Fuzzy Logic Process Control of HPO-AS Process

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Abstract: The high purity oxygen activated sludge process requires more advanced controls as compared to the conventional activated sludge process. Feedback controllers have difficulty controlling process disturbances due to process delays and noisy signals, and cannot adjust to extreme upsets, such as stormwater flows. Four fuzzy logic control systems were developed for average conditions, and are superior to conventional feedback control systems in conserving energy, reducing dissolved oxygen (DO) variations, and stabilizing feed and exit gas flow rates. 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, feedforward control based on influent flow rate to adjust the stage 1 pressure setpoint, with feedback stage 4 DO control, is best. To address stormwater flows 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 prevents DO depletion under wet weather conditions, and conserves oxygen and energy during dry weather conditions.

INTRODUCTION

The high-purity oxygen activated sludge process (HPO-AS) is characterized by high-purity oxygen feed, closed aeration tanks, and several tanks-in-series. Fig. 1 shows a typical process. Several covered aeration tanks or stages (usually 4) are arranged in series to increase treatment efficiency and oxygen utilization. Ninety-seven percent or higher oxygen purity is normally used in large plants, where cryogenic oxygen production is economical. Smaller plants often use pressure-swing oxygen generators that produce lower oxygen purities (~90%). The high-purity feed results in high oxygen partial pressure in each stage, which greatly increases the transfer capacity of the aeration system (2 to 5 times) as compared to an open air system. For this reason it is common to use higher mixed-liquor dissolved oxygen (DO) concentrations (4–10 mg/L) than normally used in air activated sludge processes.

Conventional HPO-AS control systems use stage 1 total pressure, which is maintained slightly above atmospheric pressure [e.g., 1.008 atm, or 5 to 15 cm (2 to 6 in.) water column], as a feedback control signal. Stage 4 oxygen purity can also be used as a feedback control signal. Both techniques are problematic, as will be shown later, because of disturbances and process lags. Stage 1 total pressure can respond to liquid flow rate, introducing noise into the controller's function. There are long lags between changes in stage 4 purity and controller functions, which makes stage 4 feedback controllers slow in responding.

Fuzzy logic controllers (FLCs) can potentially improve HPO-AS control, because they can incorporate additional knowledge in the control algorithm. The effect of process disturbances can be incorporated into the control law, even if the effect can only be empirically described. Nonlinear behavior is also more easily accommodated.

In this paper we review some of the conventional HPO-AS process control strategies. Next we discuss newer approaches for gas phase control, which rely upon fuzzy logic algorithms (FLAs) and controls. Using a dynamic model that was calibrated in earlier studies with pilot plant and full scale plant data (Tzeng 1992; Yuan 1994), we simulate a hypothetical treatment plant, and compare the conventional and fuzzy logic control strategies. The comparison shows the superiority of the fuzzy logic control strategies.

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CONVENTIONAL CONTROL STRATEGIES

Control strategies for the HPO-AS process have as their goal the maintenance of adequate DO in the aeration tanks while minimizing energy consumption. Energy consumption for aeration in the HPO-AS process is in two forms: energy to operate the aerators and energy to produce high-purity oxygen. A trade-off exists between aerator energy and oxygen production energy. A greater use of high-purity oxygen will increase oxygen purity, which increases the driving force for transfer. This will reduce the required energy for operating variable speed aerators. Alternatively, increasing aerator energy will increase the mass transfer coefficient, which will reduce the driving force needed for oxygen transfer. The reduced driving force requires less high-purity oxygen feed, and will result in energy savings in the oxygen production facility. Operating at excessive effluent dissolved oxygen (DO) in the HPO-AS process is more expensive than in an air activated sludge process, because the energy to provide the high-purity oxygen, as well as the energy to transfer it, are wasted.

There exists an optimal operating point that balances capital cost and the two energy costs. The optimum point depends on site-specific conditions, as well as the design of the treatment plant. Maximum capacity can be achieved by providing aerators with high mass transfer coefficients, while operating at the greatest oxygen purity in each stage. During periods of reduced plant load, aeration can be reduced by feeding less oxygen or reducing aerator energy, which is more economical and practical. Design engineers can manipulate both to meet a plant's required peak capacity.

A variety of HPO-AS process control systems have been developed to conserve energy and meet oxygen demand. Compared to a conventional activated sludge process, HPO-AS process control systems are more complicated and difficult to operate because of the need to control both gas phase oxygen purity and liquid phase DO concentration. Gas phase control

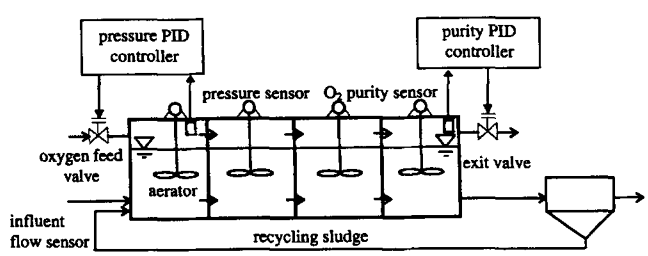

FIG. 1. Flow Diagram for A HPO-AS Process

can be difficult because of the lag between a control system's action (e.g., increasing oxygen feed rate) and the response of the controlled variable (e.g., oxygen purity in stage 4). The lag is introduced by the gas residence time in each stage, which may be only 2 h in stage 1, but may increase to 12 h in stage 4. The residence time in each stage increases because efficient oxygen utilization reduces the gas flow from stages 1–4.

This problem is further complicated by the delay in peak oxygen demand as compared to peak flow rate. When an increase in substrate loading occurs, the oxygen demand does not immediately increase to the maximum, since a finite length of time is needed for the microorganisms to assimilate the substrate (Olsson and Andrews 1978, 1981; Clifft and Andrews 1986; Tzeng 1992). The maximum oxygen demand usually lags the peak influent load. A conventional proportional-integral-derivative (PID) gas phase controller does not use influent flow rate as an input, since it is not a controlled or manipulated variable. Furthermore, this knowledge would be difficult to implement into simple PID control laws. As a result oxygen depletion may occur when the oxygen demand is high, and over aeration may occur when the demand is small. This lag, when combined with the lag due to the reactor retention time, makes it difficult for feedback controllers to track the setpoint.

Fig. 1 shows two commonly-used feedback controllers for stage gas purity or oxygen utilization by manipulating high purity-oxygen flow rate. Stage 1 pressure is sometimes used as a setpoint (McWhirter and Vahldieck 1978). The volume of oxygen gas consumed by biological growth is much more than the volume of carbon dioxide liberated. Much of the carbon dioxide remains dissolved, and does not contribute to the total pressure. For this reason, controlling total system pressure maintains relatively constant oxygen purity and utilization. Using total system pressure has the advantage of not being impacted by the residence time of the stages. A pressure decrease in stage 4 is quickly observed in stage 1. Unfortunately, changes in liquid flow rate can change total system pressure, and upset this control technique (Norman et al. 1985). When the liquid flow rate quickly increases, the liquid level in the aeration tank increases, which compresses the head space volume, and creates a pressure increase. When the pressure sensor detects this increase, the controller reduces the oxygen feed rate in attempting to return to the setpoint, which is usually the exact opposite of the desired control action. Gas phase pressure transients frequently occur when influent flow is regulated by switching on and off fixed speed pumps.

Fig. 1 also shows a feedback controller for stage 4 oxygen purity by manipulating stage 4 venting rate. This controller increases gas flow from stage 4 when the purity is too low, and reduces flow when the purity is too high. The increase or decrease in gas flow rate changes the pressure in stage 1, and the pressure controller will introduce more or less oxygen to keep the pressure at the setpoint. Tzeng (1992) showed that these two control systems, in combination using optimized proportional integral (PI) or proportional-integral-derivative (PID) control laws, can effectively control stage 4 purity and overall oxygen utilization, over a limited range of operating conditions. The pressure signal from stage 1 must be free from pressure transients caused by liquid flow rate changes, and valve venting stage 4 must be accurate. The controller must be finely tuned, and will not function over widely ranging process conditions, such as stormwater flow or process upsets.

A shortcoming of these control schemes is the low pressure required in stage 4. The low pressure (2 to 4 cm water column) makes flow metering and venting valve operation difficult. Few flow meters and valves operate well with less than 2 to 4 cm pressure drop. It is not practical to operate at higher pressures, because of the structural requirements of the tanks and oxygen losses through the cracks and pin holes in the aeration tank covers. A new approach proposed by Clifft (1991) suggests using lower than atmospheric pressure in stage 4. An exhaust gas apparatus, such as the suction of a positive displacement blower, is used in the last stage to vent the exit gas. Since the reactors can be operated at less than, or nearly equal to, atmospheric pressure, oxygen losses can be reduced. Clifft simulated this strategy for both the wet and dry weather conditions. He showed improved control over the conventional strategies.

METHODOLOGIES

Model and Control Strategies

A dynamic, structured high-purity oxygen activated sludge process model developed by Stenstrom (1990) was used to simulate the fuzzy control systems. It consists of the structured biological process model developed by Clifft (1980), which is the last of a series of models developed by Andrews and coworkers (Blackwell 1971; Busby and Andrews 1975; Stenstrom 1976). The gas phase balances were described earlier by Stenstrom et al. (1989). The combined process models were calibrated by Tzeng (1992) based on pilot plant data (Samstag 1989; Stenstrom 1990) 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 to observe the fuzzy control systems performance.

The fuzzy logic algorithm and the rule base were coded in several separate blocks (or subroutines). When the process inputs, such as influent flow rate, stage 4 gas purity, and stage 4 DO concentration at each sampling step are obtained, these subroutines are invoked, so that corresponding controlled outputs are calculated. These controlled outputs, such as oxygen feed valve opening, gas transfer coefficient (K_La), and exit venting valve opening, are fed back to the simulation program to obtain the process responses.

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-, proportional-derivative- (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 disadvantage of increased complexity. Therefore, a P-like fuzzy logic controller was adopted for setpoint control throughout this investigation. A feedforward loop was implemented in the control system based on the influent wastewater flow rate, which can usually be 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.

To handle the extreme weather flows, such as storm and extreme dry season flows, an adaptive fuzzy control system was 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 three-speed or variable-speed aerator drives (high, media and low speeds that correspond to wet, normal and dry weather flows) are installed, the system is further enhanced and an even better performance can be achieved.

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. Tong et al. (1981) described the first application of a fuzzy logic algorithm to control the activated sludge process. They concluded that the algorithm works well, and a fuzzy controller would be a useful and practical way of regulating the activated sludge process. Chen et al. (1990) developed a fuzzy controller with more than 100 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 pressure error to illustrate how the FLA works (Fig. 2). The pressure error is the difference between the pressure setpoint (desired) and the measured pressure.

Fig. 2 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 Fig. 1 represents a fuzzy membership function or a fuzzy set, and each set has a linguistic meaning, such as "large" and "negative large." 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 for simplicity and computational ease. In the present 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.

Fuzzification maps a crisp controller input signal into the fuzzy membership functions such that fuzzy sets are obtained.

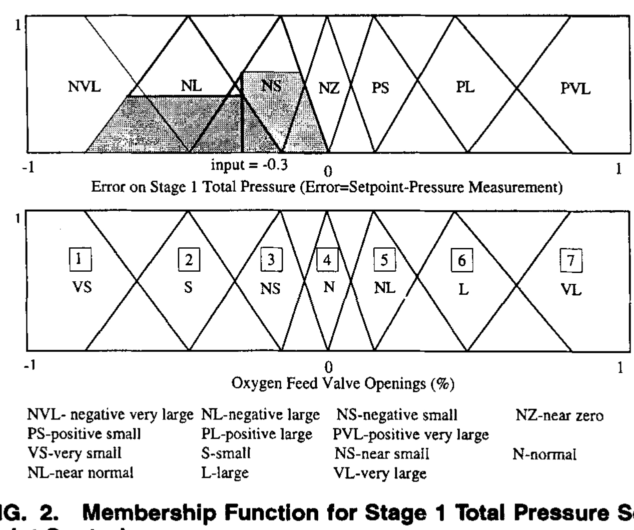

FIG. 2. Membership Function for Stage 1 Total Pressure Setpoint Control

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 Fig. 2.

There are seven rules in the stage 1 pressure controller as shown in Fig. 2. The following are 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 setpoint. 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 antecedences 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, defuzzification is needed to convert the projected fuzzy sets into a crisp control output. This is performed by calculating a 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 the fuzzy logic algorithm. Fig. 3 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 antecedences 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.

An 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 that involves phase changes (process lags or delays) or requires changing from one working state to another. An example of a change in working states might be during periods of very high process loading, such as in wet weather. In this case the oxygen feed valve is opened to a very large value to prevent DO depletion. The HPO-AS process is characterized by these unwanted lags in both the gas and liquid phases, and can experience storm-water washout. 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 greater detail.

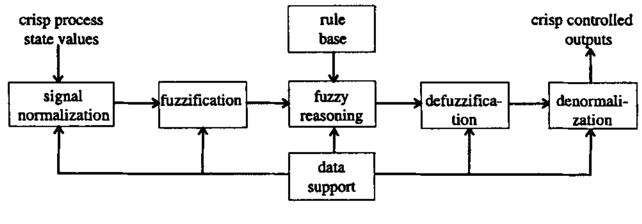

FIG. 3. Typical FLC Structure

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 a DO sensor in the clarifier or exit channel are also assumed.

Modified Fuzzy Logic Controller Structure

Fig. 4 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 setpoints, such as stage 1 total pressure, exit gas oxygen purity, stage 4 DO, or for regulating K_La's that are directly related to the aerator motor speed. Setpoint adjustment is made through a rule base that consists of 18 rules. For example, if the influent flow rate increases, and is large, a large value of the setpoint of stage 1 pressure is assigned, which results in an increase in oxygen feed. In this way the controller is more resistant to gas phase disturbances, and can trace the oxygen demand. A detailed explanation will be given in the Feedforward Control section.

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 seven 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 Analysis section.

Feedforward Control

One of the major purposes of performing gas phase control is to maintain relatively constant DO concentrations in each stage under dynamically varying input conditions. This goal can be realized by tracking oxygen demand with oxygen supply. 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 inference-based on the influent flow measurement.

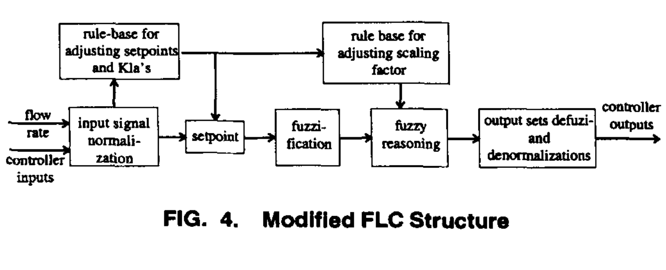

FIG. 4. Modified FLC Structure

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

FIG. 5. Fuzzy Rule Relation Matrix for Stage K_La Control

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 for normal weather flow. The feedforward loop contains 18 rules. Fig. 5 shows the fuzzy rule relation matrix for K_La control of the four stages. The horizontal axis represents the magnitude of the flow rate, such as extremely small and very small. 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 the following:

> 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 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 after the peak flow, which is not addressed by this rule. To correctly address these phenomena, an extremely large value of K_La is given when the flow is very large and flow rate is decreased (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 setpoints in the feedforward loops was used. Since there is large delay in the operation of stages in the gas phase, a further shift in rules is required.

K_La Control

The mass transfer coefficient K_La can be affected by many factors. In most situations, K_La should be 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, K_La control (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.

Fuzzy 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 setpoints are also discussed. The control alternatives were combined and formulated as shown in Table 1. Strategy 5 is not a fuzzy strategy and is provided for reference purpose.

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 (Fig. 5). 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. For example, if the DO error is negative large, it implies that the DO concentration is higher than the setpoint and the valve opening is reduced.

Strategy 2 consists of two control loops: stage 1 pressure control and vent gas oxygen purity control. The setpoint of the pressure controller is adjusted based on the influent flow rate, and the adjusted setpoint 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 (Fig. 5) 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 be 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 setpoint is adjusted by the stage 4 DO error and the adjusted setpoint is maintained by regulating vent gas flow rate.

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 technique for the fourth stage purity and DO controls, respectively. In strategy 3 we introduce another feedforward loop to dynamically adjust the purity setpoint based on the flow rate. The setpoint is then traced by manipulating vent gas flow rate. The rules in this loop are different from those in the stage 1 pressure control loop. In general, when flow is large a high oxygen purity setpoint is assigned to ensure large oxygen transfer rate. A rule shift between the peak flow and the highest setpoint is arranged in the rule set. This is to account for the delay in the oxygen demand. A closed loop fourth stage DO control is provided in strategy 4.

It should be noted that strategy 5 is a conventional control scheme without feedforward control and fuzzy logic algorithms, and uses conventional PID controllers to control stage 1 total pressure and state 4 oxygen gas purity. This strategy is used for comparison to the first four fuzzy control strategies. The controller gains (K_p, K_i, and K_d) used in the strategy were adapted from Tzeng's work (1992), and represent near optimal control.

TABLE 1. Control Strategies for Gas Phase Control

Strategy number (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 O_2 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[a]	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

[a]This strategy is most similar to conventional strategies and is provided for comparison.

RESULTS AND ANALYSIS

Model Inputs and Plant Data

We used the pilot plant data as the simulation inputs. Table 2 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 were observed in the plant Samstag (1989). To mimic this pattern, we employed a sinusoidal pattern for both influent flow rate and influent substrate concentration as the process inputs, with the means equalizing the average flow rate and substrate concentrations.

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 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 influent substrate concentration for both wet and dry weather conditions is still assumed to have a sinusoidal pattern, with the same magnitude as for normal weather. The other operating conditions are the same as for normal weather.

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, sach as DO concentration, oxygen uptake rate, food-to-biomass ratio and

TABLE 2. 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-h
Gas volume	1.13 m^3	Stage 2 O_2 uptake rate	96 mg O_2/L-h
Gas pressure	3 cm w.c.	Stage 3 O_2 uptake rate	48 mg O_2/L-h
O_2 consumption	0.16–0.29 kg O_2/kg BOD_5	Stage 4 O_2 uptake rate	41 mg O_2/L-h
Average flow rate	6 m^3/h	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/h)	Average stage 3 DO	5.5 mg/L
O_2 flow out	0.07 SCMH (Standard m^3/h)	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/h	Stage 2 O_2 purity	82.8%
O_2 utilization rate	N/A	Stage 3 O_2 purity	71.0%
Influent total BOD_5	88 mg/L	Stage 4 O_2 purity	65.6%
Average MLSS	1,346 mg/L	Average temperature	19.5°C

TABLE 3. 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 (h^{-1})	2.5 (avg)	2.5	2.5	2.5	2.5
Stage 2 K_La (h^{-1})	5.12 (avg)	5.0	5.0	5.0	5.0
Stage 3 K_La (h^{-1})	3.55 (avg)	3.5	3.5	3.5	3.5
Stage 4 K_La (h^{-1})	3.49 (avg)	3.0	3.0	3.0	3.0
O_2 utilization rate (%)	85	83	84	82	81
Total O_2 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 O_2 purity (%)	46.6	47.6	46.3	47.8	47.8
Maximum percent of DO of the average in stage 2 (%)	5.3	13.8	10.9	13.5	32.1
Standard Deviation of DO for Stage 2	0.242	0.467	0.402	0.444	1.048
Maximum percent of DO off the average in stage 4 (%)	4.6	2.7	7.5	2.2	46.3
Standard deviation of DO for stage 4	0.171	0.166	0.272	0.104	1.861
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 O_2 Purity set-point (%)	N/A	47.41	43.37	N/A	40
Stage 2 average O_2 Uptake rate (mg/L-h)	79.3	79.0	79.0	79.1	78.2
Stage 4 average O_2 Uptake rate (mg/L-h)	44.1	44.1	43.9	44.1	44.2

mean cell residence time. For gas phase control of the HPO process, maintaining a relatively constant DO concentration at a suitable setpoint is required to conserve energy and avoid sludge bulking. Energy savings can be evaluated by comparing the total mount of oxygen feed, oxygen utilization rate and aerator power. To evaluate the fuzzy control system performance we chose DO concentrations in each stage, oxygen feed mass, oxygen utilization rate and aerator power, as well as system stability, as the performance indices of the control systems.

Four fuzzy control systems were simulated and compared with the conventional strategy. The simulation results are summarized in Table 3. Fig. 6 shows the DO profiles of 5 strategies and their corresponding oxygen feed during 48 h 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 four fuzzy control strategies, setpoint 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 state 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. Improved DO control is most significant in stage 2, where the variations of the influent flow and concentration have the most profound effects.

For strategies 2, 3, and 4 we assumed that aerator speed is not adjustable. The feedforward loop is used to adjust the stage 1 pressure setpoint. Oxygen feed is regulated by matching oxygen demand. These strategies are all affected by gas phase delays; a large change in the oxygen feed to stage 1 cannot simultaneously change DO concentration in stage 4. 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 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 3). Reducing oxygen feed usually requires increasing in K_La's, if a specified DO concentration is to be maintained, or vice versa (McWhirter and Vahldieck, 1978). As discussed earlier, K_La control is more effective than the

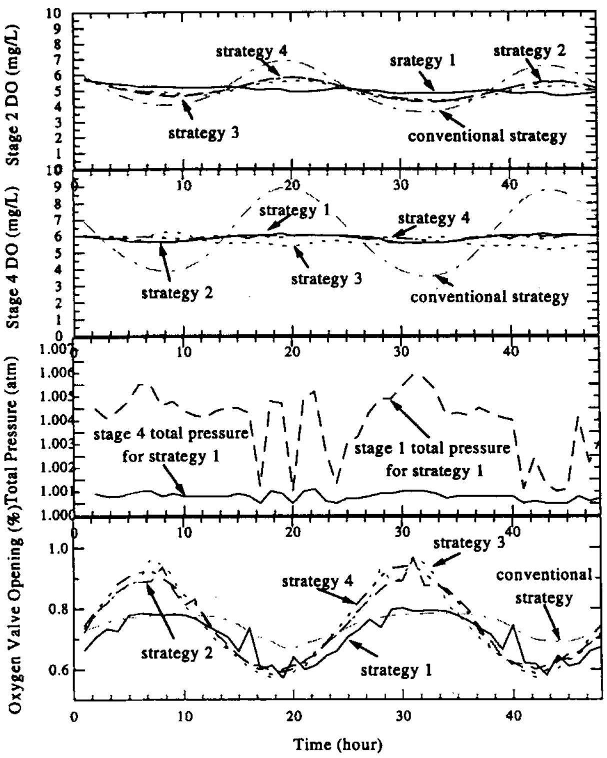

FIG. 6. DO Profiles and Oxygen Feed for Normal Weather Simulation

other indirect controls. Increasing the K_La can also increase the oxygen utilization rate with a corresponding reduction of oxygen purity in stage 4 and oxygen feed rate. The disadvantage is the need for variable speed aerators and increased aerator power at peak loading. It should be noted that variable speed drives may have lower efficiency than constant speed drives. This effect is not investigated in this study, but should be if variable speed drives are evaluated. An alternative way may be to use two- or three-speed motors to provide variable speed.

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 22, and 38 to 40 h. This results in peaks in stage 1 total working pressure (Fig. 6). The same phenomena are also observed in strategies 2 and 3 at time periods of 6 to 11, and 26 to 33 h. 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 or an optimization technique. Nevertheless, the fluctuations are small and would not cause system instability.

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 in the DO in prior stages hinder stage 4 DO control in the conventional control scheme (strategy 5). For all four fuzzy control systems, less DO variations in stages 2 and 3 help to achieve a constant DO concentration, as evidenced in Fig. 6 and Table 3 (standard deviations for stages 2 and 4).

In the conventional control, since the stage 4 total pressure almost equals atmospheric pressure, the exit gas flow is too small to regulate and meter with a simple valve and flow meter that introduces pressure drop. 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 simpler than in strategies 2 and 3, since only a DO error control is used. Adjusting the FLC setpoint in the feedback loop is not required. This simplification greatly reduces the number of rules, and a more stable oxygen feed is obtained using this strategy. In the next section we developed an adaptive system based on strategy 4 for extreme weather flow simulation. Strategy 4 also serves as a comparison basis for the adaptive control system.

Extreme Weather Condition Simulations

Large and small flows are often experienced in wastewater treatment plants during wet and dry seasons. The range of flows can be large and may be too large for a simple controller. One method for controlling these extreme cases, is for the controller to self-adjust to different working states. Conventional PID controllers and control strategies have difficulty in satisfying this requirement (Norman 1985; Clifft 1991).

To accommodate the extreme weather flows, a fuzzy adaptive control system was developed 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

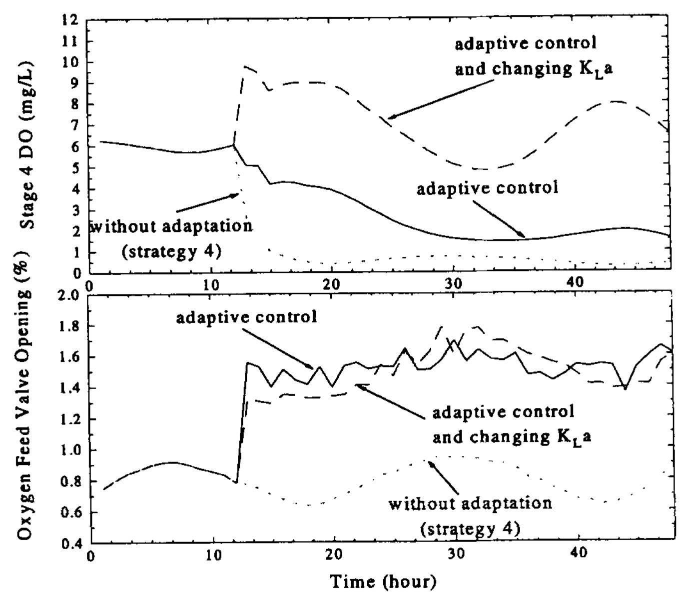

FIG. 7. Stage 4 DO and Oxygen Feed for Wet Weather Simulation

TABLE 4. Simulation Results for Extreme Weather Flows

Parameter (1)	Wet Weather: Adaptive control (2)	Wet Weather: Adaptive and changing K_La (3)	Wet Weather: Strategy 4 (4)	Dry Weather: Adaptive control (5)	Dry Weather: Adaptive and changing K_La (6)	Dry Weather: Strategy 4 (7)
Stage 1 K_La (h^{-1})	2.5	3.75	2.5	2.5	1.75	2.5
Stage 2 K_La (h^{-1})	5.0	7.5	5.0	5.0	3.5	5.0
Stage 3 K_La (h^{-1})	3.5	5.25	3.5	3.5	2.75	3.5
Stage 4 K_La (h^{-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 (%)	63	57	41	37	41	53
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 (%)	153	150	78	38	38	50

smaller. The adaptive system was implemented with control strategy 4 (Table 2).

Fig. 7 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 increased stormwater load. The average DO concentrations for stages 2 and 4 for strategy 4 are 1.6 and 0.6 mg/L, respectively. Although 10% reduction in head space volume was simulated to reduce gas space retention time and lag, the control system could not reduce the oxygen feed in response to the pressure increase. This is an improvement over conventional PID system (Clifft 1991), and occurs because the fuzzy rules in the feedforward loop provide a higher pressure setpoint. However, the oxygen feed is not elevated to address the stormwater, which results in DO depletion in each stage.

Fig. 7 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 4 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 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 153% as compared with 78% 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 63% 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 motors: high, low and medium, which correspond to wet, dry and normal weather operations. Fig. 8 shows the simulated results with K_La increased by 50%.

The average oxygen feeds for adaptive and adaptive plus changing K_La control systems are almost the same. The DO concentrations in stages 2 and 4 are elevated to 6.0 and 7.1 mg/L, respectively, for the adaptive system with higher K_La. This is very close to the 6.0 mg/L setpoint 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

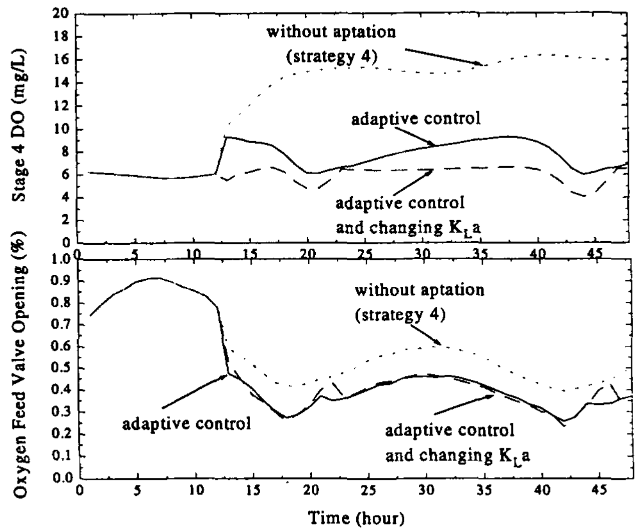

FIG. 8. Simulation Results for Extremely Dry Weather Flows

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 strategy 4 to the adaptive control system, the adaptive system with variable 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. Fig. 8 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 4.

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.

The adaptive control system with variable K_La has better performance than the adaptive system with a fixed K_La. The two systems have the same oxygen feed, but a 30% reduction in the average value of K_La was achieved. The DO concentrations of stages 2 and 4 are controlled at 5.9 and 6.0 mg/L by applying the reduced K_La, and are closer to the DO setpoints (6.0 mg/L).

CONCLUSIONS

Four fuzzy control systems have been developed for performing gas phase control of the high purity oxygen activated sludge (HPO-AS) process for normal weather conditions. All four systems showed improved control, in comparison with conventional PID control systems. The fuzzy logic control systems reduced diurnal DO variations, stabilized oxygen feed and reduced energy consumption. 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), provided 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 setpoint, 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.

Manipulating aerator motor speed is the most effective method for maintaining a constant DO and conserving energy. This is especially true for the extreme weather flows. Another advantage of manipulating aerator speed is increased oxygen utilization.

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. Even better performance can be achieved if three speed or variable speed aerator motors 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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