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Artificial intelligence for management and control of pollution minimization and mitigation processes

Christine W. Chan[a,*], Guo H. Huang[b]

[a] Department of Computer Science, University of Regina, Regina, Sask., Canada S4S 0A2
[b] Environmental Systems Engineering Program, Faculty of Engineering, University of Regina, Regina, Sask., Canada S4S 0A2

Abstract

The reduction of environmental pollution and the conservation and recycling of natural resources are significant social and environmental concerns. As valuable means for pollution control, minimization and mitigation remain attractive approaches. However, interactive, dynamic and uncertain features are associated with these processes, resulting in difficulties in their management and control. Artificial intelligence (AI) is an effective approach for tackling these complexities. In this study, the recent advancements of AI-based technologies for management and control of pollution minimization and mitigation processes are examined. Literature relevant to the area of application of AI to control and management of pollution minimization and mitigation processes is investigated. Especially, technologies of expert systems, fuzzy logic, and neural networks, which emerge as the most frequently employed approaches for realizing process control, are highlighted. The results not only provide an overview of the updated progress in the study field but also, more importantly, reveal perspectives of research for more effective environmental process control through the AI-aided measures. Several demanding areas for enhanced research efforts are discussed, including issues of data availability and reliability, methodology validity, and system complexity.

Keywords: Artificial intelligence; Environment; Expert systems; Fuzzy logic; Mitigation; Minimization; Neural networks; Process control

1. Introduction

Most of environmental engineering problems are related to a number of factors with multi-source, multi-layer, multi-stage, and multi-objective characteristics. Effective reflection of these complexities is currently an important issue emphasized by many public-sector decision-makers and private industries for sound management and control of pollution minimization and mitigation processes. Previously, many modeling tools have been developed for simulating processes in water/wastewater treatment plants, solid waste incinerators and air pollution control facilities. However, the uncertain, interactive and dynamic features of these processes often lead to difficulties in obtaining desired system performance. Integrated consideration that incorporates a number of uncertain and dynamic components in the study systems within a general framework rather than examining them in isolation is needed for potential improvement (Rynk, 1992).

Artificial intelligence (AI) is an effective approach for tackling the above complexities. For example, the complicated interrelationships among a number of system factors and activities can be explicated through the process of knowledge acquisition. Also, the gap between result generated from detailed modeling efforts and applicability of that result to a practical situation can be filled by building an automated system, allowing incorporation of implicit, and often qualitative considerations deemed crucial by engineers and/or operators. A knowledge-based system can perform trade-off analysis to compare the costs/benefits of economic versus environmental concerns. Besides, the modeling result usually does not satisfactorily address specific issues concerning impacts of a control action. An automated system can investigate the key variables in greater detail and provide more insight into the specific implications of a generalized solution. For effective real-time control, an expert system can provide more insight

*Corresponding author. Tel.: +1-306-585-5225; fax: +1-306-585-4745.
E-mail address: christine.chan@uregina.ca (C.W. Chan).

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into the specific implications of a generalized solution and can complement or refine a simulation program (Liang, 2001).

Recently, some applications of AI to real-time control of pollution minimization and mitigation processes have been reported. They demonstrate an emerging area for more extensive studies. The objective of this paper is to examine the recent advancements of AI-based technologies for management and control of pollution minimization and mitigation processes. Literature relevant to the area of application of AI to control and management of pollution minimization and mitigation processes will be investigated. Especially, technologies of expert systems, fuzzy logic, and neural networks, which emerge as the most frequently employed approaches underlying AI for realizing process control, will be highlighted.

This paper is organized as follows. Section 2 provides an overview of the related technologies for environmental process control. This is followed by a review of works on the development of expert systems and decision support systems that are critical to process control. Section 4 describes neural networks and their applications to the area of pollution minimization and mitigation; and Section 5 presents works that adopt a hybrid approach to system development and integrate expert systems, neural networks, and fuzzy logic. Section 6 concludes this review study.

2. Overview of AI-based technologies for environmental process control

Application of AI for controlling an environmental process involves a number of subprocesses that need to be managed or automated. For example, in a pollution–mitigation–plant environment, there are several levels at which to address the problem of management and control. At the lowest level, there are instruments that monitor, sense, and manipulate process variables. The instruments are often connected to a control structure that is capable of implementing a control law. The next level is the supervisory host computer that is usually connected to some control hardware by network communications. The supervisory host computer maintains the applications that are one level above the primary control functions such as the database. The supervisory host computer may in turn be connected to a plant-wide and then the corporate-wide computer systems (Rynk, 1992).

In the most general terms, AI is the use of computers to emulate the reasoning and decision-making processes of humans (Walker, 1993). There are many opportunities for applying AI and expert systems into process control and management. These opportunities are most often realized by implementing functionality on the supervisory host computer, and can include applications such as computer-aided instruction and training, maintenance, configuration, plant planning and optimization, scheduling, alarm management, and operator decision support (Stock, 1989). Most studies on application of AI to the process industries involve the technologies of expert systems, fuzzy logic, and neural networks.

Expert systems can emulate human problem solving by representing the expertise in its knowledge base. An expert system usually consists of three major components: a knowledge base, an inference engine, and a working memory. The knowledge base contains facts and heuristics associated with the application domain. The inference engine searches the knowledge base for applicable rules, and applies the rules for solving the problem. The working memory is the repository to store the new information generated as the inference engine searches and selects rules. In addition to the three components, an expert system typically contains other components such as a user interface and explanation facility.

Fuzzy logic has emerged as an alternative to classical or binary valued logic in application areas ranging from industrial process control to consumer products to aerospace and bioengineering (Langari and Yen, 1995). The role that fuzzy logic plays in the diverse applications is to bridge the gap between symbolic processing and numerical computation in shaping a suitable rule-based and linguistic control strategy. In bridging the gap, fuzzy logic has expanded the domain of application of control engineering to those that have traditionally fallen outside its realm if a strictly binary valued logic has been applied. Hence, fuzzy logic forms the basis for implementation of control strategies in the "wide sense" to enable decision-making or supervisory control. The major distinctions between "fuzzy logic" and "expert systems" are the use of linguistic rather than numeric variables, and the use of fuzzy conditional statements rather than exact expressions. Rules that incorporate linguistic and inexact data can be manipulated as a useful tool for reasoning about difficult process management and control situations (Walker, 1993).

Neural networks are a computational paradigm modeled on the human brain. The three important similarities to the brain's capabilities are the ability to filter out essential data from a larger set of data containing irrelevant information, the ability to learn from experience, and the ability to generalize from previous experience to predict new outcomes (Walker, 1993). An artificial neural network (ANN) model is made of input and output connections, which simulates the human mental processes. This paradigm has become increasingly popular for two main reasons. Neural networks are inherently parallel machines. They can be