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Rough set-based hybrid fuzzy-neural controller design for industrial wastewater treatment

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Abstract

Recent advances in control engineering suggest that hybrid control strategies, integrating some ideas and paradigms existing in different soft computing techniques, such as fuzzy logic, genetic algorithms, rough set theory, and neural networks, may provide improved control performance in wastewater treatment processes. This paper presents an innovative hybrid control algorithm leading to integrate the distinct aspects of indiscernibility capability of rough set theory and search capability of genetic algorithms with conventional neural-fuzzy controller design. The methodology proposed in this study employs a three-stage analysis that is designed in series for generating a representative state function, searching for a set of multi-objective control strategies, and performing a rough set-based autotuning for the neural-fuzzy logic controller to make it applicable for controlling an industrial wastewater treatment process. Research findings in the case study clearly indicate that the use of rough set theory to aid in the neural-fuzzy logic controller design can produce relatively better plant performance in terms of operating cost, control stability, and response time simultaneously, which is effective at least in the selected industrial wastewater treatment plant. Such a methodology is anticipated to be capable of dealing with many other types of process control problems in waste treatment processes by making only minor modifications.

Keywords: Optimal control; Rough set; Genetic algorithm; Neural network; Fuzzy logic control; Wastewater treatment; Artificial intelligence; Soft computing; Knowledge discovery; Machine learning

1. Introduction

Since the operation of a wastewater treatment process is intimately linked with wastewater sources, chemical composition, flow rate, biological process conditions, and the recycle rate of the settled sludge, real-time control for achieving better effluent quality, anticipated cost-effectiveness, and required treatment efficiency under dynamic loading conditions has become increasingly challenging. Traditional control theory, such as programmable logic control, is essentially based on mathematical models of the controlled system that was mainly a trial and error process based on a minimal amount of human expertise. As a result, intervention by an operator's judgment and experience sometimes was required when coping with unexpected on-line upset conditions. Without continuous corrective control inputs, however, the wastewater treatment processes will diverge from steady state easily and the compliance with effluent quality standards could become problematic.

Dynamic modeling and control of activated sludge processes have been widely studied using BOD as the primary parameter [1–10]. Advanced analysis concerning nitrification/denitrification effects in activated sludge

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Nomenclature

$x(t)$	$n \times 1$ state vector of the system
$u(t)$	$p \times 1$ vector of actuated signal
$y(t)$	$q \times 1$ output vector of the system
f	nonlinear function for $\mathrm{d}x(t)/\mathrm{d}t$
g	nonlinear function for $y(t)$
f'	nonlinear function for $x(t+1)$
g'	nonlinear function for $y(t)$
Y_k	kth output variable in the neural network model
O_k	the predicted value of kth output variable in the neural network model
p	the number of output variables
r	the number of experimental data sets
$x_1, \ldots, x_k$	state variables defined by those membership functions $A_1^n, \ldots, A_k^n$ in the antecedent part of fuzzy control rule
$y_1, \ldots, y_k$	control variables defined by those membership functions $B_1^n, \ldots, B_k^n$ in the consequence part of fuzzy control rule
$R^1, \ldots, R^n$	a set of fuzzy control rules in the rule base
pH at B1	the pH value at B1
pH at H1	the pH value at H1
pH at I1	the pH value at I1
TP	total phosphorous in the aerobic process (mg/L)
TN	total nitrogen in the aerobic process (mg/L)
TFR	the flow rate of treatment effluent (m^3/d)
EL	the amount of electricity consumption (kW h/d)
HAC	acetic acid at equalization basin (mg/L)
BA	benzoic acid at equalization basin (mg/L)
Ptol	paratoluic acid at equalization basin (mg/L)
TA	terephthalic acid at equalization basin (mg/L)
TOC	total organic carbon at equalization basin (mg/L)
COD	COD in the effluent (mg/L)
SS	SS in the effluent (mg/L)

processes has also been reported [11]. Due to the inherent complexity of treatment mechanisms, engineering applications of artificial intelligent (AI) associated with conventional knowledge-based control technologies have been popular for handling various types of waste treatment processes to minimize both the environmental and economic impacts simultaneously [12–14]. In the late 1980s, fuzzy logic controls (FLCs) have demonstrated their utility in various industrial applications to assist in stabilizing on-line upset conditions. But designing FLCs would require a series of prerequisites, including the determination of the input and output variables, the parameters of membership functions, and the fuzzy control rules. The proper acquisition of an operator's experience to help identify a suitable set of control rules is often quite difficult in some cases since many uncertain factors, including the physical and chemical properties of wastewater streams as well as the degradation mechanisms exhibited by biological processes, may significantly affect the operational efficiency of wastewater treatment plants. Nevertheless, using FLCs to handle those wastewater treatment systems with highly nonlinear features represents a contemporary progress in the field of artificial intelligence. These technologies at least are capable of incorporating the operator's or expertise's experience into the computer models that have successfully been applied to both aerobic biological treatment [15–22] and anaerobic biological treatment [23].

A recent trend in control engineering applications focuses on the integration of various merits embedded in neural networks (NNs) and genetic algorithms (GAs) to meet different control needs. For example, Lin and Lee [24] proposed the idea of coordination between fuzzy control and NN models for decision analysis. Spall and Cristion [25], Lee and Park [26], and Chen et al. [27] verified the potentials of using NN models for assessing effluent quality in the wastewater treatment systems. Besides, many previous studies have pinpointed an advanced need of using proper tool for screening out the essential control rules from experimental input–output data pairs that lack linguistic or knowledge information. These studies include the use of fuzzy clustering method [28], Takagi–Sugeno approach, in which the output variables of each rule, i.e., fuzzy partition space, are expressed by a linear combination of input variables [29], optimal parameter searching approaches using learning ability of NN models [30,31] and the solution searching ability of genetic algorithms [12,32]. Moreover, the integration of NNs and GAs for meeting various control needs is advancing at a rapid pace, as reported elsewhere [33–35,13,36]. With the aid of genetic programming technique, Chang and Chen [12] presented improved algorithm for increasing the forecasting accuracy in the conventional Takagi–Sugeno FLCs. Advanced hybrid fuzzy controller design implementing multiple AI paradigms, including FLCs, NNs, and GAs techniques, for waste treatment was also found in the literature [14,27].

In the last two decades, rough sets and fuzzy sets turned out to be two contemporary progresses in analyzing inexact, imprecise, uncertain, or vague knowledge. The former, introduced by Pawlak [37], captures the distinct aspect of indiscernibility in knowledge, while the latter, introduced by Zadeh [38], describes the inherent feature of vagueness in linguistics and decision-making. The role of fuzzy systems in control may vary depending on the level of assistance of AI technologies required in the process. As to the use of rough sets to aid in the capability of FLCs, several pioneering topics were conducted in recent years. For example, Cho et al. [39] and Hong et al. [40] explored the principles of extraction and autogeneration of fuzzy rules and membership functions for fuzzy modeling via the use of rough set theory. Felix and Ushio [41] presented the minimum rule induction approach based on an inconsistent and incomplete database using RS technique associated with a GA-based search procedure for exploring the inherent features embedded in the information system. Jagielska et al. [42] systematically investigated the applications of NNs, fuzzy logic, genetic algorithms, and rough sets in relation to automated knowledge acquisition for solving classification problems. Therefore, there exist increasing potential to incorporate the merit of the rough set theory into the control rule extraction when designing a sound fuzzy-neural controller. This paper represents a companion study of Chen et al. [14]. It is the aim of this paper to explore the use of rough set theory to aid in the fuzzy controller design and verify that such a new scheme could produce relatively better plant performance in terms of operating cost, control stability, and response time simultaneously than the others in some waste treatment systems. To illustrate such a progress, this paper employs a three-stage analysis that integrates RS and GA models with a fuzzy-neural logic control system. The practical implementation of such ideas was assessed by a case study in an industrial wastewater treatment plant that contains both anaerobic and aerobic treatment units in its process train.

2. The essence of advanced hybrid fuzzy control algorithms

Fuzzy control, integrating many types of artificial intelligence techniques, such as rule-based expert systems, fuzzy sets theory, and even basic control knowledge, departs significantly from traditional control mechanisms. The fuzzy control methodology tries to establish the controller from domain knowledge directly relying on extracting the experience of expertise through a normal working procedure. However, the knowledge provided by experts or operators in a specific domain is usually qualitative and knowledge acquisition inevitably contains different sources of uncertainties. Due to the rising concerns of environmental and economic impacts from the wastewater effluents, improved process control algorithms, using hybrid machine learning technologies, have received increasing attention recently. Fig. 1 illustrates the fundamental architecture of an integrated RS-based fuzzy control system (RsFLC). In general, the fuzzy logic controller consists of four principal components: fuzzification interface, fuzzy rule base, fuzzy inference engine, and defuzzification interface. The fuzzification interface converts real-world data into an acceptable form for the fuzzy controller using fuzzy membership function as a tool. The fuzzy rule base contains a set of IF–THEN rules relating measured variables to control variables. The antecedent part of each rule classifies the behavior of measured variables by fuzzy membership functions, while the consequence part expresses the essential action in terms of a set of control variables. Available domain experts must be invited to build the rule base in most cases. The purpose of the inference engine is to derive a reasonable action with respect to a specific situation based on the given rule base. It can be viewed as a procedure by which a possibly imprecise conclusion is deduced from a collection of imprecise premises. Finally, the defuzzification interface converts the fuzzy control action to the nonfuzzy action that can be accepted by the real-world systems. However, a hybrid fuzzy controller design may be divided hierarchically into levels, some of which are established by fuzzy systems and the others by NNs or rough set theory. Or it can be configured in a parallel fashion based on a competitive or corporative relationship among various AI paradigms.

In this study, four soft computing approaches, including FF, NN, GA, and RS, are integrated together to produce a relatively reliable FLC for improving wastewater treatment process control in terms of operating cost, control stability, and response time. The potential of using rough set theory as an indispensable tool to aid in the rule extraction when designing the fuzzy controllers is emphasized in a three-stage integrated framework. It first identifies a representative state function, using an integrated

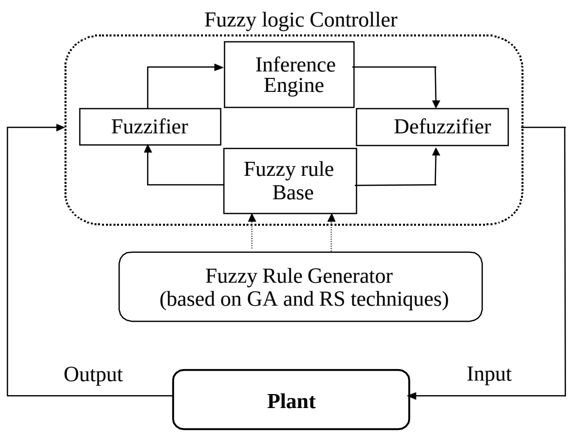

Fig. 1. The system configuration of RsFLC.

GA-NN algorithm that normally provides greater flexibility in representing the complexity of various process features. Then, based on the functionality of GA, the second-stage analysis is required using GA to search for a set of multi-objective control strategies for a particular controlled system that can be described using the previously identified state function as a surrogate to mimic the overall system behavior. Finally, recorded process data are utilized for tuning the hybrid neural-fuzzy controller with the aid of GA and RS techniques. This framework may help determine the most appropriate parameter values in these membership functions used in the fuzzy control rules. The implementation of such an advanced hybrid fuzzy controller was assessed using available knowledge about the industrial wastewater treatment process in this study via the following three-stage analysis.

3. Stage 1 analysis: identifying the state function of wastewater treatment system

One of the difficulties associated with the development of a better fuzzy control system is tied to the complexity of the system dynamics. In a highly nonlinear system, such as a biological wastewater treatment process, the state variables are so highly coupled that it is relatively difficult to decouple the system adequately and to implement control strategies easily. In order to improve the situation, Narendra and Parthasarathy [43] suggested using NN models for identification and control of dynamic systems. The first-stage analysis integrates the advantages of using both NN and GA techniques together to derive a representative state function for use in system control and simulation. The NN model is used to describe the features and behaviors of the state function, while GA is designed to optimize the structure of the NN model. To illustrate this idea, consider that a conventional nonlinear dynamic system can be expressed as

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = f(x(t), u(t), t), \tag{1}$$

$$y(t) = g(x(t), u(t), t) \tag{2}$$

in which $x(t)$ is the $n \times 1$ state vector of the system, $u(t)$ the $p \times 1$ vector of actuated signal, $y(t)$ the $q \times 1$ output vector of the system, f the nonlinear function for $\mathrm{d}x(t)/\mathrm{d}t$ and g the nonlinear function for $y(t)$.

The index t in the context stands for time. The above nonlinear dynamic system can be further discretized as

$$x(t+1) = f'(x(t), u(t), t), \tag{3}$$

$$y(t) = g'(x(t), u(t), t) \tag{4}$$

in which f' is the nonlinear function for $x(t+1)$ and g' the nonlinear function for $y(t)$.

Hence, when using the NN model to identify the discrete state function, the nonlinear dynamic system would become

$$x(t+1) = f'(x(t), x(t-1), \ldots, x(t-k), u(t), t), \tag{5}$$

$$y(t) = g'(x(t), x(t-1), \ldots, x(t-k), u(t), t) \tag{6}$$

in which the $x(t)$, $x(t-1)$, …, $x(t-k)$, and $u(t)$ represent those nodes in the input layer and $y(t)$ stands for the nodes in the output layer.

It is known that a typical NN model consists of three types of layers: input, hidden, and output layers. Each independent layer is comprised of several processing neurons. While input and output layers perform as boundary between the NN and the environment, the hidden layers and input/output layers may interconnect with each other through the information flow channels between the neurons. Each processing neuron is assumed to have a small amount of local memory and may convert inputs to the neuron outputs via the use of a selected transfer function. The most widely used NN model is based on the back-propagation neural network (BNN) approach. The BNN model learns the input–output relationship by making changes in its weights through the back-propagation approach. Assume that there are r input-output pairs (x, y) available for training the networks, the criterion used is to minimize the mean squared error, E (squared residual), which is defined as

$$E = \sum_{m=1}^{r} \sum_{k=1}^{p} (Y_k^{(m)} - O_k^{(m)})^2 \tag{7}$$

in which Y_k is recorded value of kth output variable in the NN model; O_k is the predicted value of kth output variable in the NN model; p is the number of output variables; and r is the number of experimental data sets.

The success of implementing an NN model depends on determining the optimal structure with respect to the number of hidden layers and the number of nodes in each layer. This must rely on the capability of global search in GA for deriving a representative state function based on an optimal NN model architecture. GA, introduced by Holland [44], is designed for a continuous evolutionary process via reproduction, crossover, mutation, in which the full BNN procedure is implemented for each newly modified member of the GA population to search for the optimal number of hidden layers and associated count of the node in each layer. The possible coding structures is that the number of node in each layer and the learning speed can be organized by binary code in a chromosome so as to be used in search of the optimal structure of NN model. Both the initial population in a GA procedure and initial weights in an NN model could be influential in the way to derive the state function.

4. Stage 2 analysis: searching for multi-objective control strategies

The primary control objectives for a complex non-linear process is to maintain its state trajectories in accordance with some desired target profile. Based on the observed database, a GA-based screening procedure in search of the multi-objective control strategies with respect to the well-trained state function that is generated by an NN model in stage 1 was derived [12]. Two objectives were considered in this analysis. One is to provide a desired level of control performance in achieving the effluent quality standards. The other is to minimize the operating cost of wastewater treatment. The optimization issues required to analyze in this stage are to determine what the optimal levels of all related control variables are when achieving those designated control goals in the controlled system. Overall, the optimal design of an advanced hybrid fuzzy controller in accordance with a set of multi-objective control strategies identified at this stage is anticipated by using a conventional fuzzy-neural control system.

5. Stage 3 analysis: tuning fuzzy control rule base

The major difficulty arising from the real-world application of fuzzy control systems is how to acquire an experts' knowledge in order to build the most representative fuzzy control rules and how to tune the parameters in the membership functions to be used in formulating the control rules by the most effective and efficient way. While it is desirable to design FLCs with a small number of rules, attention must be taken to select appropriate screening algorithms and to preserve important features and behavior of the system and relationships between state variables. A careful balance between the number of control rules and accurate representation of the coupling state variables in the system is required for achieving the design goals in an advanced hybrid fuzzy controller. Although there exist a variety of possibilities for integrating fuzzy systems with other AI paradigms in the way to design an advanced hybrid fuzzy controller, the integration between GA and RS techniques in order for deriving the most representative control rule base by the most effective and efficient way in a fuzzy control model could be more promising. Overall, this paper focuses on a new combination of two paradigms—the fuzzy sets theory and rough set theory—by such a way that they are arranged into a parallel fashion to form a revised fuzzy control mechanism. Based on the extraction of initial rule base by human expertise, the appropriate base and dispersion of membership functions in the antecedent and consequence parts can be properly identified by RS technique at the same time as the systematic aspects of the rule induction reaches its final status based on an effective GA search procedure. The well-tuned control rules therefore can be basically employed as a supervisor, implementing knowledge representation as well as reasoning functionalities. The following subsections illustrate such an idea.

A fuzzy model is determined by organic combination of linguistic variables and describing rule base in which the membership functions of linguistic variables are obtained by fuzzy partition of input and output variables. The algorithm for the parameter identification of those fuzzy control rules can be divided into three steps, consisting of choice of premise variables, premise parameters identification, and consequence parameters identification. In Takagi and Sugeno's model [29], a fuzzy control model consists of a series of implications that are defined in the following format in which the antecedent part is characterized by "and" connective and the consequence part is represented by a linear equation

$$
\begin{array}{lll}
R^1: & \text{If } x_1 \text{ is } A_1^1, \ldots\ldots \quad \ldots, & x_k \text{ is } A_k^1 \\
 & \text{then } y_1 \text{is } B_1^1, \ldots\ldots\ldots & y_k \text{ is } B_k^1 \\
 & \vdots & \vdots \\
 & \vdots & \vdots \\
 & \vdots & \vdots \\
R^n: & \text{If } x_1 \text{ is } A_1^n, \ldots\ldots \quad \ldots, & x_k \text{ is } A_k^n \\
 & \text{then } y_1 \text{is } B_1^n, \ldots\ldots\ldots & y_k \text{ is } B_k^n
\end{array} \tag{8}
$$

in which $x_1, \ldots, x_k$ are state variables defined by those membership functions $A_1^n, \ldots, A_k^n$ in the antecedent part and $y_1, \ldots, y_k$ are control variables defined by those membership functions $B_1^n, \ldots, B_k^n$ in the consequence part.

Since fuzzy partition of input and output variables implies formation of basic modeling space in a conventional fuzzy model, it is desirable to perform the partition in such a way that given data are distributed evenly in each partitioned space. But the accuracy and comprehensibility in deriving the rule base in fuzzy control could be further improved by rough set theory when considering the indiscernibility relation of the recorded data [45]. The rough set theory, proposed by Pawlak [37], has an ability to express the consistency between condition and decision attributes of data by numerical values. Nowadays, the rough set theory has been used at different stages of the process of rule induction and data preprocessing [41]. This paper particularly explores the potential of rule base extraction based on such a fact that the same premises might have different consequent values implying that the inconsistency of assigned linguistic variables could be influential. Following this observation, Fig. 2 describes the logics in the derivation of a fuzzy control rule base and shows that how can the rule base be fitted into the tuning architecture.

To ease the application, the use of rough set theory to improve the extraction of control rule base may follow those steps as below:

1. Create a set of random attributes to divide the universe of state variables and control variables;
2. create the next generation of chromosomes by using crossover and mutation operators;
3. reduce the information system vertically and horizontally;
4. generate partitions and classifications;
5. generate lower and upper approximation spaces;
6. extract local rules;
7. perform fuzzy reasoning;
8. calculate the fitness value of each rule for overall justification; and
9. go to step 2 if not satisfied; otherwise stop the iteration.

6. Case study

6.1. Process description

An industrial wastewater treatment plant, responsible for handling the effluent from a petrochemical production process in South Taiwan, was selected as a typical example for the purpose of illustration. Three types of wastewater inflows were characterized in the initial design of this wastewater treatment system. Domestic wastewater collected from the dormitory within the plant, laboratory discharges, production line, and terephthalic acid residuals constitute the first stream of wastewater. The effluents collected from the areas of coal and liquid storage sites are denoted as the second stream of wastewater. The third stream of wastewater mainly consists of the blow-down from boiler and cooling tower operation. These three wastewater streams, generated in either a batch or continuous mode, are analyzed separately using both qualitative

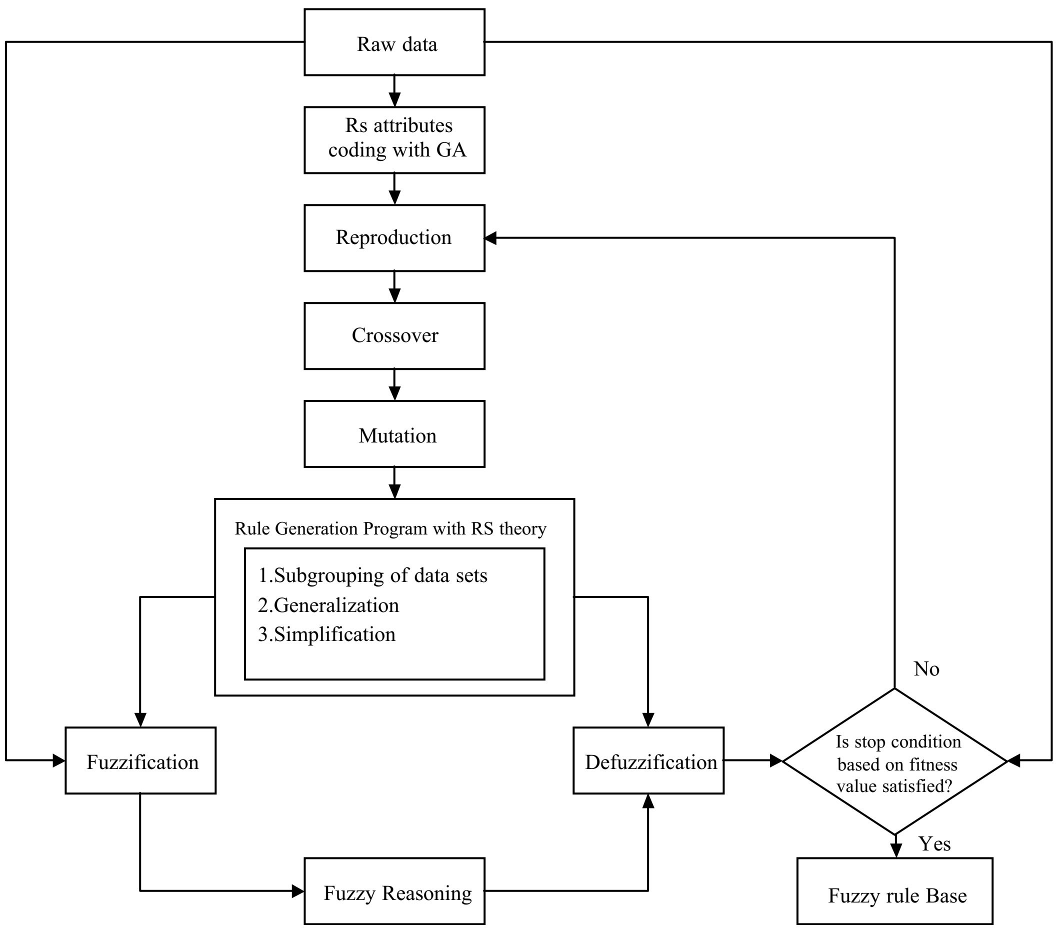

Fig. 2. The analytical procedure of RsFLC rule base.

and quantitative parameters, as listed in Table 1. Fig. 3 shows the schematic of the wastewater treatment system, which is a biologically hybrid system using both anaerobic and aerobic processes simultaneously. The anaerobic reactors are responsible for achieving acid-ogenesis and methanogenesis processes, while the sequencing batch reactors (SBR) are designed for handling the effluent from the anaerobic reactors and removing the organic compounds with lower molecular weight. Two equalization basins are designed prior to the SBR operation to adjust levels of required nutrients, such as phosphorous and nitrogen compounds, in the aerobic biological process. The buffer basin, where pH adjustment is made, receives and stores the inflows from all the three different wastewater streams. A weir at the end of the equalization basin controls the overflow rate for the entire anaerobic and aerobic treatment process. The measurement devices for monitoring and control are denoted by a series of square boxes marked closely to each unit operation in Fig. 3. These devices are linked to the treatment processes via a distributed control system. In fact, the overflow rate from the weir installed at the end of equalization tank dominates the magnitude of flow rate destined for subsequent anaerobic and aerobic treatment processes. They are of significance in system identification.

Unfortunately, there is no any observation regarding the aeration condition, such as the dissolved oxygen meter (DO), or the oxidation reduction probe, and the air flow rate supplied by a blower, that makes further control actions become intractable. To ease the situation, an alternative method using the electricity consumption rate as a surrogate index of DO level in the SBR process is applied to assist in the control practice in this analysis. However, the information of cost data in relation to chemical oxygen demand (COD) removal is available so that economic consideration can be included as one of control goals and factored into the optimal control scheme. Overall, while COD and suspended solids (SS) are selected as two indices in response to the effluent quality, electricity consumed in the treatment process is selected as a surrogate index of operational cost.

Table 1
The design characteristics of wastewater inflows

Source and quality of the wastewater streams	Parameter value
The first wastewater stream	
Quantity (m^3/d)	5280 (maximum value)
COD (mg/L)	15100 (maximum value)
SS (mg/L)	500
Acetic acid (mg/L)	1103
Benzoic acid (mg/L)	1058–1587
Paratoluic acid (mg/L)	1587–2116
Terephthalic acid (mg/L)	952
Temperature (°C)	37
pH	4.5–12.5
The second wastewater stream	
Quantity (m^3/h)	5760 (maximum value)
COD (mg/L)	ND
SS (mg/L)	450 (maximum value)
Cu (mg/L)	2
Zn (mg/L)	7
Fe (mg/L)	31
Temperature (°C)	30
pH	7–9
The third wastewater stream	
Quantity (m^3/h)	1992 (maximum value)
COD (mg/L)	25 (maximum value)
SS (mg/L)	ND
pH	3–8

6.2. Control framework

In general, the identification of state and control variable is very important in designing a controller since it is closely related to the inherent nature of treatment plant itself. Table 2 summarizes the information of state and control variables in which five state variables (HAC, BA, Ptol, TA, and TOC) and seven control variables (pH, effluent flow rate, TP, TN, and electricity required for aeration) are identified mainly based on the domain knowledge and measurement capacity in this plant. Fig. 4 illustrates the hybrid fuzzy control architecture in which the state function is derived based on a GA-based NN model in stage 1. To account for the time-lag effect, such a NN model distinguishes itself based on at least one feedback loop. The given conditions that cover a set of typical measurements at the location of equalization tank in 1997 include HAC (560 mg/L), BA (380 mg/L), Ptol (400 mg/L), TA (560 mg/L), and TOC (1510 mg/L), which are prepared particularly for this modeling analysis. This would help derive the multi-objective control strategy in stage 2 with the aid of GA. The control goals consist of the environmental concerns of COD and SS removal and the economic consideration with respect to operational cost. Based on such findings of multi-objective control strategy, overall fitting of the neural-fuzzy controller using both GA and RS as an integrated tool may become achievable in stage 3. Combining all the efforts within three stages would help build the advanced hybrid neural-fuzzy controller for wastewater treatment. In terms of data management, two groups of process data are separately prepared for the following case study. One is for the three-stage analysis, while the other is for simulation analysis.

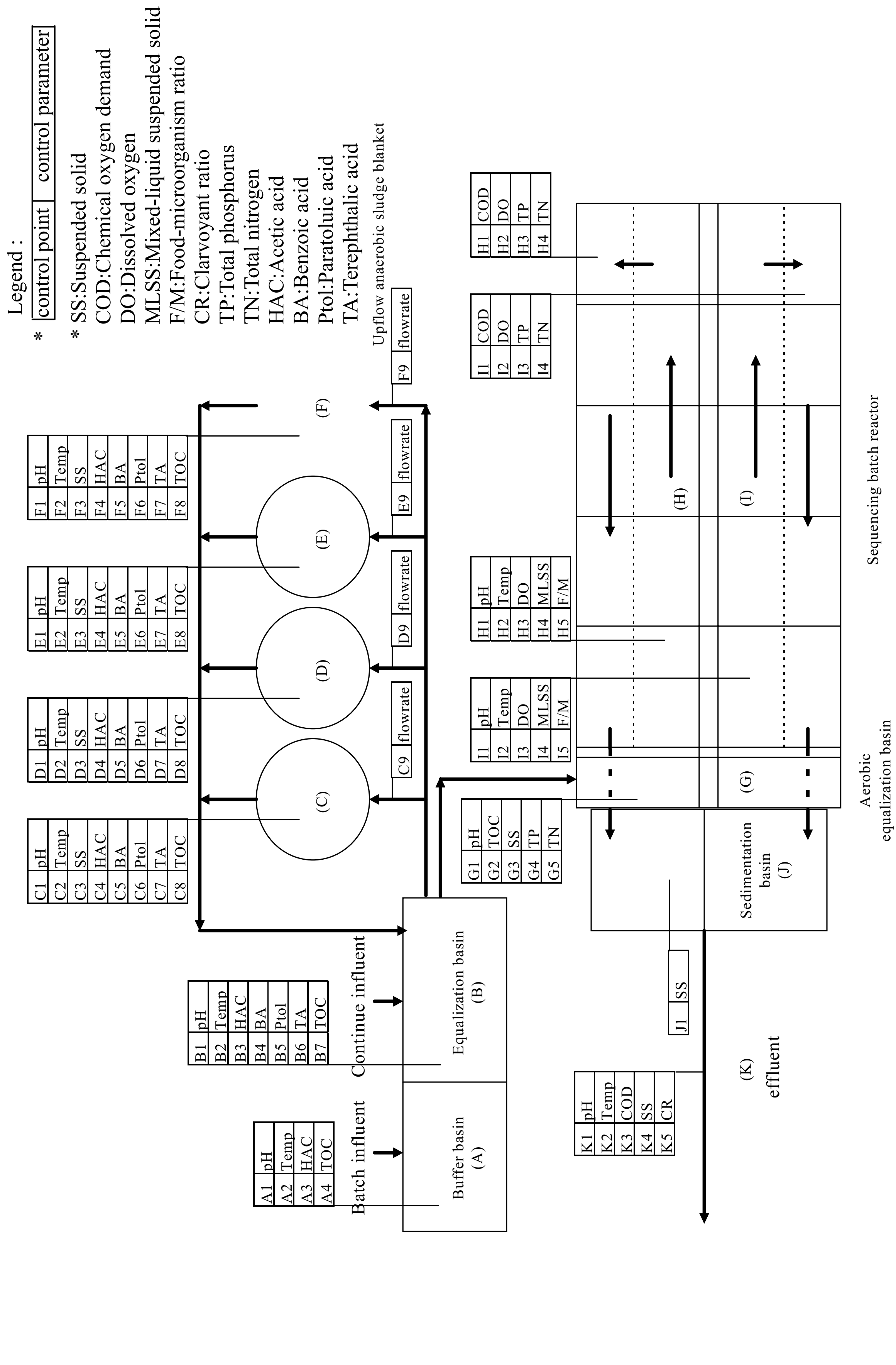

Fig. 3. Schematic of wastewater treatment process.

7. Results and discussions

7.1. The first-stage analysis

In the proposed NN model, the COD and SS in the wastewater inflow as well as the corresponding operational cost can be arranged as the input vector while the output vector is addressed by the effluent quality of COD and SS. A continuously differentiable nonlinear activation function commonly used in multiplayer perceptrons is the sigmoid function. This analysis retains this focus. To search for the optimal structure of the NN model with the aid of GA, the number of chromosomes in the initial pool is 70. An initial run without including GA functionality is applied for the determination of the initial weight of an NN model. This run is achieved based on an NN model that is designed for having only two hidden layers, using the values of learning time of 10,000, learning speed of 0.3875, and momentum factor of 0.2 as the basic settings. Finally, using the mutation rate of 0.1 and the reproduction rate of 0.7 would make the evolutionary process converges within 100 generations. The use of GA appears to be able to generate the smallest mean square errors when comparing with three other subjectively determined NN structures. It also suggests that the behavior of such a biological wastewater treatment process can be fully identified and represented by such a GA-based NN model with a structure of eight hidden layers in which each layer is comprised of nine nodes.

Table 2
The definitions of parameters for modeling analysis

Parameters	Definition
Control variables	
pH at B1	The pH value at B1
pH at H1	The pH value at H1
pH at I1	The pH value at I1
TP	Total phosphorous (mg/L)
TN	Total nitrogen (mg/L)
TFR	The flow rate of treatment effluent (m^3/d)
EL	The amount of electricity consumption (kW h/d)
State variables	
HAC	Acetic acid at equalization basin (mg/L)
BA	Benzoic acid at equalization basin (mg/L)
Ptol	Paratoluic acid at equalization basin (mg/L)
TA	Terephthalic acid at equalization basin (mg/L)
TOC	Total organic carbon at equalization basin (mg/L)
Control goals	
COD	COD in the effluent (mg/L)
SS	SS in the effluent (mg/L)
cost	Partial operatingcost (NT$/ton COD removal)

The currency ratio is 27.5NT$/1 US$ in 1996.

7.2. The second-stage analysis

The integrated GA-NN algorithm further helps generate a set of multi-objective control strategies in terms of seven selected control variables. At this moment, GA may perform a quick search in the decision domain using the derived or well-trained state function (i.e., the GA-based NN model) as a black box for the prediction of optimal system response. To comply with the required effluent standards (e.g. COD 50 mg/L and SS 10 mg/L), the essential multi-objective control strategies for the case selected provide a set of systematic information regarding pH at B1 (5.6), pH at H1 (7.9), pH at I1 (8.6), effluent flow rate (4,124 m^3/d), TP (45.7 mg/L), TN (255.0 mg/L), electricity (9544.0 kW-h/d), COD (39.8 mg/L), SS (4.6 mg/L), and operational cost (1513.0 NT$/ton COD). It unambiguously implies that the anticipated levels of COD and SS along with the associated costs for COD removal can be foreseen once the suggested control level for the seven selected control variables can be maintained for handling the given condition of inflow quality. The outputs in the evolutionary process of GA indicate that it generally would take about 500 generations of chromosomes' evolution to reach a convergence level.

7.3. The third-stage analysis

Defining fuzzy membership functions has long been recognized as the most time consuming and challenging aspect of fuzzy controller design. GA and RS techniques have their individual potential to be used to generate the fuzzy rules and associated fuzzy set parameters at the same time [39,40,32]. With taking advantage of the optimization capabilities of GA, discovering regularities in the recorded data in relation to linguistic variables is

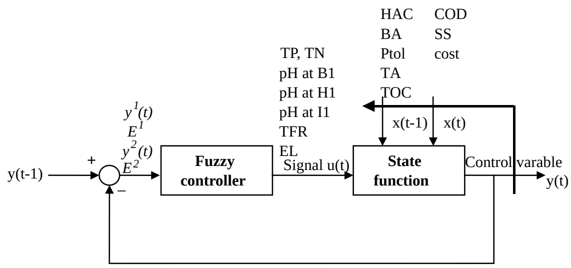

Fig. 4. Control architecture proposed for the industrial wastewater treatment plant.

then achievable when tackling imprecise and inconsistent information. The coding structure of chromosomes in the initial GA pool requires that all the attributes of measured variables have to be expressed integratively by a set of binary codes. The maximum attribute number, initial population of chromosome, maximum generation number, crossover rate, and mutation rate are 9, 70, 1000, 0.7, and 0.1, respectively. Such a hybrid rule induction system eventually leads to an autogeneration of rule base with 29 control rules in the context of rough sets. Fig. 5 depicts the convergence through the global search via the use of genetic algorithms in the way to help RS perform autotuning of rule base. Convergence would reach an acceptable point after 200 generations. The rule clauses derived in this study as indicated in Table 3 may become illustrative when taking the attributes gained and presented as those in Table 4 into account as a whole. Those ranges would reflect the optimal choice of base of fuzzy membership functions in both antecedence and consequence parts in fuzzy control rules being made by the integrated capability of GA and RS. Findings indicate that the individual influence of TP, TN, Ptol and TA are not phenomenal since substitution effects provided by other variables are apparent.

7.4. Simulation analysis

Comparative study is made in terms of the performance in between SFLC and RsFLC based on the same state function and multi-objective control strategies. The second group of process data is used for simulation runs in both cases of RsFLC and SFLC; and the inflow condition remains the same as the given conditions above that cover a set of typical measurements at the location of equalization tank in 1997 include HAC (560 mg/L), BA (380 mg/L), Ptol (400 mg/L), TA (560 mg/L), and TOC (1510 mg/L). Twenty-nine fuzzy control rules derived in the third stage using GA and RS techniques as an integrated tool are applied as the new fuzzy control rule base that would be able to provide a powerful inference engine in the fuzzy control practice. Based on the control performance over a period of time, observations confirm that RsFLC may exhibit comparative advantages over SFLC. Comparative statistics, as listed in Table 5, further verify that higher stability and lower operational cost with less response time can be achieved on an average basis via the use of RsFLC.

Overall, all outputs behave as would be expected in terms of satisfying three control goals simultaneously. The Takagi–Sugeno model, in which the output variables of each rule (i.e., fuzzy partition space) are expressed by a linear combination of input variables [29], has its merit in describing a general nonlinear system. But it is not the case when the problems become highly complex. The rough set theory, proposed by Pawlak [37], has an ability to express the consistency between condition and decision attributes of data by numerical values even when the problem is highly complex. The findings in this paper conclude that the use of rough set theory to aid in the neural-fuzzy controller can produce relatively better plant performance in terms of operational cost, control stability, and response time simultaneously than the others at least for wastewater treatment. Such a methodology is anticipated to be capable of dealing with many other types of process control problems in waste treatment processes by making only minor modifications.

8. Conclusions

The hybrid fuzzy controller designed in this analysis brings the spirit of human thinking and reasoning into a neural network structure that help derive the representative state function for use in simulating system behavior. With the global search capability of genetic algorithms, it finally present the advantages of using the

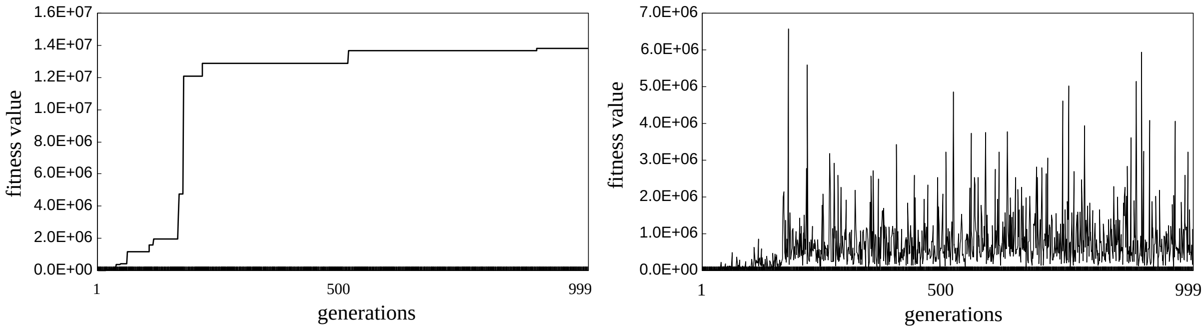

Fig. 5. Evolutionary process of GAs in simulation run.

Table 3
The derived fuzzy rule table based on GA and rough set theory

Rule no.	State variables					Control variables						
	a	b	c	d	e	f	g	h	i	j	k	l
1	4	3	—	—	6	2	1	2	3	3	—	—
2	5	3	—	—	6	4	2	3	7	6	—	—
3	4	3	—	—	4	3	2	4	6	2	—	—
4	3	3	—	—	4	2	1	2	3	3	—	—
5	5	3	—	—	7	3	2	4	6	2	—	—
6	4	3	—	—	5	3	3	3	6	5	—	—
7	5	3	—	—	4	2	2	3	5	5	—	—
8	3	3	—	—	6	2	3	3	7	5	—	—
9	2	2	—	—	4	2	2	3	3	5	—	—
10	4	3	—	—	3	3	2	4	6	2	—	—
11	2	3	—	—	3	2	1	2	3	3	—	—
12	5	3	—	—	5	4	2	3	7	6	—	—
13	2	3	—	—	5	4	2	4	7	5	—	—
14	2	2	—	—	2	4	3	1	2	3	—	—
15	4	2	—	—	5	3	3	4	5	4	—	—
16	2	3	—	—	4	2	2	3	3	5	—	—
17	3	3	—	—	5	2	3	3	7	5	—	—
18	2	2	—	—	5	4	2	3	7	6	—	—
19	3	3	—	—	3	3	2	4	6	2	—	—
20	2	3	—	—	2	4	2	3	7	6	—	—
21	5	2	—	—	5	2	2	1	4	6	—	—
22	2	2	—	—	3	2	1	3	4	2	—	—
23	4	2	—	—	6	2	1	3	4	2	—	—
24	2	2	—	—	6	2	2	3	5	6	—	—
25	1	3	—	—	3	3	2	4	6	2	—	—
26	4	2	—	—	7	2	3	3	6	6	—	—
27	1	3	—	—	2	4	2	3	7	6	—	—
28	4	2	—	—	3	2	2	3	5	5	—	—
29	5	2	—	—	3	4	3	1	2	3	—	—

Note: a—Acetic acid at equalization basin (mg/L).
b—Benzoic acid at equalization basin (mg/L).
c—Paratoluic acid at equalization basin (mg/L).
d—Terephthalic acid at equalization basin (mg/L).
e—Total organic carbon at equalization basin (mg/L).
f—The pH value at B1.
g—The pH value at H1.
h—The pH value at I1.
i—The flow rate of treatment effluent (m^3/d).
j—The amount of electricity consumption (kW h/d).
k—Total phosphorus.
l—Total nitrogen.

rough sets theory to help save the rule-matching time of the inference engine and screen out the essential rule base in a neural-fuzzy control system. Such an advanced hybrid fuzzy control approach effectively achieves the required real-time control objectives and may become an efficient and cost-effective tool to deal with the unexpected uncertainties in the wastewater treatment process. Based on a series of computer simulation runs, results are provided demonstrating the control performance of the hybrid fuzzy controller in terms of environmental and economic objectives simultaneously. Such an advanced hybrid fuzzy control system may provide immediate guidance and control with respect to multi-objective requirements for distributed control system using on-line process data. It is believed that the control architecture that has been developed in this paper may even function well within limited of time for various types of physical, chemical, and biological waste treatment systems when coping with on-line upset conditions.

Table 4
The attribute domains of measured variables

Attribute	*a*	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*
1	152–916	126–422	107–303	317–1060	690–1423	6–6.5	5.8–6.9	6.1–6.8	3543–4129	7390–9765
2	916–1680	422–717	303–500	1060–1803	1423–2156	6.5–7	6.9–7.9	6.8–7.4	4129–4716	9765–12221
3	1680–2444	717–1013	500–696	1803–2546	2156–2889	7–7.5	7.9–9	7.4–8.1	4716–5302	12221–14677
4	2444–3208		696–892		2889–3621	7.5–8		8.1–8.7	5302–5889	14677–17132
5	3208–3972	—	—	—	3621–4354	—	—	—	5889–6475	17132–19588
6	—	—	—	—	4354–5087	—	—	—	6475–7062	19588–22044
7	—	—	—	—	5087–5820	—	—	—	7062–7648	22044–24500

Table 5
The statistics of control performance

(a)

Performance	SFLC		RsFLC	
	Average	Standard deviation	Average	Standard deviation
Control stability				
COD in effluent (mg/L)	41.49	2.55	41.33	2.45
SS in effluent (mg/L)	7.36	0.82	7.23	0.78
Operational cost (NT$/ton)[a]	1545.68	187.88	1526.88	187.88

(b)

Performance	SFLC			RsFLC		
	COD[b]	SS[c]	OC[d]	COD[b]	SS[c]	OC[d]
Response Time (h)	16	7	17	9	8	13

[a] The currency ratio is 27.5NT$/1 US$ in 1996.
[b] COD in effluent.
[c] SS in effluent.
[d] Operational cost.

References

[1] Busby JB, Andrews JF. Dynamic modeling and control strategies for the activated sludge process. J Water Pollut Control Fed 1975;47(5):1055–65.

[2] Cashion BS, Keinath TM, Schuk WW. Control strategies for the activated sludge process. J Pollut Control Fed 1975;51(4):815–23.

[3] Hiraoka M, Tsumura K. An approach to the control of the activated sludge system by use of a succession model. Water Sci Technol 1989;13:327–32.

[4] Hughey PW, Meredith DD, Middleton AC. Algorithm for optimal activated sludge operation. J Environ Eng 1982;108(2):349–63.

[5] Hiraoka M, Tsumura K. System identification and control of the activated sludge process by use of a statistical model. Water Sci Technol 1989;21:1161–72.

[6] Kabouris JC, Georgakakos AP, Camara A. Optimal control of the activated sludge process: effect of sludge storage. Water Res 1990;26(4):507–17.

[7] Lech RF, Grady CP, Lim HC, Koppel LB. Automatic control of the activated sludge process: efficiency of control strategies. Water Res 1978;12:91–110.

[8] Novotny V. Real time control of wastewater treatment plant operations. Water Sci Technol 1992;125(4):89–101.

[9] Ossenbruggen PJ, Constantine K, Collin MR, Bishop PL. Toward optimum control of the activated sludge process with reliability analysis. Civ Eng Syst 1987;4:27–44.

[10] Stenstrom MK, Andrews JF. Real time control of activated sludge process. J Environ Eng 1979;105(2):245–56.

[11] Naci H, Michael O, Stenstrom K. KBES for process control of nitrification in activated sludge process. J Environ Eng ASCE 1994;120(1):87–107.

[12] Chang NB, Chen WC. Fuzzy controller design for municipal incinerators with the aid of genetic algorithms and genetic programming techniques. Waste Manage Res 1999;18(5):429–43.

[13] Chang NB, Chen WC, Shieh WK. Optimal control of wastewater treatment plants via integrated neural network and genetic algorithms. Civ Eng Environ Syst 2001;18:1–17.

[14] Chen WC, Chang NB, Shieh WK. Advanced hybrid fuzzy controller for industrial wastewater treatment. J Environ Eng ASCE 2001;127(11):1048–59.

[15] Tong RM, Beck MB, Latten A. Fuzzy control of the activated sludge wastewater treatment process. Automatica 1980;16:659–701.

[16] Czogala E, Rawilk T. Modeling of a fuzzy controller with application to the control of biological process. Fuzzy Sets and Systems 1989;31:13–22.

[17] Fu CS, Poch M. Fuzzy model and decision of COD control for an activated sludge process. Fuzzy Sets and Systems 1998;41:281–92.

[18] Fu CS, Poch M. Fuzzy modeling pattern recognition for dynamic process and its application for an activated sludge process. Chem Eng Sci 1995;50(23):3715–25.

[19] Tsai YP, Ouyang CF, Chiang WL, Wu MY. Construction of an on-line fuzzy controller for the dynamic activated sludge process. Water Res 1994;28(4):913–21.

[20] Tsai YP, Ouyang CF, Wu MY, Chiang WL. Effluent suspended solid control of activated sludge process by fuzzy control approach. Water Environ Res 1996;68(6):1045–53.

[21] Watanabe S, Baba K, Yoda M, Wu WC, Enbutsu I, Hiraoka M, Tsumura K. Intelligent operation support system for activated sludge process. Water Sci Technol 1993;128(11):325–32.

[22] Yi C, Cao Z, Kandel A. Application of fuzzy reasoning to the control of an activated sludge plant. Fuzzy Sets and Systems 1990;38:1–14.

[23] Boscolo A, Mangiavacchi C, Drius F, Rongione F, Pavan F, Cecchi F. Fuzzy control of an anaerobic digester for the treatment of the organic fraction of the MSW. Water Sci Technol 1993;27(2):57–68.

[24] Lin CT, Lee CSG. Neural-network-based fuzzy logic control and decision system. IEEE Trans Comput 1991;40(12):1320–36.

[25] Spall JC, Cristion JA. A neural network controller for systems with unmodeled dynamics with applications to wastewater treatment. IEEE Trans Syst, Man Cybern-Part B: Cybernetics 1997;27(3):369–75.

[26] Lee DS, Park JM. Neural network modeling for on-line estimation of nutrient dynamics in a sequentially operated batch reactor. J Biotechnol 1999;75:229–39.

[27] Chen JC, Chang NB, Shieh WK. Assessing wastewater reclamation potential by neural networks model. Eng Appl Artif Intell, 2001, in press.

[28] Delgado M, Gomez AF, Martin F. A fuzzy clustering-based rapid prototyping for fuzzy rule-based modeling. IEEE Trans Fuzzy Syst 1997;5(2):223–33.

[29] Takagi T, Sugeno M. Fuzzy identification of systems and its application to modeling and control. IEEE Trans Syst, Man, Cybern 1985;15(1):116–32.

[30] Enbutsu I, Baba K, Hara N, Waseda K, Nogita S. Integration of multi AI paradigms for intelligent operation support systems-fuzzy rule extraction from a neural network. Water Sci Technol 1993;28(11/12):333–40.

[31] Chen WC, Chang NB, Shieh WK. A hybrid fuzzy control scheme for municipal wastewater treatment using neural networks and genetic algorithms. Water Environ Res, 2001, in review.

[32] Ishibuchi H, Nozaki K, Yamamoto N. Selecting fuzzy rules by genetic algorithm for classification problem. Proceedings of the Second IEEE International Conference on Fuzzy Systems, San Francisco, 1993. p. 1119–24.

[33] Culevski N. Artificial neural networks and genetic algorithms: computational models. Ph.D. thesis. California State University, Long Beach, 1996.

[34] Maclennan GA. The application of genetic algorithms to neural networks. MS thesis. Dalhousie University, Canada, 1994.

[35] Sandhu SS. Training of feedforward neural networks with quardratic random optimization and genetic algorithms. MS thesis. University of Nevada at Reno, USA, 1995.

[36] Williams V. Evolutionary neural networks: models and applications. Ph.D. thesis. Aston University, United Kingdom, 1996.

[37] Pawlak Z. Rough sets. Int J Comput Inform Sci 1982; 11:341–56.

[38] Zadeh LA. Fuzzy Sets, Inform Control 1965;8:338–53.

[39] Cho Y, Lee K, Yoo J, Park M. Autogeneration of fuzzy rules and membership functions for fuzzy modelling using rough set theory. Control Theory Appl, IEE Proc 1998;145(5):437–42.

[40] Hong TP, Wang TT, Wang SL, Chien BC. Learning a coverage set of maximally general fuzzy rules by rough sets. Expert Syst Appl 2000;19(2):97–103.

[41] Felix R, Ushio T. Rule induction from inconsistent and incomplete data using rough sets. IEEE Syst, Man, Cybern, SMC '99 Conf Proc 1999;5:154–8.

[42] Jagielska I, Matthews C, Whitfort T. An investigation into the application of neural networks, fuzzy logic, genetic algorithms, and rough sets to automated knowledge acquisition for classification problems. Neurocomputing 1999;24(1–3):37–54.

[43] Narendra KS, Parthasarathy K. Identification and control of dynamical systems using neural networks. IEEE Trans Neural Networks 1990;1:4–27.

[44] Holland JH. Adaptation in natural and artificial systems. Ann Arbor, MI: University of Michigan, 1975. p. 183.

[45] Czogala E, Mrozek A, Pawlak Z. The idea of rough-fuzzy controller. Fuzzy Sets and Systems 1995;72:61–3.