp: Vent gas purity (VGP) is low. Act: There might be errors on DO concentration and VGP measurements; Re-measure DO using potable DO meter, and run the system again.	95
35	Exp: Vent gas purity (VGP) is normal or high. Act: Reduce vent gas valve (VGV) by X%.	95
36	Exp: Air recirculating rate (ARR_4) of stage 4 is low or normal (only applied for aerator with diffuser systems). Act: Increase air recirculating valve (ARR_4) position by of stage 4 by X%.	95
37	Exp: Air recirculating rate (ARR_4) of stage 4 is high (only applied for aerator with diffuser systems). Act: There might be errors on DO, ARR_4 and VGP measurements; remeasure DO using potable DO meter, and run the system again.	95
38	Exp: Air recirculating rate (ARR_4) of stage 4 is low (only applied for aerator with diffuser systems). Act: There might be errors on DO, ARR_4 and VGP measurements; remeasure DO using potable DO meter, and run the system again.	95
39	Exp: Air recirculating rate (ARR_4) of stage 4 is normal or high (only applied for aerator with diffuser systems). Act: Reduce air recirculating valve (ARR_4) position by of stage 4 by X%.	95

Figure A-4 Elementary Logic Tree for Sludge Age (SA) Diagnosis

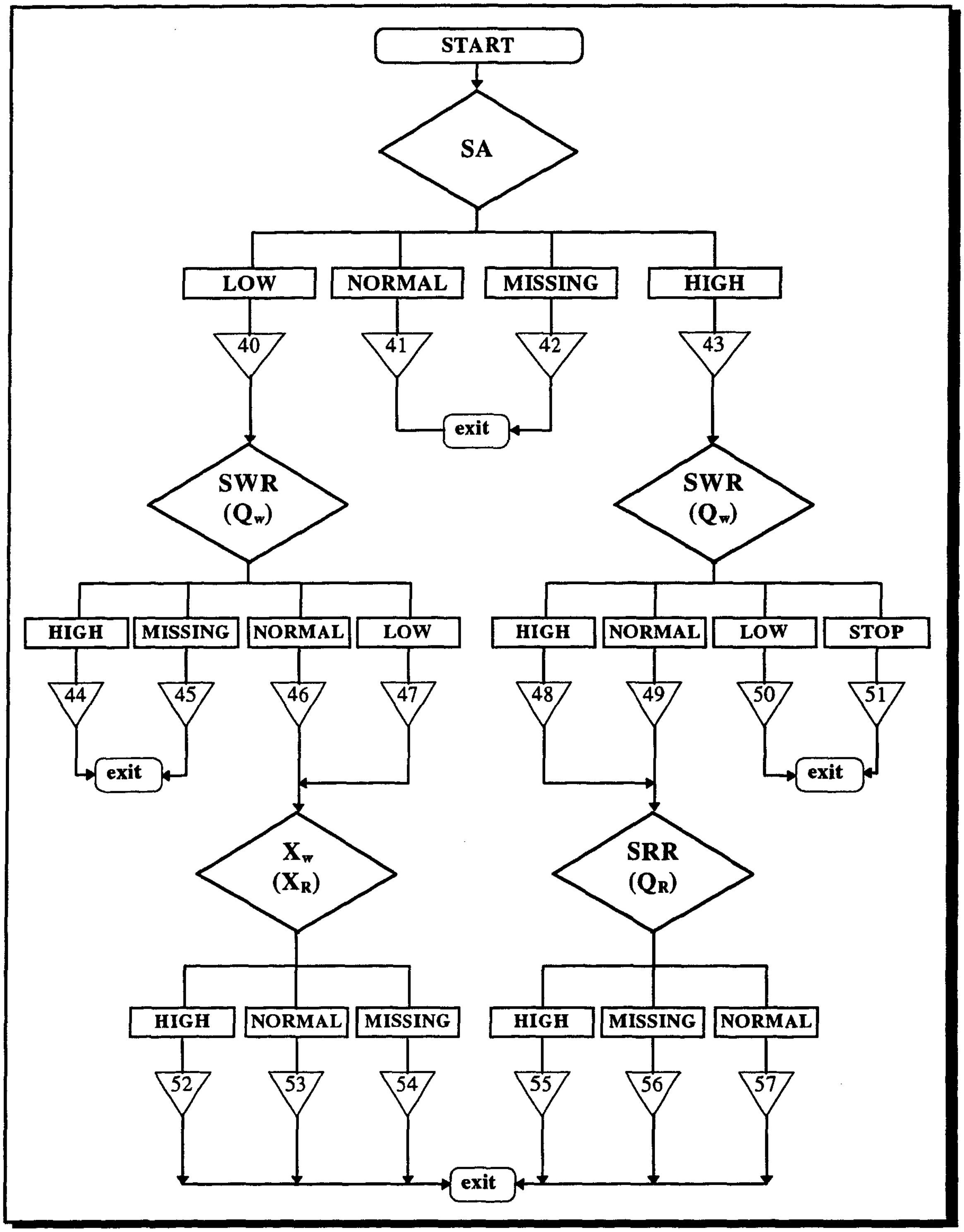


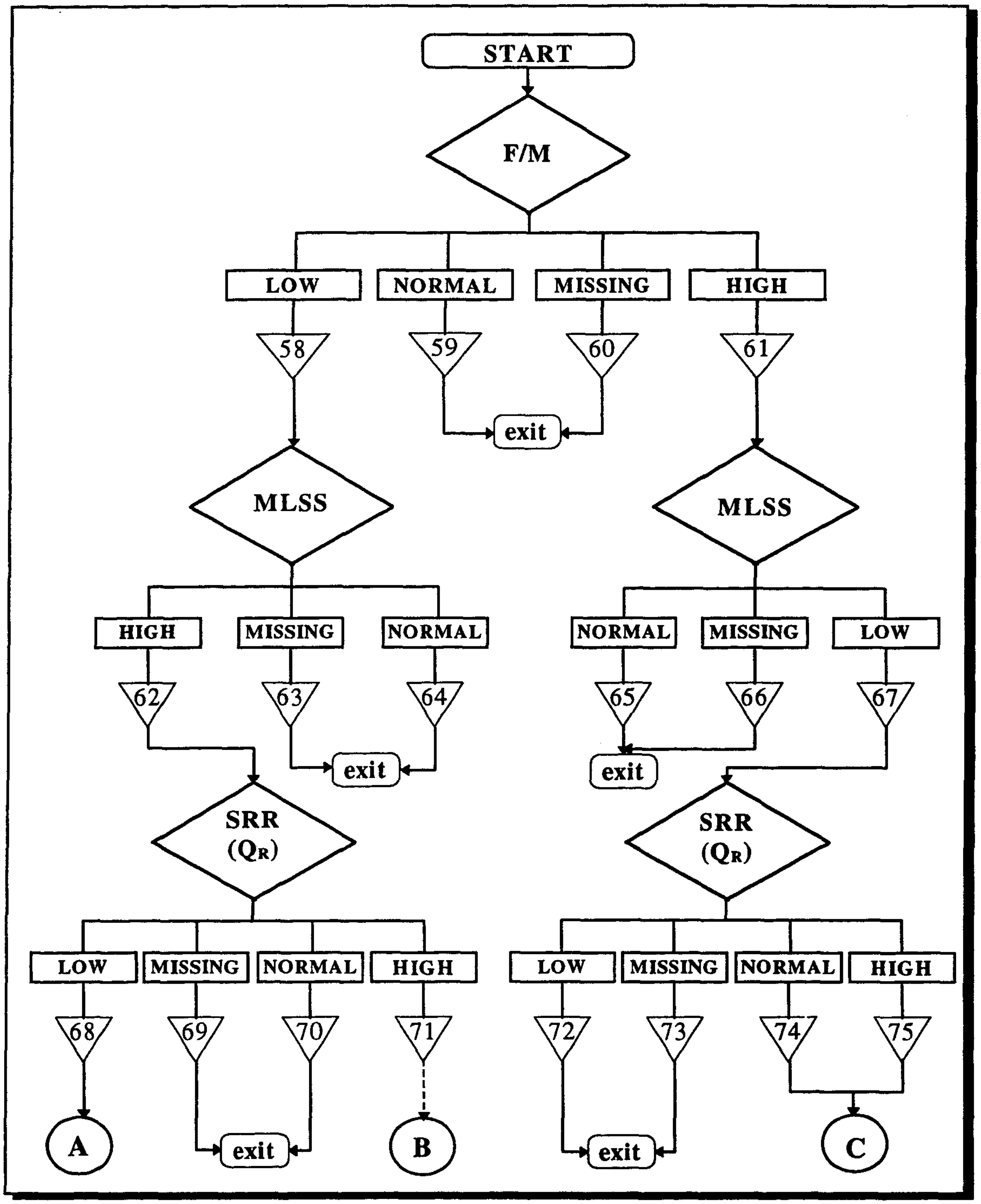
Table A-4 Inferencing Results for Sludge Age (SA) Diagnosis

IR	Explanation (Exp) and Action (Act)	CF
40	Exp: Sludge age (SA) is low. Act: a) Confirm SA calculation manually; b) If faulty, correct and run the system again.	95
41	Exp: Sludge age (SA) is normal. Act: a) Confirm SA calculation manually; b) If faulty, correct and run the system again.	95
42	Exp: Sludge age (SA) is unknown. Act: Calculate SA; input SA to the database; run the system again.	100
43	Exp: Sludge age (SA) is high. Act: a) Confirm SA calculation manually; b) If faulty, correct and run the system again.	95
44	Exp: Sludge waste rate (Q_W) is high. Act: a) Confirm sludge waste rate measurement; b) If correct, reducing Q_W by gpm.	95
45	Exp: Sludge waste rate (Q_W) is unknown. Act: Obtain Q_W measurement; input Q_W to the database; run the system again.	100
46	Exp: Sludge waste rate (Q_W) is normal. Act: Confirm sludge waste rate measurement; If faulty, correct and run the system again.	95
47	Exp: Sludge waste rate (Q_W) is low. Act: There might be errors on SA calculation and Q_W measurement; confirm them and run the system again.	95
48	Exp: Sludge waste rate (Q_W) is high. Act: a) Confirm measurement; b) If faulty, correct and run the system again..	95
49	Exp: Sludge waste rate (Q_W) is normal. Act: a) Confirm measurement; b) If faulty, correct and run the system again..	95
50	Exp: Sludge waste rate (Q_W) is low. Act: a) Confirm measurement; b) If correct, increase sludge waste rate by X gpm.	95
51	Exp: Sludge waste rate (Q_W) is stopped. Act; Begin to waste sludge, and set sludge waste rate to X gpm	100

Continued from Table A-4

IR	Explanation (Exp) and Action (Act)	CF
52	Exp: Sludge wasting concentration (X_W or X_R) is high. Act: a) Confirm X_W measurement; b) If correct, reduce sludge waste rate and increase sludge recycling rate may be needed.	95
53	Exp: Sludge wasting concentration (X_W or X_R) is normal. Act: There might be errors X_W and Q_W on measurements, and SA calculation; confirm them and run the system again.	95
54	Exp: Sludge wasting concentration (X_W or X_R) is unknown. Act: Obtain X_W; input X_W to the database; run the system again.	100
55	Exp: Sludge recycling rate (SRR, Q_R) is high. Act: a) Confirm Q_R measurement; b) If correct, increase SWR and reduce SRR.	95
56	Exp: Sludge recycling rate (SRR, Q_R) is unknown. Act: Obtain Q_R; input Q_R to the database; run the system again.	100
57	Exp: Sludge recycling rate (SRR, Q_R) is normal. Act: a) There might be errors on SA calculation, and Q_R and Q_W measurements; b) If correct, increasing SWR (Q_W) is suggested.	95

Figure A-5 Elementary Logic Tree for F/M Diagnosis



Continued from Figure A-5

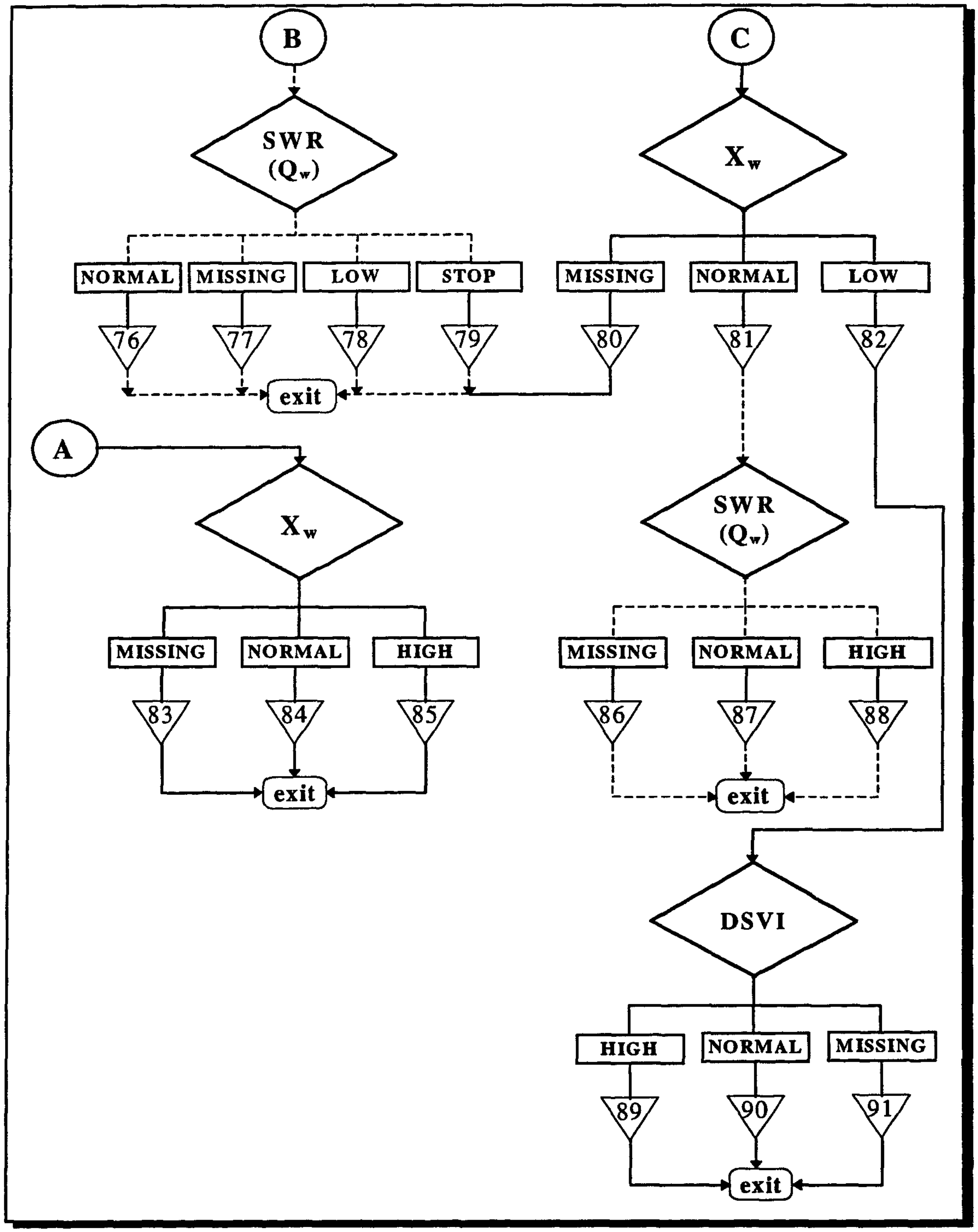


Table A-5 Inferencing Results for F/M Diagnosis

IR	Explanation (Exp) and Action (Act)	CF
58	Exp: Food to biomass ratio (F/M) is low. Act: Confirm the measurements and calculation; If faulty, correct and run the system again.	95
59	Exp: Food to biomass ratio (F/M) is normal. Act: Confirm the measurements: BOD_5 and MLSS; manually perform the calculation.	90
60	Exp: Cannot calculate Food to biomass ratio (F/M). Act: Obtain the BOD_5 and MLSS values, calculate and run the system again.	100
61	Exp: Food to biomass ratio (F/M) is high. Act: Confirm the measurements and calculation; If faulty, correct and run the system again.	95
62	Exp: MLSS concentration in aeration tank is high. Act: a) Confirm MLSS measurement; b) If correct, reducing in sludge recycling flow rate (SRR, Q_R) may be needed.	95
63	Exp: MLSS concentration is unknown. Act: a) Obtain MLSS value; b) Update data base; c) Run the system again.	100
64	Exp: MLSS concentration is normal. Act: a) Confirm MLSS measurement; If faulty, correct and run the system again; b) If correct, lower organic loading may occur.	90
65	Exp: MLSS concentration is normal. Act: a) Higher organic loading is occurring; b) Increase sludge recycling valve (SRV) position by X%; c) Reduce sludge wasting valve (SWV) position by X%.	90
66	Exp: MLSS concentration is unknown. Act: a) Obtain MLSS value; b) Update data base; c) Run the system again.	100
67	Exp: MLSS concentration is low. Act: There might be errors on BOD_5 and MLSS measurements; confirm them and run the system again.	95
68	Exp: Sludge recycling rate (SRR, Q_R) is low. Act: There might be errors on BOD_5, MLSS and sludge recycling rate (Q_R); confirm them and run the system again.	95
69	Exp: Sludge recycling rate (SRR, Q_R) is unknown. Act: a) Obtain sludge recycling rate measurement; b) update data base; c) run the system again.	100

Continued from Table A-5

IR	Explanation (Exp) and Action (Act)	CF
70	Exp: Sludge recycling rate (SRR, Q_R) is normal. Act: a) Lower organic loading is occurring; b) Slightly reduce sludge recycling valve (SRV) position by X%.	90
71	Exp: Sludge recycling rate (SRR, Q_R) is high. Act: Reduce sludge recycling valve (SRV) by X%.	95
72	Exp: Sludge recycling rate (SRR, Q_R) is low. Act: a) confirm sludge recycling rate measurement; b) If correct, increase sludge recycling valve (SRV) by X%.	95
73	Exp: Sludge recycling rate (SRR, Q_R) is unknown. Act: a) Obtain sludge recycling rate measurement; b) update data base; c) run the system again.	100
74	Exp: Sludge recycling rate (SRR, Q_R) is normal. Act: a) confirm sludge recycling rate measurement; b) If faulty, correct and run the system again.	95
75	Exp: Sludge recycling rate (SRR, Q_R) is high. Act: a) confirm sludge recycling rate measurement; b) If faulty, correct and run the system again.	
76	Exp: Sludge wasting rate (SWR, Q_w) is normal. Act: a) Confirm sludge wasting rate measurement; b) If correct, increase sludge wasting valve (SWV) by X%.	90
77	Exp: Sludge wasting rate (SWR, Q_w) is unknown. Act: a) Obtain sludge wasting rate measurement; b) update data base; c) run the system again.	100
78	Exp: Sludge wasting rate (SWR, Q_w) is low. Act: a) Confirm sludge wasting rate measurement; b) If correct, increase sludge wasting valve (SWV) by X%.	95
79	Exp: Sludge wasting rate (SWR, Q_w) is zero. Act: Start to wasting sludge, and set sludge wasting valve (SWV) to X%.	100
80	Exp: Sludge wasting concentration (X_w) is unknown. Act: a) Obtain sludge wasting concentration; b) update data base; c) run the system again.	100
81	Exp: Sludge wasting concentration (X_w) is normal. Act: a) Organic shock loading is occurring; b) Increase sludge recycling valve (SRV) position by X%.	90

Continued from Table A-5

IR	Explanation (Exp) and Action (Act)	CF
82	Exp: Sludge wasting concentration (X_w) is low. Act: a) Confirm sludge wasting concentration measurement; if faulty, correct and run the system again; b) If correct, sludge bulking is suspected.	95
83	Exp: Sludge wasting concentration (X_w) is unknown. Act: a) Obtain sludge wasting concentration; b) update data base; c) run the system again.	100
84	Exp: Sludge wasting concentration (X_w) is normal. Act: a) Confirm sludge wasting concentration measurement; b) If correct, reduce sludge recycling valve (SRV) position by X%.	90
85	Exp: Sludge wasting concentration (X_w) is high. Act: a) Confirm sludge wasting concentration measurement; b) If correct, reduce sludge recycling valve (SRV) position by X%.	95
86	Exp: Sludge wasting flow rate (SWR, Q_w) is unknown. Act: a) Obtain sludge wasting flow rate value; b) update data base; c) run the system again.	100
87	Exp: Sludge wasting flow rate (SWR, Q_w) is normal. Act: a) Confirm sludge wasting flow rate measurement; b) If correct, reduce sludge wasting valve (SWV) position by X%.	90
88	Exp: Sludge wasting flow rate (SWR, Q_w) is high. Act: a) Confirm sludge wasting flow rate measurement; b) If correct, reduce sludge wasting valve (SWV) position by X%.	95
89	Exp: DSVI is high. Act: a) Sludge bulking is occurring; b) Inform the management about sludge bulking; c) Recommended measures: 1> Stop sludge wasting; 2> Chlorination; 3> addition of polymer; 4> Run DSVI SLT to see the causes of sludge bulking.	98
90	Exp: DSVI is normal. Act: a) Organic shock loading is occurring; b) Set sludge recycling valve (SRV) position to maximum.	98
91	Exp: DSVI is unknown. Act: a) Perform DSVI test; b) Update data base; c) Run the system again	100

Figure A-6 Elementary Logic Tree for Oxygen Uptake Rate (OUR)

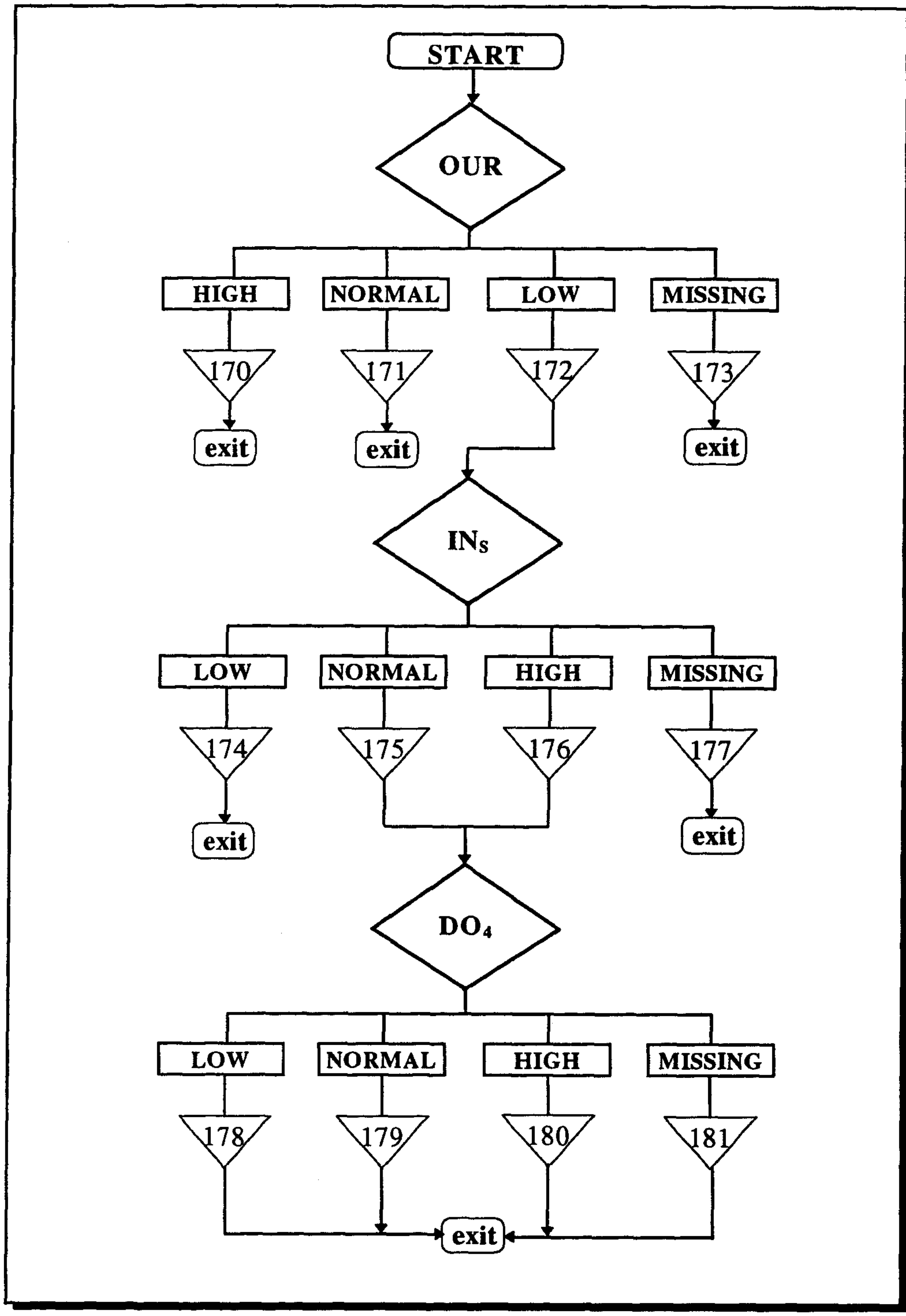


Table A-6 Inferencing Results for Oxygen Uptake Rate (OUR) Diagnosis

IR	Explanation (Exp) and Action (Act)	CF
170	Exp: Oxygen uptake rate (OUR) is high. Act: Confirm OUR test; if faulty, correct and run the system again.	90
171	Exp: Oxygen uptake rate (OUR) is normal. Act: Confirm OUR test; if faulty, correct and run the system again.	90
172	Exp: Oxygen uptake rate (OUR) is low. Act: Confirm OUR test; comparing it with estimated OUR (from on-line estimator)	90
173	Exp: Oxygen uptake rate (OUR) is unknown. Act: Performing OUR test; update database; run the system again.	100
174	Exp: Influent substrate concentration (IN_S) is low. Act: Confirm IN_S measurement; comparing it with estimated IN_S; If large deference presents, redo IN_S measurement.	90
175	Exp: Influent substrate concentration (IN_S) is normal. Act: Confirm IN_S measurement; comparing it with estimated IN_S.	90
176	Exp: Influent substrate concentration (IN_S) is high. Act: Confirm IN_S measurement; comparing it with estimated IN_S.	90
177	Exp: Influent substrate concentration (IN_S) is unknown. Act: Measure IN_S; update database; run the system again.	100
178	Exp: Stage 4 dissolved oxygen concentration (DO_4) is low. Act: a) Confirm DO_4 measurement; b) If correct, increasing oxygen feed in stage 1 is needed.	95
179	Exp: Stage 4 dissolved oxygen concentration (DO_4) is normal. Act: a) Confirm DO_4 measurement; b) If correct, increasing oxygen feed in stage 1 may be needed.	95
180	Exp: Stage 4 dissolved oxygen concentration (DO_4) is high. Act: a) Confirm DO_4 measurement; b) Toxic compounds may be presented in the influent; c) Check for toxic compounds in the influent.	95
181	Exp: Stage 4 dissolved oxygen concentration (DO_4) is unknown. Act: Measure stage 4 DO; update database; run the system again.	100

Figure A-7 Elementary Logic Tree for Nutrient Addition

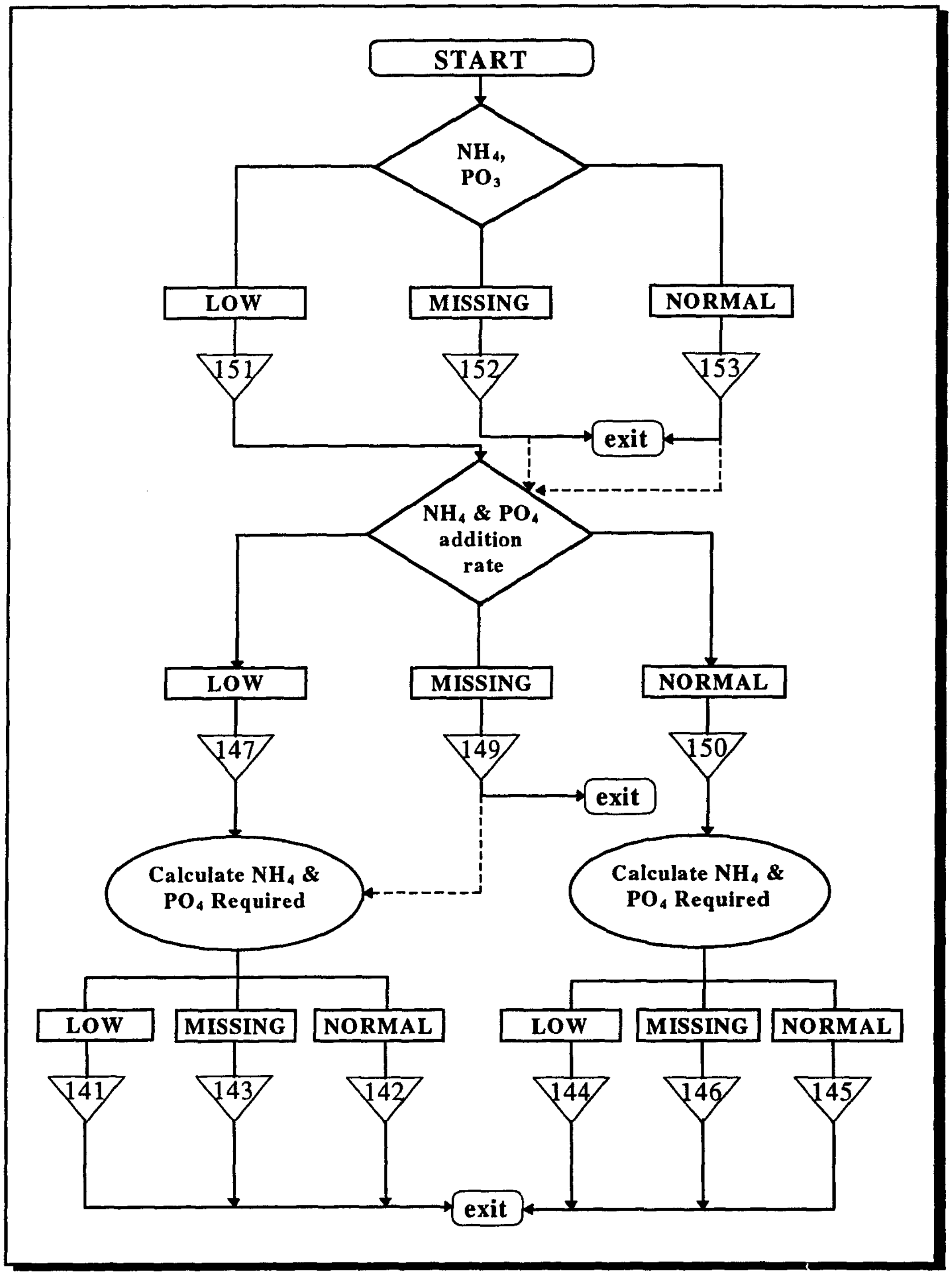
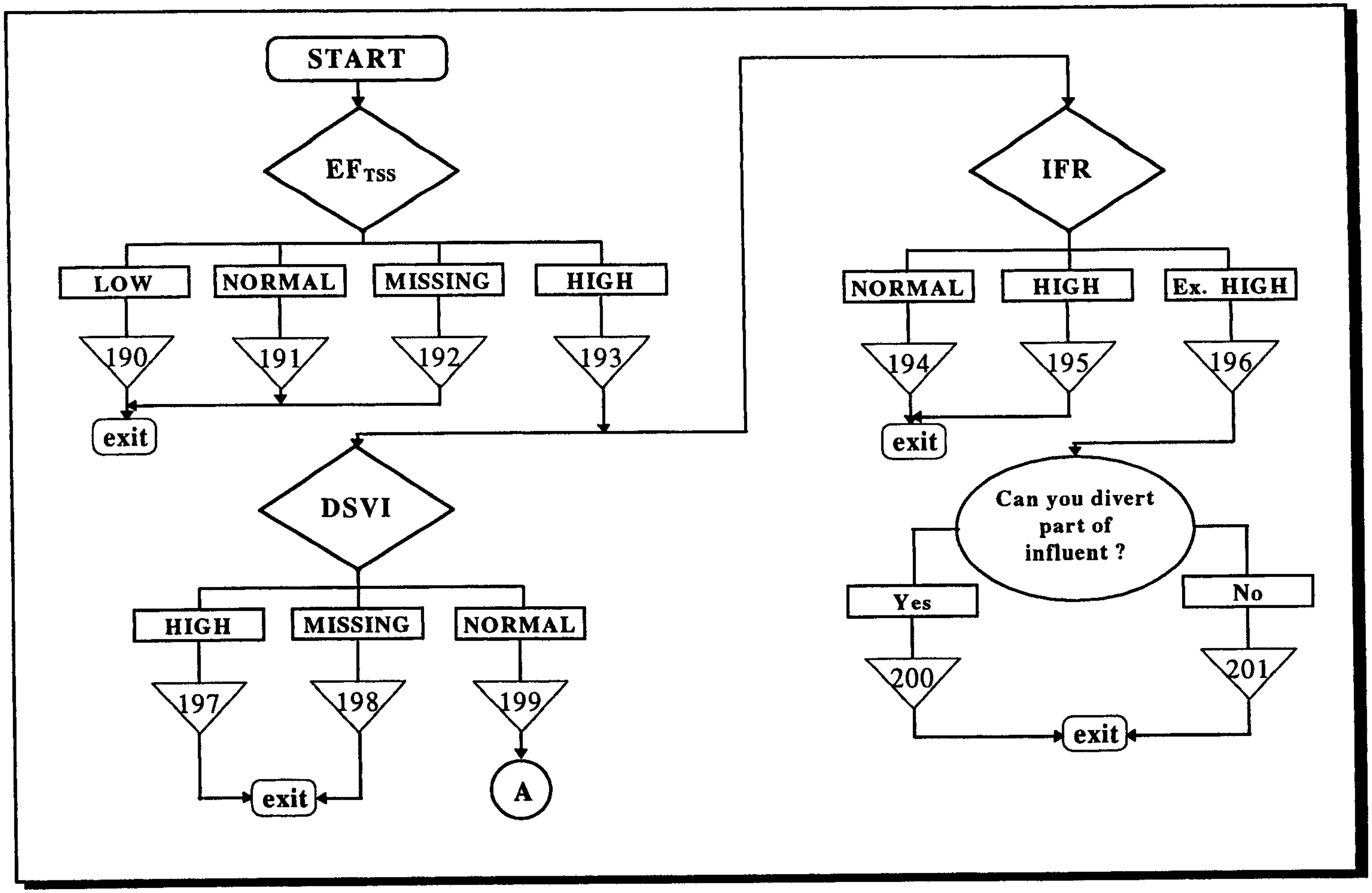


Table A-7 Inferencing Results for Nutrient Addition Diagnosis

IR	Explanation (Exp) and Action (Act)	CF
141	Exp: Nutrient addition is lower than calculated requirement. Act: Increase nutrient addition to X gpm.	98
142	Exp: Nutrient addition is higher than calculated requirement. Act: a) Check nutrient analysis; b) Increase nutrient addition to X gpm; c) Monitor the effluent nutrient concentration.	90
143	Exp: Cannot calculate nutrient requirement. Act: a) Obtain values for TOC; b) Update data base; c) Run the system again.	100
144	Exp: Nutrient addition is lower than calculated requirement. Act: Increase nutrient addition to X gpm.	98
145	Exp: Nutrient addition is higher than calculated requirement. Act: a) Check nutrient analysis; b) Increase nutrient addition to X (25%) gpm; c) Monitor the effluent nutrient concentration.	90
146	Exp: Cannot calculate nutrient requirement. Act: a) Obtain values for TOC; b) Update data base; c) Run the system again.	100
147	Exp: Nutrient addition rate is low. Act: a) Inspect nutrient addition visually; b) Check for empty nutrient tanks; c) Check for stuck nutrient tank level indicator.	90
149	Exp: Nutrient addition rate is unknown. Act; a) Obtain values for nutrient addition rate value; b) Update data base; c) Run the system again.	100
150	Exp: Nutrient addition rate is normal. Act: a) Inspect nutrient addition visually; b) Check for empty nutrient tanks; c) Check for stuck nutrient tank level indicator.	90
151	Exp: Nutrient concentrations are low. Act: Check nutrient addition analysis.	95
152	Exp: Nutrient concentrations are unknown. Act: a) Measure the nutrient concentrations; b) Update data base; c) Run the system again.	100
153	Exp: Nutrient concentrations are normal. Act: Check nutrient analysis.	95

Figure A-8 Elementary Logic Tree for Effluent Total Suspended Solids (EF_{TSS})



Continued from Figure A-8

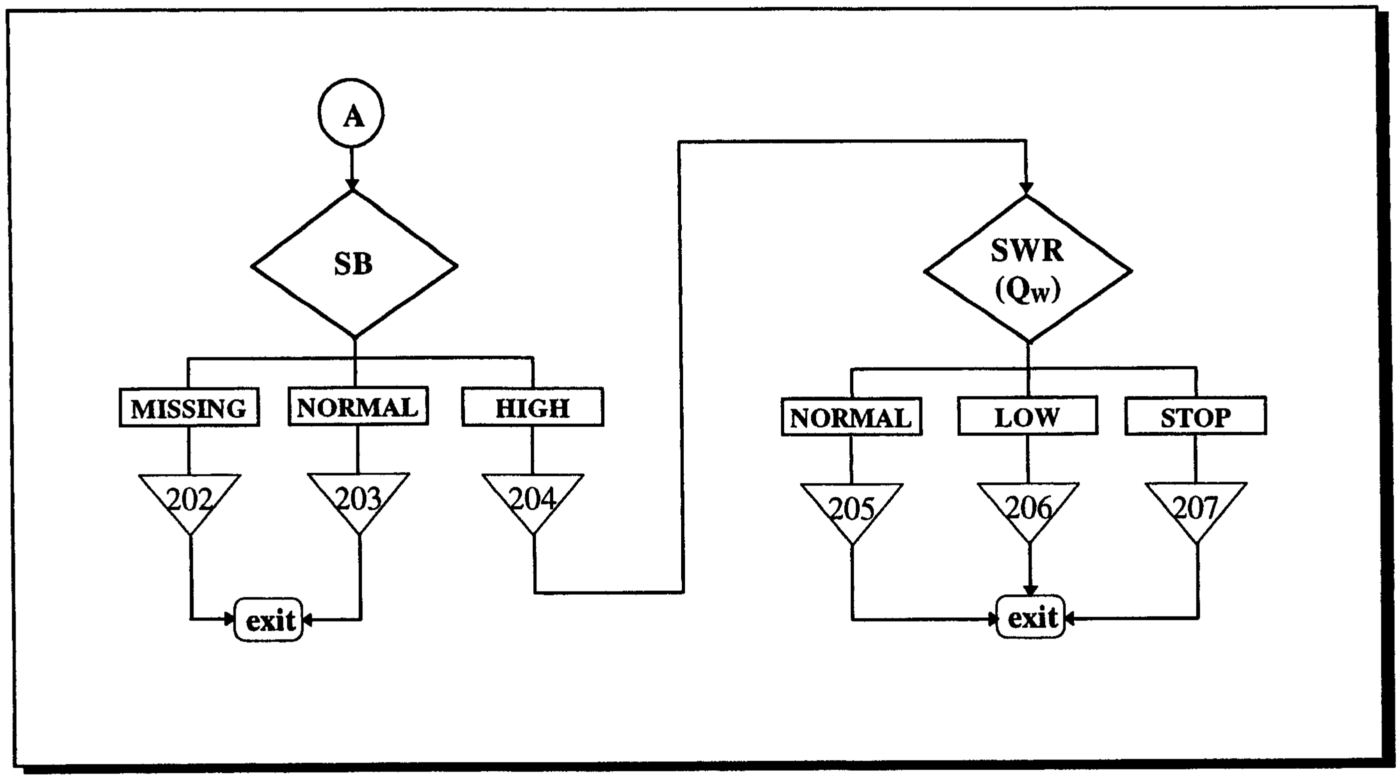


Table A-8 Inferencing Results for Effluent Total Suspended Solid (EF_{TSS}) Control

IR	Explanation (Exp) and Action (Act)	CF
190	Exp: Effluent total suspended solids (EF_{TSS}) is low. Act: Confirm EF_{TSS} measurement; if faulty, correct and run the system again.	95
191	Exp: Effluent total suspended solids (EF_{TSS}) is normal. Act: Confirm EF_{TSS} measurement; if faulty, correct and run the system again.	95
192	Exp: Effluent total suspended solids (EF_{TSS}) is unknown. Act: Measure EF_{TSS}; update database; run the system again.	100
193	Exp: Effluent total suspended solids (EF_{TSS}) is high. Act: a) Confirm EF_{TSS} measurement; b) If faulty, correct and run the system again.	95
194	Exp: Influent flow rate (IFR) is normal. Act: Confirm EF_{TSS} measurement; if faulty, correct and run the system again.	95
195	Exp: Influent flow rate (IFR) is high. Act: a) Confirm EF_{TSS} measurement; b) If correct, high EF_{TSS} may be caused by the high IFR; c) Put more train into use if available.	95
196	Exp: Influent flow rate (IFR) is extremely high. Act: a) Storm water flow may occur; b) Inform management about the storm event.	95
197	Exp: Diluted sludge volume index (DSVI) is high. Act: a) Confirm DSVI measurement; b) Possible sludge bulking occurring; c) Inform the management and take measures to control sludge bulking.	95
198	Exp: Diluted sludge volume index (DSVI) is unknown. Act: Measure DSVI; update database; run the system again.	100
199	Exp: Diluted sludge volume index (DSVI) is normal. Act: a) Confirm DSVI measurement; b) High EF_{TSS} may not be caused by sludge settling problem.	95
200	Exp: Yes, we can divert part of the influent. Act: Divert X gpm influent flow into water holding tank for Y hours.	100
201	Exp: No, we cannot divert part of the influent. Act: Inform the management about the extremely high flow rate that causes high EF_{TSS}.	100

Continued from Table A-8

IR	Explanation (Exp) and Action (Act)	CF
202	Exp: Sludge blanket (SB) height in the clarifier is unknown. Act: Measure SB; update database; run the system again.	100
203	Exp: Sludge blanket (SB) height in the clarifier is normal. Act: Confirm SB measurement; if faulty, correct and run the system again.	95
204	Exp: Sludge blanket (SB) height in the clarifier is high. Act: a) Confirm SB measurement; b) If correct, the high EF_{TSS} may be caused by this high sludge blanket.	95
205	Exp: Sludge waste rate (SWR) is normal. Act: a) Confirm SWR measurement; b) If correct, increasing SWR may be needed.	95
206	Exp: Sludge waste rate (SWR) is low. Act: a) Confirm SWR measurement; b) If correct, increasing SWR by X gpm.	95
207	Exp: Sludge waste rate (SWR) is stopped. Act: Start sludge waste pump, and set SWR to X gpm.	100

Figure A-9 Symptom-Oriented Logic Tree for Abnormal DSVI Observation (1)

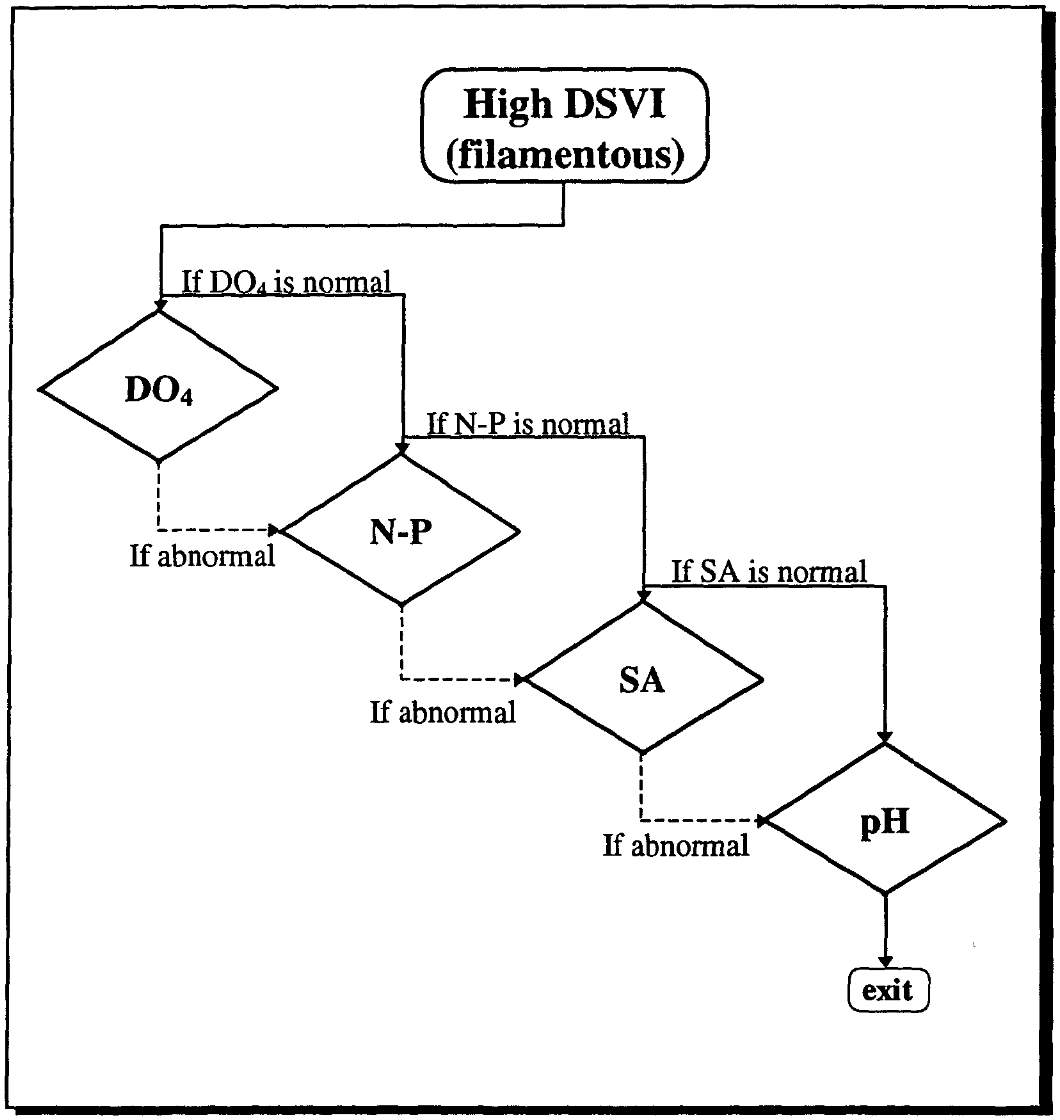


Figure A-10 Symptom-Oriented Logic Tree for Abnormal DSVI Observation (2)

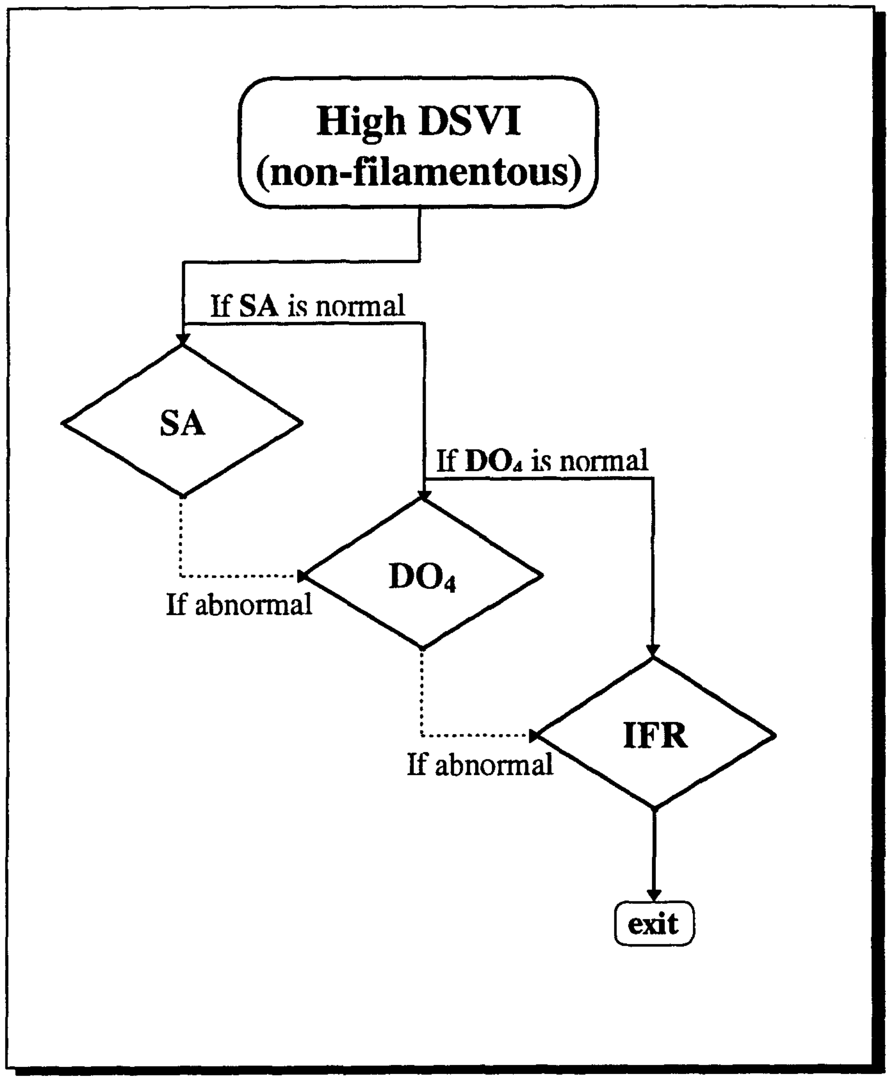


Figure A-11 Symptom-Oriented Logic Tree for BOD Violation

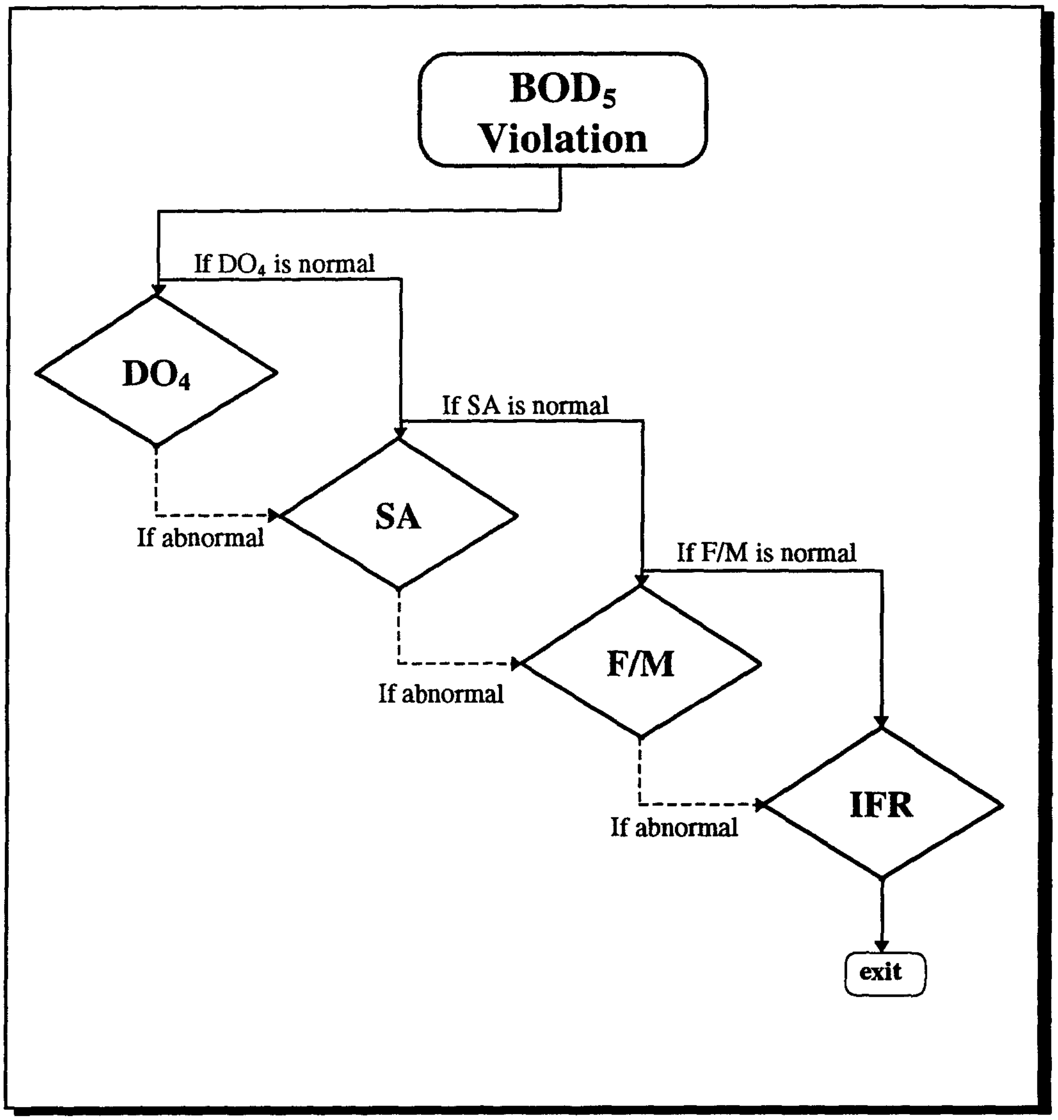


Figure A-12 Symptom-Oriented Logic Tree for Ammonia Violation

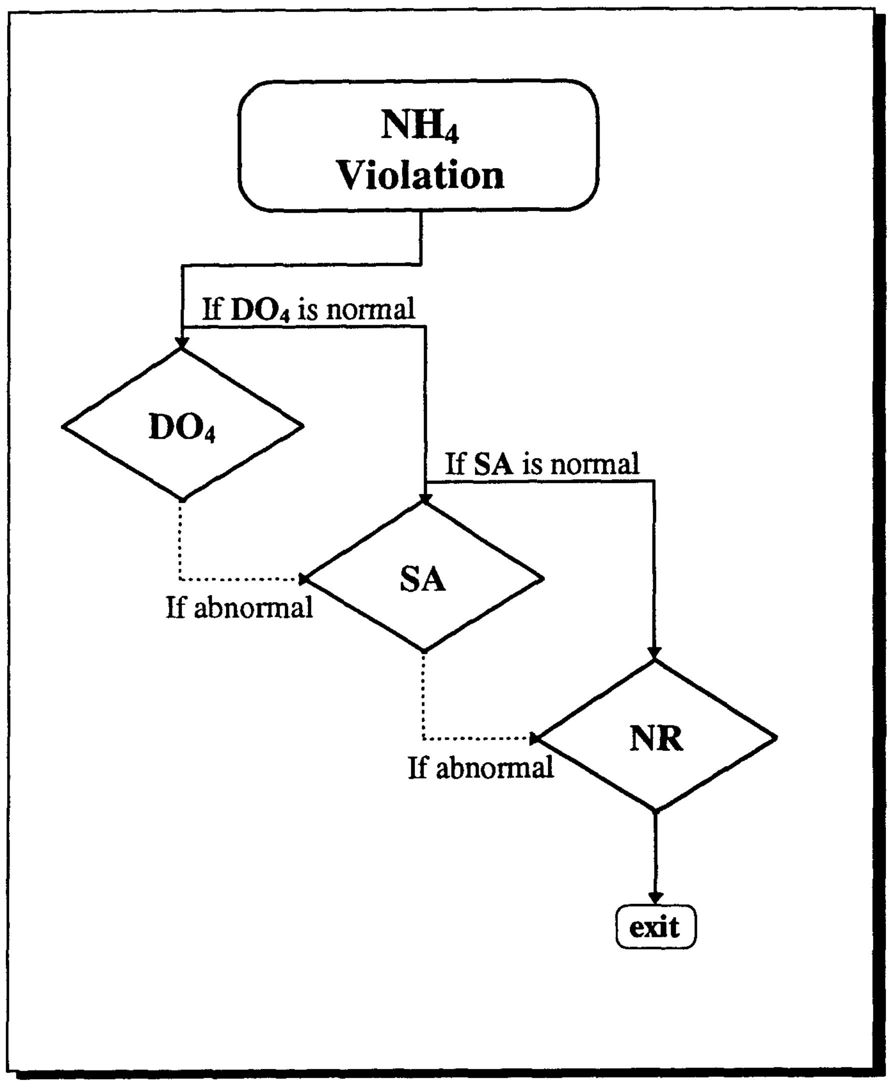


Figure A-13 Symptom-Oriented Logic Tree for High Effluent Suspended Solids (EF_{TSS})

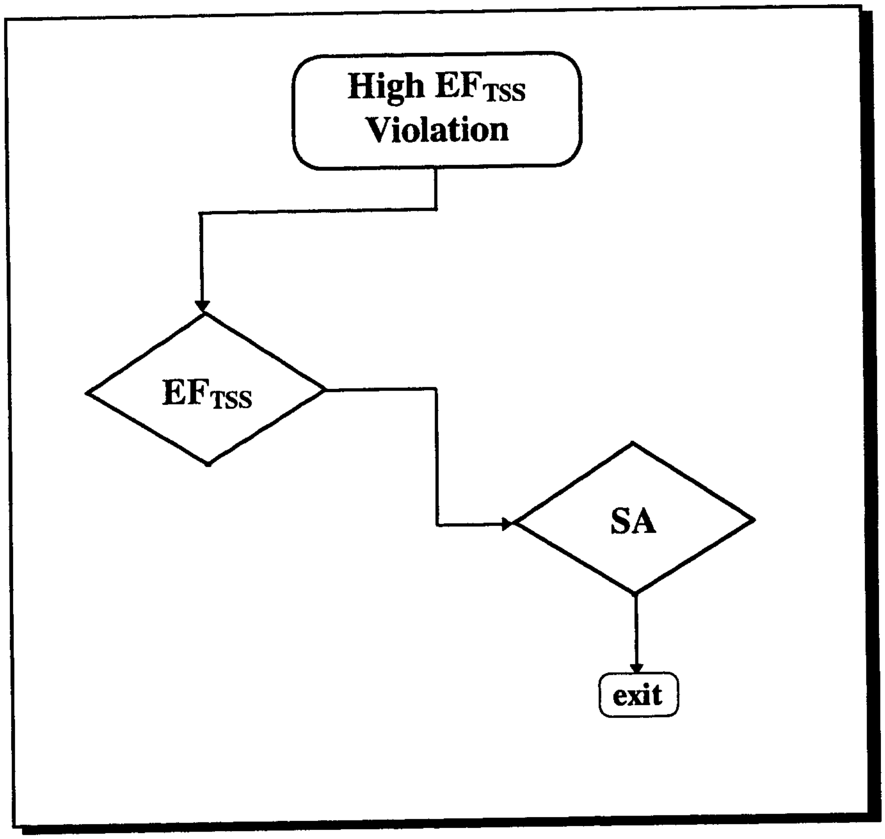


Figure A-14 Symptom-Oriented Logic Tree for Pinpoint Floc

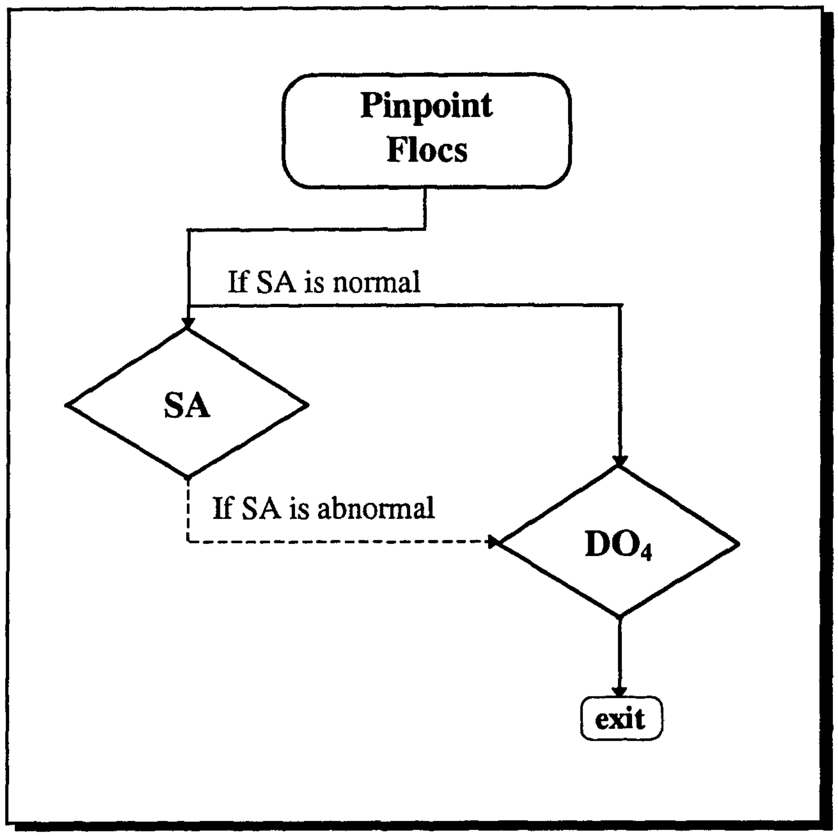


Figure A-15 Symptom-Oriented Logic Tree for Straggle Floc or White Foam