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A Quick Review on Applications of Fuzzy Logic in Waste Water Treatment

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Abstract--Fuzzy controllers were used in all processing steps of wastewater treatment. It was also observed that the fuzzy controllers provide very good results in various operating conditions. Depends on the process sensitivity the direct control methods may have lot of failures, but the application of fuzzy logic in waste water treatment become very important in recent scenario. Keeping this in mind the quick review on the fuzzy logic applications in wastewater treatment is necessary to understand the wide variety of uses. Many uncertain factors may affect the operation of Wastewater Treatment process, due to the complexity of wastewater treatment processes, classical methods showed significant difficulties when trying to control them automatically. Consequently soft computing techniques and, specifically, fuzzy logic appears to be a good idea for controlling these ill-defined, time-varying and non-linear systems. Hence the understanding of application of fuzzy logic becomes a need of the hour.

Key words: Fuzzy logic, wastewater treatment, soft computing techniques.

I. INTRODUCTION

In modeling of complex environmental problems, researchers often fail to make precise statements about inputs and outcomes, but fuzzy logic could be applied to the development of environment indices in a manner that solves several common problems, including the incompatibility of observations and the need for implicit value judgements. Nowadays environmental protection and water quality management has become an important issue in public policies throughout the world. More than that government is concerned about the quality of their environmental resources because of the complexity in water quality data sets. The application of sophisticated technical systems in wastewater treatment systems represents a suitable basis for further application of new scientific and technological achievements in order to increase the energy efficiency of the system [1]. Many uncertain factors affect the operation of wastewater treatment plants. These include the physical and chemical properties of wastewater streams as well as the degradation mechanisms exhibited by biological processes. Because of the rising concerns about environmental and economic impacts, improved process control algorithms, using artificial intelligence technologies, have received wide attention. 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, and neural networks, may provide improved control of effluent quality [2]. Fuzzy logic is a powerful methodology for solving problems with many applications in control and information processing. The use of a fuzzy controller has significantly changed the approach to control problems. Conventional controllers adjust the control sizes of the system based on a set of differential equations that represent a model of a dynamic system. In fuzzy controllers, the control values are obtained on the basis of fuzzy rules, which are similar to the model of human reasoning. Treatment efficiency in wastewater treatment systems under dynamic loading conditions is a challenging task. Because the operation of a wastewater treatment process is intimately linked with wastewater sources, chemical composition, flow rate, biological process conditions, and recycle rate of the settled sludge, process control could be a valuable tool to minimize both environmental and economic impacts. Previous experience in designing conventional controller architectures for wastewater treatment processes was mainly a trial-and-error process that employed 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 and the compliance with effluent quality standards would become problematic [3]. This paper presents a quick review on the various applications of fuzzy logic in wastewater treatment.

II. FUZZY LOGIC IN ENVIRONMENTAL SCIENCE

Over the last few decades, soft computing tools such fuzzy logic based methods, neural networks, and genetic algorithms have had

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

significant and growing impacts. But we have seen only limited use of these methods in environmental fields such as risk assessment, cost-benefit analysis, and life-cycle impact assessment. Because fuzzy methods offer both new opportunities and unforeseen problems relative to current methods, it is difficult to determine how much impact such methods will have on environmental policies in the coming decades. Here we consider some obvious advantages and limitations. Quantitative models with explicit and crisp delineations of systems have long been the currency of discourse in engineering and the physical sciences, where basic physical laws form the foundations of analyses [4]. These fields place high value on the causal linkages implicit in model structure and parameterization. But problems that involve human values, language, control theory, biology, and even environmental systems have had to rely more on descriptive and empirical approaches. In these latter fields our goal is often to summarize the observations in an efficient and useful manner. For these important areas of science and health, fuzzy logic based methods should be further investigated as alternative and perhaps more appropriate methods to confront uncertain and complex systems. For the types of complex and imprecise problems that arise in environmental policy, the ability to model complex behaviors as a collection of simple if-then rules makes fuzzy logic an appropriate modeling tool. Because fuzzy arithmetic works well for addressing linguistic variables and poorly characterized parameters, fuzzy methods offer the opportunity to evaluate and communicate assessments based in linguistic Terms that could possibly match those of the public and decision makers. Moreover approximate reasoning methods such as fuzzy arithmetic do not require well characterized statistical distributions as inputs. Another key advantage of fuzzy logic in risk assessment is the ability to merge multiple objectives with different values and meaning, for example combining health objectives with esthetic objectives. It also provides rules for combining qualitative with quantitative objectives. But we must recognize and confront the potential limitations of fuzzy logic for expressing health risk and other environmental impacts. One problem is the strong reliance on subjective inputs. Although this is a problem in any type of impact assessment, fuzzy methods might provide more opportunity to abuse the use of subjective inputs. Moreover, although well suited to addressing uncertainty (lack of knowledge), some argue that for addressing variability (heterogeneity) fuzzy logic has not been shown as superior to standard statistical descriptions. Ferson and Tucker have noted that that, because it can fail to capture the value range of complex data sets and the correlations among parameters, fuzzy arithmetic may not be appropriate for Routine use in risk assessments concerned primarily with variability. However, Ozbek and Pinder have addressed both variability and uncertainty in a fuzzy logic approach to the risk equations in a groundwater remediation problem. They use statements and preferences of practicing toxicologists to construct fuzzy rules and relate these rules to relate a pattern of exposure of benzene to its carcinogenic effects. Rules describing individual susceptibility address parameters typically represented by variability in other risk assessments. The rules constrain the risk model in a way that preserves inter individual differences. Although probabilistic assessments based on tools such as Monte Carlo are analogous to assessments based on fuzzy logic, these two methods differ significantly both in approach and interpretation of results. One key advantage of fuzzy logic over Monte Carlo methods is the ability to confront linguistic variables (safe, unsafe, Acceptable, unacceptable). With Monte Carlo methods, we must often force continuous distributions to fit linguistic variables for probabilistic assessments. Fuzzy arithmetic combines outcomes from different sets in a way that is analogous to but different from Monte Carlo methods [5]. Possibility theory can be used as an alternative to probabilistic analysis, but this creates the potential for interpreting membership functions as probability distributions.

III. COMPARISON OF FUZZY LOGIC TO PROBABILITY

Fuzzy logic and probability address different forms of uncertainty. While both fuzzy logic and probability theory can represent degrees of certain kinds of subjective belief, fuzzy set theory uses the concept of fuzzy set membership, i.e., *how much* a variable is in a set (there is not necessarily any uncertainty about this degree), and probability theory uses the concept of subjective probability, i.e., *how probable* is it that a variable is in a set (it either entirely is or entirely is not in the set in reality, but there is uncertainty around whether it is or is not). The technical consequence of this distinction is that fuzzy set theory relaxes the axioms of classical probability, which are themselves derived from adding uncertainty, but not degree, to the crisp true/false distinctions of classical Aristotelian logic. Lotfi A. Zadeh argues that fuzzy logic is different in character from probability, and is not a replacement for it. He fuzzified probability to fuzzy probability and also generalized it to possibility theory [6]. More generally, fuzzy logic is one of many different extensions to classical logic intended to deal with issues of uncertainty outside of the scope of classical logic, the inapplicability of probability theory in many domains, and the paradoxes of Dempster-Shafer theory.

IV. FUZZY CONTROLLERS

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Fuzzy controllers are very simple conceptually. They consist of an input stage, a processing stage, and an output stage. The input stage maps sensor or other inputs, such as switches, thumbwheels, and so on, to the appropriate membership functions and truth values. The processing stage invokes each appropriate rule and generates a result for each, then combines the results of the rules. Finally, the output stage converts the combined result back into a specific control output value [7]. The most common shape of membership functions is triangular, although trapezoidal and bell curves are also used, but the shape is generally less important than the number of curves and their placement. From three to seven curves are generally appropriate to cover the required range of an input value, or the "universe of discourse" in fuzzy jargon. As discussed earlier, the processing stage is based on a collection of logic rules in the form of IF-THEN statements, where the IF part is called the "antecedent" and the THEN part is called the "consequent". Typical fuzzy control systems have dozens of rules [8]. Fuzzy control system design is based on empirical methods, basically a methodical approach to trial-and-error. The general process is as follows:

Document the system's operational specifications and inputs and outputs.

Document the fuzzy sets for the inputs.

Document the rule set.

Determine the defuzzification method.

Run through test suite to validate system, adjust details as required.

Complete document and release to production.

Consider implementing with a microcontroller chip a simple feedback controller in Figure 1:

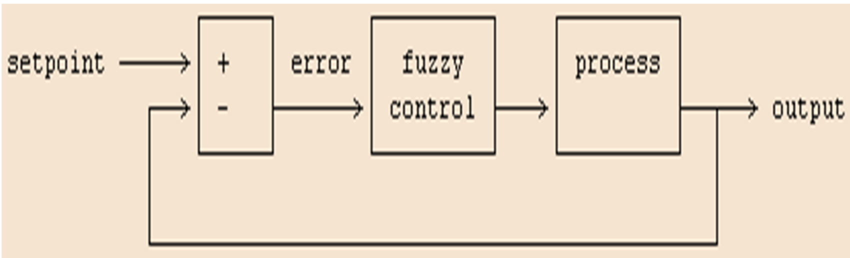

Figure 1. Feedback controller

A fuzzy set is defined for the input error variable "e", and the derived change in error, "delta", as well as the "output", as follows:
LP: large positive, SP: small positive, ZE: zero, SN: small negative, LN: large negative

V. APPLICATIONS OF FUZZY LOGIC

An activated sludge plant in Avedore, Denmark, was modelled using Matlab/Simulink and control strategies were tested with the calibrated model. A modified activated sludge model No. 2d (ASM2d) was used for modelling the activated sludge tanks and a reactive settler model for modelling the secondary clarifiers. Also online recordings of all the direct and indirect control handles were used as model inputs for calibration purposes. 30 days of control inputs preceding the measurement campaign were applied to obtain proper initial conditions for the plant simulation states [9]. Rodríguez presented a wastewater treatment modelling methodology based on Excel and Matlab Simulink for researchers without programming expertise. The proposed framework also provides programming expert researchers a highly flexible and modifiable platform on which to base more complex process model implementations. The use of Excel interface for most of the implementation tasks makes the methodology accessible for non-programming researchers by providing them with clear overview of the models in a spreadsheet file; in the same way, it shortens time and effort necessary to implement and modify model structures also for researchers with programming expertise. Most of the information defining the model, its parameters and a feeding schedule are provided using just an Excel interface. Only the equations to calculate the rates of reactions and transfer processes have to be defined in a Matlab file. The model implementation methodology presented has been successfully used for a number of model implementations in research applications. It also provides a useful tool for teaching by demonstrating the dynamics and factors affecting a wastewater treatment process. Several applications of stochastic models to forecasting of treatment process time series have been reported in the literature. For example, univariate and multivariate process models were applied by [6] to make one day ahead predictions of the water flow and SS based on measurements of rainfall with good results. Stochastic models have also been incorporated into a prototype Real Time Control (RTC) system for the control of an activated sludge process in Denmark by [10]. The data originated from Fnjoskadalur wastewater treatment plant. The goal was to predict the flow and the predictions were to be used for on-line automatic control in the wastewater treatment plant. The input data were precipitation, measured at the wastewater treatment plant, and the output data were flow data from the last pumping station before the treatment plant. Expert systems (ES) models are implemented using expert knowledge and database [6]. Since the 1980s, several demonstration and research projects using ESs for control of WWTPs have been used [11] [12]. However, these models may not be generally applicable to every system as it is generally difficult to collect the expert's knowledge [13]. Fuzzy logic models are a compromise between the vague statements which humans often use and the strict logic of expert systems. No complex mathematical relationships are required in the construction of fuzzy logic applications. Besides, it is believed to be conceptually easy to understand, flexible and tolerant of imprecise data allowing the modelling of complex non-linear functions. However, the drawback of fuzzy models is that tuning the parameters of the fuzzy membership functions is difficult and time consuming. Furthermore, the main difficulty is to define the number of necessary fuzzy rules. Because Fuzzy logic models can handle highly non-linear, imprecise and uncertain systems that are poorly understood mathematically and depend not only on black box concepts, such as ANN, but also use a combination of knowledge of the system and operational experience, they have been suggested and applied to model wastewater treatment plants. Most of these applications are to simulate or control pilot plants [14] [15] [16].Only few studies have used fuzzy modelling of the whole process including biological reactors and secondary settler [17][18][19][20]. Du et al. (1999) develop a fuzzy- neural network hybrid model to predict the sludge age of the activated sludge process. It was found that fuzzy-neural network model is able to extract fuzzy rules from a set of numerical data that can be used to carryout heuristic reasoning. The model has three input variables; feed flow rate of activated sludge process (m^3/day); feed substrate concentration of activated sludge process (g COD/m^3) and sludge recycle rate (m^3/day). The model has one output variable, the sludge age. The data record were obtained from rigorous ASM1 simulation investigation because real data were unavailable. They assumed that the feed stream of the activated sludge process under study is described in terms of the feed flow rate and the feed substrate concentration and they ignored other parameters or assumed them to be time invariant. The recycle rate is assumed to be the only manipulated variable. Traore et al. (2006) developed a fuzzy model of the sludge height in the secondary settler. The modelling strategy was based on simple on-line data (influent, removal and recycle flows) and daily analytical values of the sludge volume index (SVI) allowing the fuzzy algorithm to reduce sludge height variations and thus to increase the settling process efficiency. The developed model has then been adapted and applied to the Cassa de la Selva activated sludge WWTP (Spain). The influent flow and the sludge volume index have been used as inputs to estimate the sludge recycle and removal flows. The use of fuzzy logic as control tool made it possible to combine two kinds of knowledge. The process qualitative knowledge or fuzzy rules were obtained from experts and operators working on the plant. The results obtained showed the fuzzy controller efficiency for both increasing and decreasing SVI values. The application of the controller to the Cassa-WWTP data also allowed an important reduction of suspended solids concentration fluctuations.

VI. CONCLUSIONS

In this present study, the quick review on the application of fuzzy logic in various wastewater treatment systems were discussed. The key advantage of fuzzy methods is the way they reflect the human mind in its remarkable ability to store and process information which is consistently imprecise, uncertain, and resistant to classification. These advantages of fuzzy methods makes us to use effectively for the wastewater treatment, since wastewater treatment process is a very sensitive process, it needs an expert system. As per this quick review, it is found that the fuzzy logic has wide applications in wastewater treatment systems.

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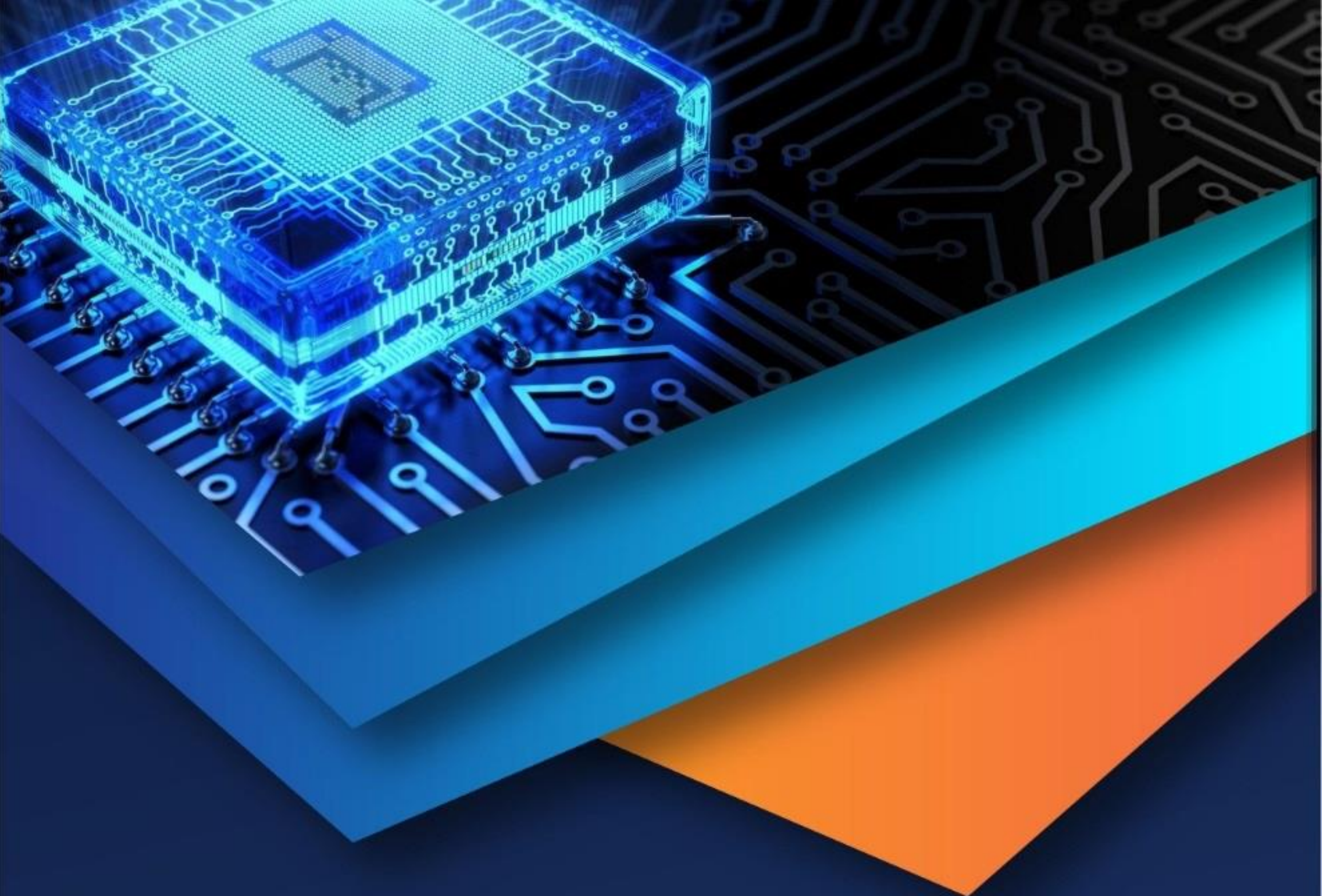

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