KBES for Process Control of Nitrification in Activated Sludge Process

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Abstract: Knowledge-based system technology has recently been introduced in activated sludge plant operations. A knowledge-based expert system (KBES) called ASPX (Activated Sludge Process Expert) is developed for nitrification process control of a specific petroleum refinery activated sludge plant. This knowledge-based system has been created to diagnose and correct problems with the nitrification process using rule-based knowledge (heuristics), statistics, and a predictive mathematical model. The knowledge base consists of rules for each of six process control parameters. For each parameter the process control strategy is executed by the knowledge compiled in logic trees. Database functions such as data entry, statistical evaluation, and the simulation model for effluent ammonia concentration are also included. A user-friendly interface enables operators who are not familiar with computers to use all of the program functions with little or no difficulty. The goal of the program is to provide an inexperienced operator with the same problem solving capability as that of a senior operator with extensive practical experience.

INTRODUCTION

Compliance with the discharge standards in petroleum refinery treatment plants is a challenging task since refinery process water may contain high concentrations of toxic or inhibitory chemicals, high oil and grease, and high concentrations of other conventional pollutants. Furthermore, refineries are under constant public scrutiny because of negative publicity from oil spills. The collective impact of increased public awareness and regulatory pressure is to provide additional incentives for refinery management to comply with their National Pollutant Discharge Elimination System (NPDES) permit.

Compliance with this permit is difficult because of plants' periodic losses of nitrification. Rotation of operators and absenteeism compound the problem by making process control more difficult. Corrective measures that improve an existing plant's process control technique can improve the overall process operation with low capital investment.

The use of artificial intelligence in diagnosing and controlling problems with wastewater plants is a recent development in the wastewater engineering field. The expert systems approach has the potential to resolve many problems frequently encountered by wastewater treatment operators. Application of expert systems is a state-of-the-art solution for the control of the activated sludge process (Horan and Eccles 1986).

This paper describes the Activated Sludge Process Expert (ASPX), a knowledge-based expert system (KBES) that was developed for a specific refinery treatment plant to diagnose and correct nitrification problems. The word "problem" here refers to a process condition that is in need of cor-

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rection. Development for a specific plant means the prompts and questions are designed for that specific plant and may contain site-specific information that is not applicable to any other plant. Commercial use of the program would require significant modifications of the program code, and the writers are not developing the code for commercial sale.

The ASPX program is different from typical expert systems developed for municipal wastewater treatment plants because it handles unique properties of refinery wastewater, such as phosphate deficiency, high phenol concentrations, low oxygen uptake rate (OUR) as an indicator of toxicity, pH fluctuations, and inhibition by high ammonia concentration or high aeration basin temperature. The entire program and supported documentation are provided by Ozgur (1991).

The ASPX program diagnoses nitrification problems based on the results of daily lab analyses. These analyses include measurements of pH, dissolved oxygen (DO), temperature, and ammonia concentration that are entered at 8-hr intervals, and other measurements that are taken daily. All of these necessary input values are currently being measured and recorded as required by plant management; thus, no extra data collection is required to use the program.

The ASPX program detects abnormalities in the entered data by comparing the current values to predetermined ranges. If a parameter is determined to be out of the accepted range, a message is sent to the program to search for the process conditions or inputs which may cause the abnormalities. After the potential cause or causes of the abnormal condition are established, the program uses the control laws to suggest one or more corrective actions. The operator applies these suggestions to the plant and observes the outcome. The most typical suggestion is to make an adjustment on the process control equipment such as the air blowers, sludge pumps, or chemical delivery pumps.

Unlike a spreadsheet analysis, which compares process variables to low or high limits, ASPX identifies the probable causes for the out-of-range values and uses the appropriate control laws to give quantitative advice to make corrective process changes.

BACKGROUND

A knowledge-based system (also interchangeably referred to as a rule-based system) is a type of expert system that can access human knowledge supplied by an expert person or persons and can handle this knowledge using a human-like approach to make decisions. The basic objective of an expert system is to capture and store the knowledge of an "expert" person for later use by nonexpert people. An "expert person" is a person or persons who have comprehensive knowledge of petroleum refinery wastewater treatment.

The basic structure of a knowledge-based system consists of a knowledge base (i.e., the expert knowledge coded in a rule form), database (i.e., the plant's historical operational data), and a shell (i.e., a computer program that is capable of reasoning through rules stored in the knowledge base). A rule, which is the smallest component of a knowledge base, is constructed from IF-THEN clauses. The rules that describe a specific action are collected in a structure called a frame. In a typical knowledge base, the rules are organized in this fashion and produce a tree of multiple frames. Extensive descriptions of expert system basics and terminology are available in Alty and Coombs (1984), Edmunds (1988), and Pedersen (1989).

The first application of expert knowledge for modeling and controlling wastewater treatment plants was in the late 1970s (Beck et al. 1978). It took approximately 10 years for the first real-time application to be successfully performed (Geselbracht et al. 1988; Patry and Chapman 1989). Many others have applied expert systems to different areas in wastewater treatment: operation control strategies with expert systems (Gall and Patry 1988); application of statistical models within expert systems (Berthouex et al. 1989); designing wastewater treatment plants (Rossman 1989); and diagnosing activated sludge problems (Johnston 1985; Maeda 1985; Chan and Koe 1991). Moreover, correlations between sludge bulking and treatment plant design were investigated by Geselbracht et al. (1988), who employed a rule-based expert system to find the likelihood of having sludge bulking in various wastewater treatment plant designs.

The foregoing work and that of others established a new technology to improve control of both water resources and environmental engineering processes (Reboh et al. 1982; Barnwell et al. 1986; Mikroudis et al. 1986; Jenkins and Jowitt 1987; Rossman and Siller 1987).

DEVELOPMENT OF ACTIVATED SLUDGE PROCESS EXPERT

The following steps were taken during the development of the ASPX expert system.

1. Predevelopment stage
   a. Collect literature on the nitrification process (initial knowledge acquisition)
      (1) Compile hypothetical knowledge from the literature and university faculty members
      (2) Make a list of crucial questions to ask expert persons
   b. Set up interviews with expert persons
   c. Select and purchase software and hardware environment. Consider ability to handle over 300 rules, ability to run fast on a PC, and cost.
2. Knowledge base development stage
   a. Create knowledge base
      (1) Perform knowledge acquisition
         (*a*) Conduct a written questionnaire with plant operators and engineers
         (*b*) Modify draft rules according to questionnaire results to include practical aspects of the application
      (2) Organize the rules within the knowledge base
      (3) Perform initial testing of the rules by hypothetical problems
   b. Create database functions
      (1) Convert existing data into a format that ASPX can utilize
      (2) Create graphics tools for better data presentations
   c. Adopt statistical and mathematical models
      (1) Apply Bayesian statistical equations
      (2) Adopt basic structure of the mathematical model equations
      (3) Customize model expressions
   d. Write or adopt a graphical user-interface program: Design an easy-to-use graphical menu–driven user-interface program
3. Testing stage
   a. Test models

(1) Run models with hypothetical data and verify predictions
(2) Verify model predictions by the actual plant data

b. Test knowledge base to bring it to its final form
(1) Test rules by more-complex hypothetical problems
(2) Test rules by statistical and mathematical model simulations
(3) Test rules by using the actual plant database values

c. Test user-interface program integrity

Knowledge Base Development

The ASPX knowledge base was categorized based on the major parameters that affect the nitrification process. The following parameters were chosen for this purpose: dissolved oxygen concentration, pH, sludge age (*MCRT*), temperature, influent and effluent ammonia concentrations, and effluent phosphate concentration. Each parameter represents a frame (i.e., where all affiliating knowledge for that parameter is stored) and was organized in a manner as shown in Fig. 1.

Fig. 1 illustrates the knowledge base frame structure of ASPX, which is also the root frame of the knowledge base. The ASPX frame expands into two frames, "Nitrification" and "Sludge Settling." The "Sludge Settling" frame has a limited number of rules and is intended to be used only as an indicator for sludge settling problems. Diagnosing and correcting sludge settling problems (bulking) is an important task, but was beyond the scope of this project. The "Initial" frame is the first of seven frames under "Nitrification" and consists of rules to transfer input parameters from the input text files. The remaining six frames represent the parameters that are most significant in the nitrification process. These six frames have subframes of their own. Each parameter is divided into two frames to facilitate its use and handling.

The ASPX knowledge base consists of 338 rules and 173 different conclusion statements. The confidence factors (i.e., the degree of confidence that the expert person has in the knowledge) are assigned to the rules and conclusion statements based on the degree of reliability of the acquired knowledge. These confidence factors are estimated by the writers. Fig. 2 illustrates some of the rules that are used to evaluate the effluent ammonia concentration and to determine the result code (i.e., conclusion statement), and is illustrative of how the rules are written in the knowledge base.

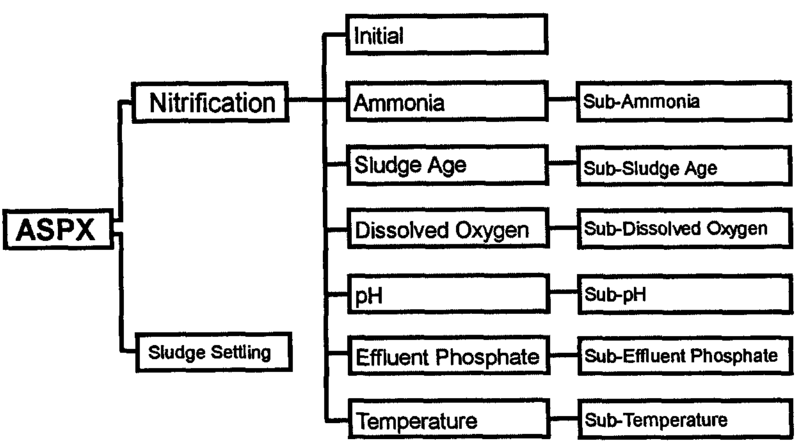

FIG. 1. Frame Structure of ASPX Knowledge Base

RULE032
IF Result of Effluent Ammonia Concentration evaluation is high,
THEN there is strongly suggestive evidence (95%) that Result Code is 14.

RULE033
IF Current Effluent Ammonia Concentration is higher than 75% of NPDES,
THEN there is evidence equal to the measure of certainty associated with Current Effluent Ammonia Concentration that Result of Effluent Ammonia Concentration evaluation is High.

...

RULE036
IF 1) Result of Effluent Ammonia Concentration evaluation is okay, and
2) Result of Effluent Nitrite Concentration evaluation is High,
THEN there is strongly suggestive evidence (98%) that Result Code is 16.

RULE037
IF 1) Result of Effluent Nitrate Concentration evaluation is Low, and
2) Current Effluent Nitrite Concentration is greater than or equal to Lower limit of Effluent Nitrite Concentration,
THEN there is evidence equal to the measure of certainty associated with Current Effluent Nitrite Concentration that Result of Effluent Nitrite Concentration evaluation is High.

...

RULE264
IF The caustic addition rate is Low,
THEN there is strongly suggestive evidence (98%) that Result Code is 133.

RULE265
IF 1) Result of pH Level check is Low, and
2) Current caustic addition rate is less than the calculated caustic addition,
THEN it is definite (100%) that caustic addition rate is Low.

RULE267
IF 1) Result of pH Level check is High, and
2) Current caustic addition rate is less than or equal to calculated caustic addition,
OR 1) Result of pH Level check is Low, and
2) Current caustic addition rate is greater than or equal to the calculated caustic addition,
THEN it is definite (100%) that caustic addition rate is okay.

Result Code : 14
Explanation : Effluent ammonia concentration is high. Nitrification has failed.
Reliability : CF 95
Suggestion : Check effluent ammonia analysis for a possible error in reading.

Result Code : 16
Explanation : Effluent nitrite (NO_2) concentration is high. Partial nitrification is occurring.
Reliability : CF 98
Suggestion : Divert X gpd flowrate to temporary holding tanks for X hours.

FIG. 2. Example Rules and Result Codes from ASPX Knowledge Base

The expert system shell evaluates the rules based on a comparison of current values to the defined lower and higher limits. For example, the series of rules below determine the current pH level by comparing the pH value to the lower and higher limits.

IF (Current pH) $\leq$ (Low pH limit) THEN (pH level) = (Low)
IF (Current pH) $\geq$ (High pH limit) THEN (pH level) = (High)
IF (Current pH) > (Low pH limit) AND
(Current pH) < (High pH limit) THEN (pH level) = (Normal)

The limits are based upon the general recommendations in the cited references. Table 1 shows the preset limits for the parameters evaluated by the ASPX expert system. However, the user interface allows a supervisor to change these limits based on personal experience.

Development of Database Functions—Statistics

The use of statistics gives the expert system access to the plant's historical characteristics. The statistics are used in two ways. First, the relative frequency distribution (i.e., the frequency of an occurrence divided by the total frequency of all occurrences) is used to determine the fuzzy terms (i.e., terms describing a condition without a quantitative measurement) such as "high," "low," and "normal." Second, Bayesian statistics are used to predict the minimum *MCRT* value that produces an effluent ammonia concentration below the permit limit.

The fuzzy terms are determined based on their relative frequency (Spiegel 1961). The upper and lower 5% of the relative frequency distribution of a parameter value represents the high and low value, respectively. The median value shows the most frequently observed value for that parameter. The fuzzy terms are frequently used within the knowledge-base rules because they allow changes in the parameter values without any need for modification to the actual rules. This eliminates the need for operators to learn to use the complex expert system shell development environment.

The minimum *MCRT* is predicted by applying Bayesian statistics to achieve an effluent ammonia concentration below the NPDES permit. Bayes' theorem states that the probability of a specific condition occurring in the future due to specific evidence can be calculated [refer to Winkler (1972) for further description]. Thus, Bayesian statistics are used to predict the probability of the effluent ammonia concentration exceeding the desired concentration for a given range of *MCRT* values. Because Bayes' theorem assumes that a specific condition is solely the result of given evidence, the effects of other factors such as dissolved oxygen (DO), pH, and temperature are not reflected in the statistical equations, and limits the effectiveness of the Bayesian statistics.

In applying Bayesian statistics, the *State* variable (i.e., condition) is defined as the effluent ammonia concentration. For the *Sample* variable (i.e., evidence), the *MCRT* is chosen because it is the key process control parameter of the nitrification process. Table 2 illustrates the two conditions

TABLE 1. Preset Ranges of Limits for Parameters in ASPX Program

Parameters (1)	Preset limit ranges (2)	References (3)
Temperature (°C)	18–35	Charley et al. (1980), *Process* (1975)
Dissolved oxygen (mg/L)	>2.0	Stenstrom and Poduska (1980), Stenstrom and Song (1991)
MCRT days	>20	*Activated* (1987)
pH	7.5–8.6	*Nutrient* (1983)
BOD_5/N/P ratio	100/5/1	*Activated* (1987)
Effluent ammonia concentration	<NPDES Permit	NPDES Permit

TABLE 2. Definition of Parameter Ranges Used in Bayesian Statistical Equation

State variable (1)	Sample variable ranges (2)
No violation state:	$Sample_1 = MCRT < 5$
$State_1 = S_{NH,e} < (0.75)$	$Sample_2 = 5 \leq MCRT < 10$
S_{NPDES}	$Sample_3 = 10 \leq MCRT < 18$
Possible violation state:	$Sample_4 = 18 \leq MCRT < 25$
$State_2 = S_{NH,e} \geq (0.75)$	$Sample_5 = 25 \leq MCRT < 35$
S_{NPDES}	$Sample_6 = MCRT \geq 35$

of the state variable and the six ranges of the sample variable. $State_i$ = state variable for the Bayesian statistics ($i = 1, 2, \ldots, n$); $Sample_j$ = sample variable for the Bayesian statistics ($j = 1, 2, \ldots, m$); $S_{NH,e}$ = effluent ammonia concentration (g/m^3); and S_{NPDES} = NPDES effluent ammonia permit concentration (g/m^3).

For the state variable range, 75% of the NPDES permit concentration is selected as an action level. This percentage is chosen because it gives an adequate safety margin for compliance with the NPDES permit and because there are insufficient observations above the NPDES permit limit to obtain statistically reliable results. Moreover, it is assumed that evaluating effluent ammonia concentration based on a 1-day value (instead of a 30-day average as the NPDES permit requires) would produce an early warning of possible permit violations. The $State_1$ variable indicates no violation; the $State_2$ variable shows a possible or impending violation.

Using the state and sample ranges declared in Table 2, a table of violation probabilities based on a given sample range is created using the classical Bayesian formula. The minimum *MCRT* value is determined by selecting the lowest *MCRT* range which indicates a 90% or higher chance of no violation. This information is relayed to the expert system to indicate the chance of a violation in the future.

Development of Database Functions—Mathematical Model

The ASPX mathematical model for nitrification consists of biokinetic reactions of *Nitrosomonas*. The basic structure of the mathematical model is adopted from Poduska and Andrews (1975) and further alterations are made to account for the effects of DO, pH, temperature, and inhibition by high ammonia concentration. The model is used, first, to estimate the future effluent ammonia concentration and, second, to estimate the minimum sludge age required to achieve a nitrification rate that produces effluent ammonia concentration below the permit limits.

Poduska and Andrews (1975) developed the basic structure of the model, which consists of two non-steady-state differential equations based on the mass balance around the reactor system. Only the expression concerning *Nitrosomonas* is taken from the original model because the growth of *Nitrosomonas* is usually rate-limiting. In addition, the effects of DO, pH, temperature, and a high ammonia concentration are incorporated into the model as shown in Table 3. Table 3 itemizes the factors that are included in the model and summarizes their effects on the nitrification process. The values used for the coefficients in the equations shown in Table 3 are presented in Table 4. The kinetic constant values are based on the values reported in the literature for the activated sludge process operating above 20°C.

TABLE 3. Summary of Mathematical Model Equations, Factors, Ranges, and Effects on Nitrification Process

Factor (1)	Modeled expression (2)	Range (3)	Effects on nitrification (4)	Special conditions (5)	Reference (6)
Dissolved oxygen (mg/L)	Eq. (1)	≤0.2	Significant inhibition		Downing et al. (1964)
	Eq. (1)	≤0.5	Lower ammonia oxidation		Hanaki et al. (1990)
	Eq. (1)	0.5–2.0	Limiting factor	Depends on *MCRT* and resistance in the mass-transfer	Stenstrom and Song (1991)
	Eq. (1)	≤4.0	Limiting factor	During high organic loading	Stenstrom and Song (1991)
	Eq. (1)	≥2.0	Optimum rate	Safe practice of operations	*Nutrient* (1983)
High ammonia concentration (mg/L)	Eq. (2)	>10	Significant inhibition		Anthonisen et al. (1978)
pH	Eq. (3)	≤6.0	Significant inhibition	Very low nitrification	Painter and Loveless (1983)
	Eq. (3)	≤7.8 or ≥9.8	Inhibition	—	Wild et al. (1971)
	Eq. (3)	≤7.0 or ≥9.8	50% reduction	—	Downing et al. (1964)
	Eq. (3)	≥10	Complete inhibition	—	
	Eq. (3)	7.8	Optimum rate	Safe practice of operations	Antoniou et al. (1990)
	Eq. (3)	8.0	Optimum rate	Safe practice of operations	Downing et al. (1964)
	Eq. (3)	7.0–8.2	Optimum rate	Safe practice of operations	Loveless and Painter (1968)
	Eq. (3)	8.4	Optimum rate	Safe practice of operations	Wild et al. (1971)
Temperature (°C)		≤10	Significant inhibition	Threshold temperature for nitrite accumulation	Randall and Buth (1984)
	Included in Eq. (3) as kelvins	≤18 or ≥35	Significant inhibition	Decreased activity rate and growth rate	*Process* (1975)
		10–35	Increasing specific growth rate with temperature	With the exception of maximum ammonia oxidation at 15°C	Charley et al. (1980)
		30	Optimum rate	Safe practice of operations	Wild et al. (1971)
MCRT (days)	Eq. (4)	2–3	Minimum *MCRT* reqd for nitrification	Under laboratory conditions	Poduska (1973)
	Eq. (4)	20	Minimum *MCRT* reqd for nitrification	Under real-time operations	*Activated* (1987)

TABLE 4. Values Used for Coefficients in Mathematical Model Equations

Parameter (1)	Value used in model (2)	Reference (3)
m	4.70×10^{14}	Antoniou et al. (1990)
a	9.98×10^{3}	Antoniou et al. (1990)
b	2.05×10^{-9}	Antoniou et al. (1990)
c	1.66×10^{-7}	Antoniou et al. (1990)
Y_A (mg VSS/mg NH_4^+-N)	0.22	Argaman and Brenner (1986)
$b_A(d^{-1})$	0.101	Gee et al. (1990)
K_{NH} (mg NH_4^+-N/L)	1.5	Charley et al. (1980)
K_i (mg NH_4^+-N/L)	19.7	Rozich and Castens (1986)
$K_{O,A}$ (mg/L)	0.32	Hanaki et al. (1990)

In Table 3, the equations are as follows. In Stenstrom and Poduska (1980)

$$\mu'_A = \mu_{m,A}\left(\frac{S_{NH,e}}{K_{NH} + S_{NH,e}} \cdot \frac{S_O}{K_{O,A} + S_O}\right) - b_A \quad \ldots\ldots\ldots\ldots \quad (1)$$

In Haldane (1965)

$$\mu'_A = \mu_{m,A}\left(\frac{S_{NH,e}}{K_{NH} + S_{NH,e} + \dfrac{S^2_{NH,e}}{K_i}}\right) - b_A \quad \ldots\ldots\ldots\ldots \quad (2)$$

In Antoniou et al. (1990)

$$\mu_{m,A} = \frac{me^{-(a/T)}}{1 + \dfrac{b}{10^{-pH}} + \dfrac{10^{-pH}}{c}} + b_A \quad \ldots\ldots\ldots\ldots \quad (3)$$

Temperature in degrees Celsius is included in (3) as kelvins (K).

And for $MCRT$

$$MCRT = \frac{1}{\mu'_A} \quad \ldots\ldots\ldots\ldots \quad (4)$$

First, the model is run to estimate the future effluent ammonia concentration under the assumption that the previous day's record represents the initial conditions and these conditions are constant throughout the simulation period. The initial concentration of nitrifying bacteria is estimated by either using the BOD_5/TKN ratio method (EPA: *Process* 1975) or by solving the mass-balance equation for the autotrophic bacteria mass assuming steady-state conditions, whichever is lowest. The non-steady-state model equations are solved numerically using the fourth-order Runge-Kutta method (James et al. 1985). If the predicted effluent ammonia concentration exceeds the permit, the expert system alerts the operator about possible future violations.

Second, the model is run consecutively for different $MCRT$ values between two and 30 days using one-day increments until the minimum $MCRT$ that produces an acceptable effluent ammonia concentration is determined. The minimum $MCRT$ represents the model's estimation of the lowest possible $MCRT$ that will achieve the desired treatment efficiency. Once the minimum *MCRT* is determined, this information is transferred to the expert system program where it is used in evaluating the current *MCRT* value. The current *MCRT* is calculated by the operator based on a three-day moving average using the *MCRT* equation describing the ratio between the total solids in the system and the total solids leaving the system (Metcalf and Eddy: *Wastewater* 1991).

Development of User Interface

During the development of ASPX it was found that an easy-to-use user-interface program was needed due to the lack of computer experience by the majority of plant operators. The ASPX user interface is a Windows-like, menu-driven, mouse/keyboard-controlled, easy-to-use graphical interface program that simplifies access to all of ASPX's features. This high-performance user-interface program makes the expert system easy to use for any of the plant's personnel. The minimum hardware requirement is a PC-DOS or MS-DOS based computer having a 386 processor running at 20 MHz speed or greater, with a VGA screen, 4 MBytes of RAM, and a mouse.

The user-interface program acts like a global controller; it can access the database, the expert-system shell (PC Plus, Texas Instruments, Austin, Tex.), the models, and the report-generation program. Fig. 3 shows how these elements interact through the user interface and the global files.

The database consists of the 23 parameters that are measured at seven different sampling locations (see Fig. 4). Fig. 5 displays the location of all the ASPX process control equipment and Table 5 shows the control laws that are used to estimate the quantitative information along with the complete list of ASPX process control parameters, and the process control equipment. Using these controls laws allows ASPX to issue a quantitative suggestion. For example, from Table 5 (column 4), the amount of caustic addition may be estimated by obtaining the residual alkalinity of at least 50 mg/L (as $CaCO_3$) and by calculating the amount of caustic required for each gram of ammonia oxidized (*Design* 1992). This quantitative information is

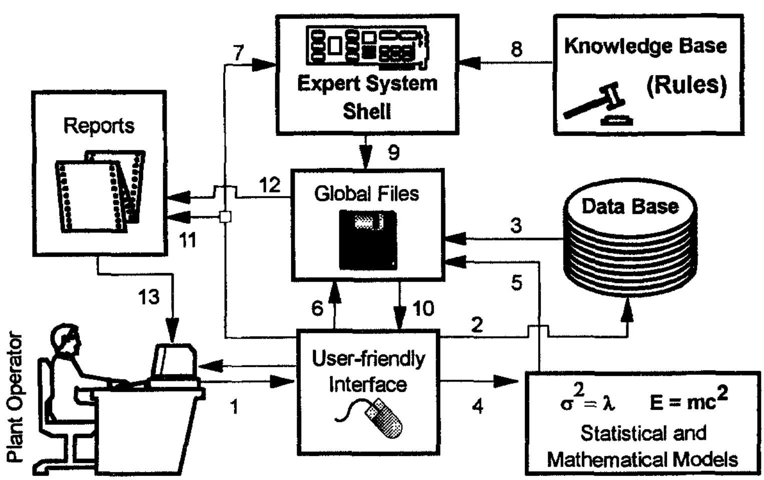

FIG. 3. Flowchart of ASPX Consultation and Interaction between Modules

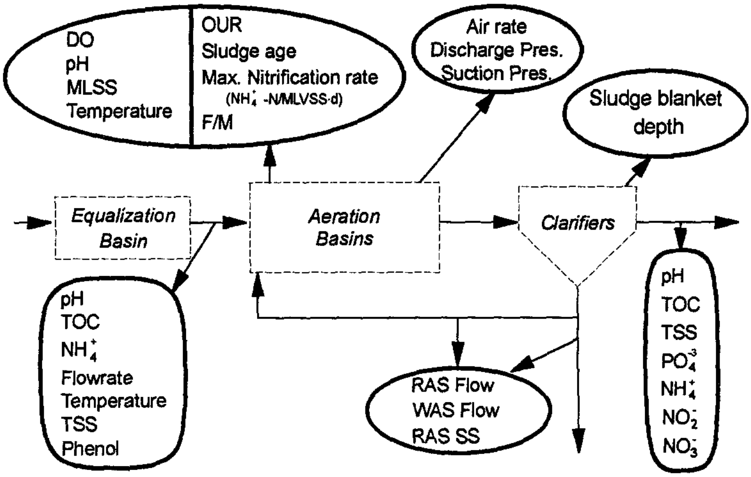

FIG. 4. Parameters and Locations Monitored by ASPX

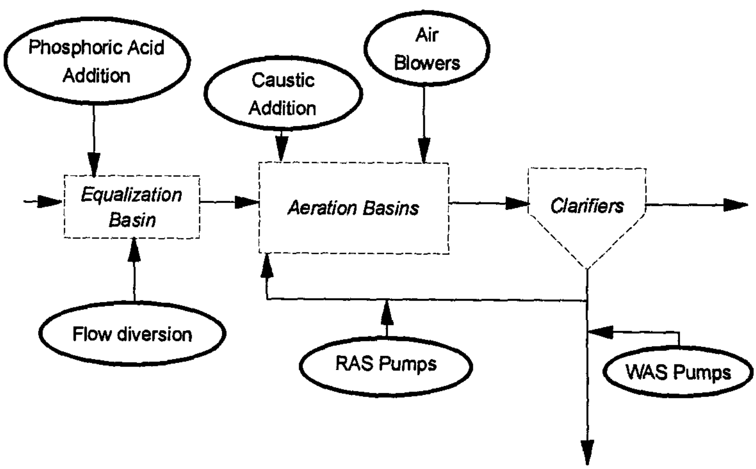

FIG. 5. Process Control Equipment Controlled by ASPX

used to describe a corrective action for one of the process control actions shown in Table 5 (column 3).

In Table 5

$$Air\ flowrate_2 \simeq \frac{Q_{K_La1}}{Q_{K_La2}} Air\ flowrate_1 \left(\frac{C^*_\infty - \mathrm{DO}_1}{C^*_\infty - \mathrm{DO}_2} \right) \quad (5)$$

$$MCRT = \frac{VX}{(QX_e + Q_wX_w)} \quad (6)$$

$$\mathrm{PO}_4 - \mathrm{P}_x \sim \frac{\mathrm{BOD}_{5,x}}{100} \quad (7)$$

TABLE 5. Process Control Parameters, Process Control Equipment, and the Equations for Quantitative Information for the ASPX Process Control Technique

	Process Control		
Unit location (1)	Parameter (2)	Equipment (3)	Control laws (quantitative estimation) (4)
Activated sludge	Dissolved oxygen	Blower ON/OFF switch	Eq. (5)
	Dissolved oxygen	Blower discharge valve	Eq. (5)
	Sludge age (three-day average)	Sludge waste pump	Eq. (6)
	pH reading	Caustic tank level indicator and metering pump	Maintain at least 50 mg/L (as $CaCO_3$) residual alkalinity. Use 14.1 g of alkalinity (as $CaCO_3$) destroyed per gram of ammonia oxidized to nitrate (as N)
	Phosphate concentration	Phosphoric acid tank level indicator and metering pump	Eq. (7)
	Mixed-liquor suspended solids (MLSS)	Sludge waste rate Return activated sludge rate	Calculated by WAS and RAS equations given below
	TOC (organic loading)	Temporary storage in holding tank	Divert 25% of the current flow rate to the temporary holding tanks
	Ammonia load		
	Flow rate		
	Temperature		
Clarifiers	Return activated slude rate	RAS pump controls	Eq. (8)
	Waste activated sludge rate	WAS pump controls	Eq. (9)
	Sludge blanket depth	RAS/WAS pump controls	Preset limit (2 to 4 ft)
	Sludge MLSS	No apparent control	No apparent control

$$Q_r = \frac{XQ - X_w Q_w}{X_w - X} \quad (8)$$

$$Q_w = \frac{VX}{(C_{MCRT})(X_w)} - \frac{QX_e}{X_w} \quad (9)$$

Testing ASPX

Testing ASPX was accomplished by a three-step procedure that consists of initial, intermediate, and advanced testing processes. The initial testing involved verification of the knowledge base by restructuring, reorganizing, and rewriting the rules to eliminate erroneous conclusions reached for given hypothetical problems. Moreover, the statistical and mathematical models were tested with both hypothetical and actual data to verify their capabilities.

During the intermediate testing stage, the rules were further modified to obtain consistency with the statistical and mathematical model simulations and the expert system conclusions. The testing procedure was completed in advanced testing stage where the expert system was tested with data from the plant. In addition, the user-interface program was also tested to provide a dependable software product.

During the testing procedure, a list of rules accessed was kept to identify the most effective rules in the knowledge base. Under the testing conditions, the rules about the sludge age, temperature, and dissolved oxygen were the most frequently accessed within the knowledge base. These three parameters were found to be most effective in constructing corrective process changes using the control laws. This finding is well correlated to the literature which identifies them as the major factors in controlling the growth of the nitrifying bacteria (*Design* 1992).

APPLICATION OF ASPX

The following example illustrates how the ASPX program is applied to the activated sludge process and how the operators use the program to advance the plant process control.

Step 1 (Fig. 6): First, the operator collects samples from the process and performs the necessary daily lab work as required by the plant management. Second, the operator enters the lab results into the ASPX database. For example, the operator enters the current pH reading as 6.5.

At this stage, the operator can perform a number of database functions such as graphically showing the trends, finding low or high values for a given range of dates, calculating frequency distributions, or transferring records to other database programs.

Step 2 (Fig. 7): Third, the operator runs the ASPX expert system to diagnose abnormalities with the nitrification process and to receive advice on how to solve the problems. Although the calculations are now shown on the screen, the computer applies the statistical and mathematical models followed by the initiation of the expert system shell. At this stage, the shell accesses the knowledge base and the rules are evaluated to diagnose the problems.

The operator may choose from "limited," "regular," or "in-depth" techniques to provide three different evaluations of the process. The limited technique detects only abnormal values and requires no additional input other than the values entered into the database, and asks no questions of the user during the consultation session. The regular analysis technique

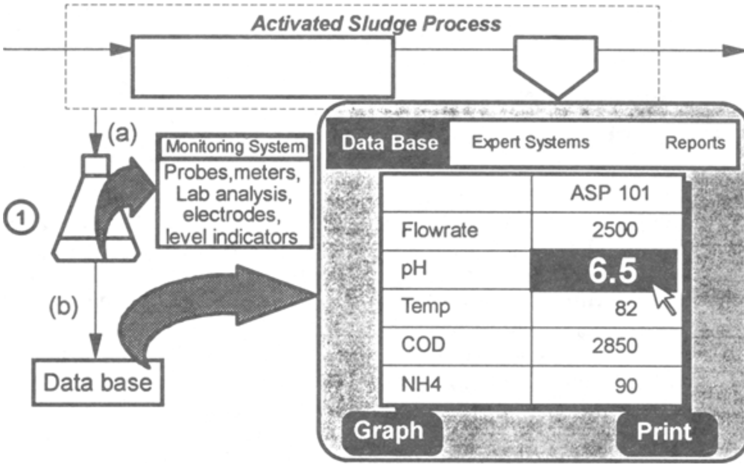

FIG. 6. Step 1: Process Monitoring and Data Entry

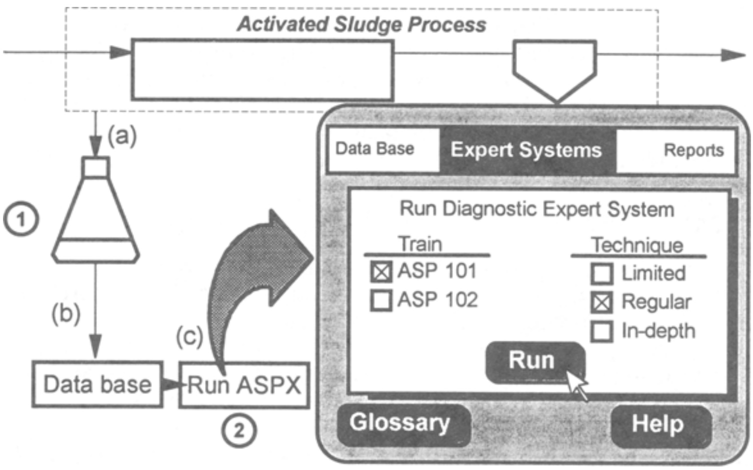

FIG. 7. Step 2: Running Program

provides a more comprehensive diagnosis by asking questions to determine the cause of the problems detected. The most extensive analysis discloses all detectable problems with the nitrification process.

The operator decides which technique to use based on the current state of the plant. Normally, the operator will use the limited technique for everyday practice. If any out-of-range value is detected, the operator may run the program using the regular technique to find the cause of the abnormal value. If the cause is not identified or the abnormal condition still exists after making adjustments, the operator may then use the in-depth technique to perform more detailed diagnostics to discover the precise cause of the problem.

In this example, the operator uses the regular technique and an out-of-range parameter is detected when the rule is evaluated to check the pH level. The expert system concludes that the current pH (6.5) is less than the allowed lower limit (7.5). Once this message is received, the expert system shell searches for the cause of the out-of-range value by evaluating additional related rules in the knowledge base. Most probable cause and alternative causes are identified, and suggested control actions are presented to the operator in decreasing order of significance. This example assumes that the most probable cause was identified inadequate caustic addition.

Step 3 (Fig. 8): Fourth, the consultation session ends after the results have been shown to the operator. In this example, the ASPX displays the abnormality of low-pH in the aeration basins, the probable cause, and a number of remedies to correct the problem causes by the low pH (e.g., increase the caustic addition to 120 L/d and check the pH again in 1 hr).

All the corrective actions given by ASPX guide the operator through a step-by-step action procedure. As shown in this example, in addition to making adjustments to the equipment, the expert system may give informative and preventive suggestions such as notifying management and preparing the emergency effluent storage tanks (this refinery has the ability to store effluent for later treatment).

Step 4 (Fig. 9): Fifth, the operator makes the recommended process control changes to correct the current problem. In this example, the operator would increase the caustic addition rate to 120 L/d by adjusting the caustic delivery pump. Furthermore, depending on the type of adjustment made the operator reconfirms the adjustments to make sure the plant is now performing at its optimum level.

Step 5: The operator observes the outcome.

The operator exercises the use of the ASPX process control procedure once per day during its regular operations. If the plant is suffering from a prolonged problem stage, the operator may run the program more frequently.

RESULTS AND COMMENT

Obtaining results from actual plant operations is still in its beginning stages. Tests implementing the database values, however, have given prom-

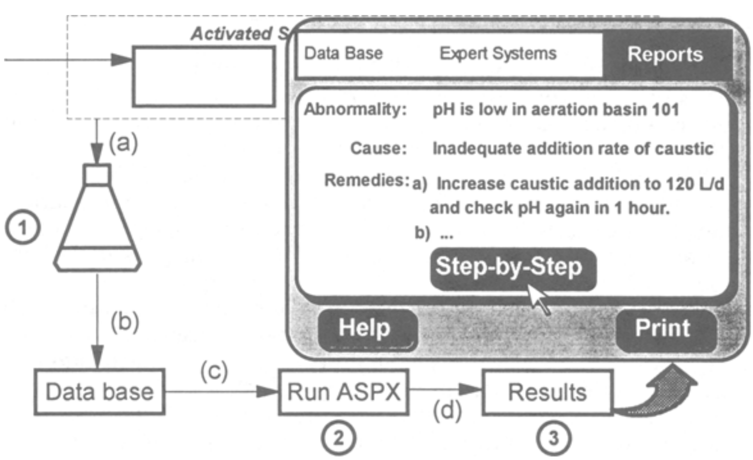

FIG. 8. Step 3: Suggestions Given by ASPX

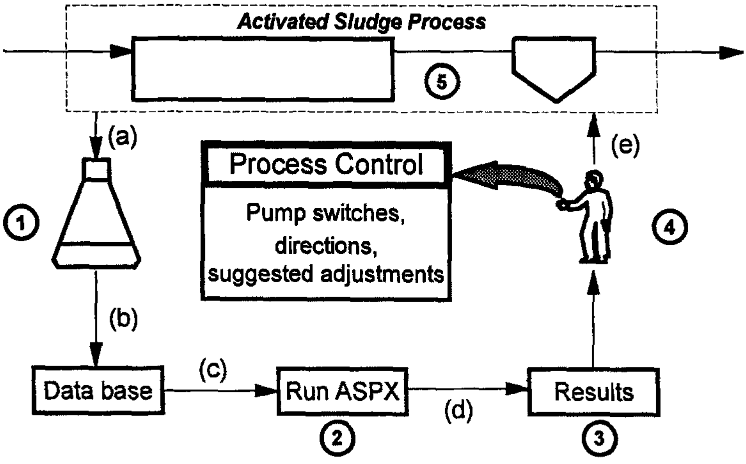

FIG. 9. Step 4: Operator Applies Suggestion to Actual Plant Process Control Equipment and Observes Outcome (Step 5)

TABLE 6. Results from Application of ASPX to Data between January 1 and March 17, 1988

Number of cases (1)	Number of cases in which a problem was identified (2)	Number of cases in which at least two causes were identified (3)	Number of cases in which control actions were suggested (4)	Number of cases in which preventive actions were suggested (5)	Number of cases in which at least one question was asked (6)
13[a]	13[a]	13[a]	13[a]	5[a]	13[a]
204[b]	—	—	—	147[b]	75[b]

[a]Possible violation.
[b]No violation.

ising indications of success. The ASPX was applied to historical database records using the values between January 1 and March 17, 1988 to diagnose and correct nitrification problems. Table 6 summarizes the results of running the ASPX using 217 cases between the dates indicated.

For the total of 217 cases, there were 13 possible NPDES violations ($State_2$) during this period. In all 13 cases, ASPX detected that a parameter was outside an expected range, identified at least two causes for the nitrification problems, and gave remedies to all the parameters identified out of range.

Among the most common identified out-of-range values were high effluent ammonia concentration, low effluent nitrate concentration, low sludge age, and low pH levels. The most common causes for the nitrification problems were identified as problems caused by high sludge blanket depth, high organic loading, low return activated sludge rate, and low waste sludge suspended solids concentration. The most common control actions included adjusting waste sludge rate, diversion of flow rate, and increasing the return activated sludge rate.

In addition, in five out of the 13 cases, the program suggested a preventive action. The most common suggestion was to increase the return activated sludge rate. In all 13 cases of the NPDES violation, the program asked at least one question of the operator.

For the remaining 204 cases, in which there were no NPDES violations ($State_1$), the ASPX suggested 147 preventive actions to improve the current operations. Out of the 204 cases, the program asked additional questions 75 times. Among the most common preventive actions given were to reduce organic loading, increase sludge age, increase phosphoric acid addition, and increase the return activated sludge rate.

The mathematical model was also run during these analyses to establish the effectiveness of the model's predictions. For approximately 87% of the 216 predictions made, the model predicted a value lower than the actual reading (188 times). The model was able to predict six of the 13 possible violations correctly but missed seven cases. For the 204 cases that had no violations, the model reported eight false predictions.

On a separate occasion, ASPX was run using the data compiled between April 14 and May 13, 1992. During this period, ASPX identified five parameters that were out of their expected ranges. The parameters identified were aeration basin temperature, dissolved oxygen concentration, food-to-microorganism ratio, sludge age, and toxic substance concentration. ASPX suggested at least one remedy for each of these parameters to keep them within their acceptable ranges. Some of the remedies included lowering the aeration basin temperatures and adjusting the sludge wasting and recycle rate. In addition, based on the proposed adjustments, the mathematical model predicted that the effluent ammonia concentration would decline to 5 mg/L or less within the next 4.5 days. Although the effluent ammonia concentration did decrease to 5 mg/L within the predicted time, it is difficult to assess the full contribution of the ASPX program since not all suggestions given by the program were followed.

Unfortunately, it is not possible to completely evaluate the appropriateness of the suggestions given by the program since the expert system has not been installed at the plant. Nevertheless, the suggestions given by the program were well correlated with the corrective actions taken at the refinery and no erroneous suggestions were given by the program.

SUMMARY AND CONCLUSIONS

This paper described newly developed expert system technology that diagnoses and corrects nitrification problems for a specific petroleum refinery wastewater treatment plant. The primary goal of the ASPX (Activated Sludge Process Expert) is to diagnose and correct problems with the nitrification process at a level comparable to that of a senior operator who has acquired substantial practical experience in plant operations. The conclusions reached in this research are summarized as follows.

A knowledge-base was created to diagnose nitrification problems. A total of 338 rules and 173 suggestions were written to correct the detected problems.

ASPX performed well under hypothetical problem testing. The statistical and mathematical models predicted exceptionally well when they were tested using hypothetical and database values. The statistical predictions assigned realistic low, high, and normal values to the parameters and realistically estimated the probability of future violations. The results of the mathematical model predictions were well-correlated with the database observations, including the estimation of the future ammonia concentration and the minimum *MCRT* requirements.

Under testing conditions, ASPX was given a total of 217 cases. The program successfully diagnosed all 13 cases with problems and identified at least two causes for each problem. The program gave corrective actions to all 13 cases and the suggestions were practical and clearly explained. In addition, the program suggested five preventive actions for the 13 cases detected as problems. For the remaining 204 cases, in which no NPDES violations existed, the program suggested preventive actions for 147 of those cases to improve plant operations.

The mathematical model predicted six of the 13 cases identified as having nitrification problems. The model made eight false predictions for the remaining 204 cases in which there were no nitrification problems. Out of 216 predictions made, the model predicted a lower value 188 times (approximately 87% of the time).

In the analyses of a separate problem, occurring after the testing period, ASPX diagnosed all five out-of-range parameters and identified at least one cause for each abnormal value. The model correctly predicted the recovery time for restoration of nitrification; however, the results were inconclusive, because not all the suggestions given by ASPX were implemented by the plant operators.

The knowledge-based expert system (KBES) developed in this paper combines the statistical, mathematical, and expert persons' knowledge in a useful way. This allows the developer to create a multifunctional knowledge-based system, which can be used as a diagnostic tool as well as a process control technique. The development of expert systems is a further step in developing better process control for the activated sludge process.

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APPENDIX II. NOTATION

The following symbols are used in this paper:

$Air\ Flowrate_x$ = air flow rate needed to reach DO_x [standard cubic feet per minute (SCFM)];
a, b, c, m = parameters;
$BOD_{5,x}$ = BOD_5 concentration at time x (g/m^3);
b_A = endogenous decay coefficient (1/d);
C_{MCRT} = constant $MCRT$ value (d);
C_∞^* = saturation concentration of oxygen (g/m^3);
DO_x = dissolved oxygen concentration at time x (g/m^3);
K_i = inhibition constant (mg/L);
K_La_x = volumetric mass-transfer coefficient for DO_x (1/h);
K_{NH} = half-saturation constant for NH_4^+ (mg/L);
$K_{O,A}$ = dissolved oxygen saturation constant for autotrophic bacteria (mg/L);
$MCRT$ = sludge age (days);
$PO_4 - P_x$ = required phosphate at time x (g/m^3);
Q = flow rate (m^3/day);
Q_{KLax} = Site-specific coefficient for K_La_x;
Q_r = return activated sludge flow rate (m^3/day);
Q_w = waste sludge flow rate (m^3/day);

Q_x = flow rate at time x (m^3/day);
$Sample_j$ = sample variable for Bayesian statistics ($j = 1, 2, \ldots, m$);
$State_i$ = state variable for Bayesian statistics ($i = 1, 2, \ldots, n$);
$S_{NH,e}$ = effluent NH_4^+-N concentration (g/m^3);
S_{NPDES} = NPDES effluent NH_4^+-N permit concentration (g/m^3);
S_O = concentration of dissolved oxygen (g/m^3);
T = temperature of wastewater (K);
V = volume of aeration basin (m^3);
X = mixed liquor suspended solids (g/m^3);
X_e = effluent TSS concentration (g/m^3);
X_w = waste sludge suspended solids (g/m^3);
Y_A = maximum yield coefficient (g autotrophic biomass produced/g NH_4^+-N consumed;
μ'_A = net specific growth rate for autotrophs (1/d); and
$\mu_{m,A}$ = maximum specific growth rate of autotrophs (1/d).