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

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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

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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 manufactured directly in VLSI hardware and provide the potential for relatively inexpensive massive parallelism and faster problem-solving capabilities. Neural networks also have the ability to learn or to adapt to different tasks by selection of numerical "weights" (Montana, 1995).

In terms of application to the process industries, both expert systems and fuzzy logic attempt to duplicate the reasoning process of one and several experts in a particular field, while neural networks try to emulate organization of the human brain and its reasoning mechanism. Expert systems can make a significant contribution to processes where knowledge can be expressed linguistically in a set of "if–then" rules that are definable. Fuzzy logic is applied in the process industries to control a process that is intrinsically non-linear and multi-variabled, while neural networks are useful for making sense out of data. Whenever knowledge is felt to be lacking, a neural network can be applied to extract from the data the relationships that are inherent (Rynk, 1992).

3. Expert systems

Complexities in pollution minimization and mitigation processes pose particular challenges in control, as they are non-linear, time varying, and often difficult to model. Alternative approaches to traditional control methods have yielded promising results, and expert system is one of these alternatives. Applications of expert systems to diverse fields have been well documented (Durkin, 2002). The predominance of medical expert systems gave way to wider adoption of this technology in the business and industrial sectors in the 1990s. A 1986 survey conducted by Waterman (1986) showed that 30% of the applications of expert system technology were in the field of medicine. By the 1990s, medical applications of expert systems decreased to account for only 10%, while business and industrial applications grew to account for 60% of the applications. Applications of expert systems to the environmental sector accounted for 5% of all the applications (Durkin, 2002).

Chowdhury and Canter (1998) discussed expert systems in general and the process of developing the systems. In the paper, they outlined 39 expert systems developed for the domain of ground water management, and discussed in detail nine among them: (i) The RPI Site Assessment System was developed for inactive hazardous waste site investigations using CPS5 and the CLISP language; it can be used to determine Hazard Ranking System (HRS) scores for site-based soil permeability levels and risk-based scores for the ground water flow direction. (ii) The DEMOTOX Expert System assesses the potential risk that organic chemicals pose for ground water contamination; the risk is calculated based on a mobility and degradation index (MDI), and a confidence adjusted MDI for ranking. (iii) The Hazardous Wastes and Management Expert System assisted site planners, managers, and other decision-makers in determining hazardous waste site cleanup procedures; the system contains five interactive modules: a knowledge base of facts and rules, an environmental and site description module, an inference module, a data bank module, and a risk/decision analysis module. (iv) The Defense Priority Model (DPM) evaluates the relative risk of hazardous waste sites to human health and the environment based on the Hazard Assessment Rating Methodology. (v) The Wellhead Area Source Evaluation System (WASES) aids users in prioritizing potential or actual sources of ground water contamination in wellhead protection areas; the system has a hierarchical structure with three layers: the first level considers four general factors, the second level adds health effects, and the third level focuses on evaluating the likelihood of contamination reaching a specific well. (vi) The Expert System for Pesticide Regulatory Evaluations and Simulations (EXPRES) assesses the potential risk that pesticides pose for ground water; the system uses three solute transport models to determine pesticide leaching and the consequences of subsurface transport processes. (vii) The Environmental Sampling Expert System (ESES) aims to help users increase the accuracy, timeliness, and cost-effectiveness of field sampling, chemical analyses, and analytical data validation within the Superfund program; the system has two versions: ESES-SM supports designing a sampling plan for determining the extent of metal pollution in soil, and ESES-GW helps the user to decide on the appropriate ground water sampling pumps and devices. (viii) The Cost of Remedial Action Model (CORA) provides remediation recommendations and determines remedial action costs. The system contains four knowledge bases and is capable of handling uncertainty. (ix) The SEPIC Expert System uses location, field data, size calculations and user type as primary variables to evaluate permit applications, and makes a recommendation on whether a permit for private sewage facilities should be issued.

In (Rynk, 1992), capability of an expert system to help control and manage a composting process was explored. An expert system-assisted computer control program was developed for an "aerated static pile" composting system, assuming a process control system with multiple sensors and control devices. The control program developed for this system integrates two expert system programs with a conventional data acquisition system (DAS) and several basic computer programs. The DAS performs the essential monitoring and control functions. The expert systems and other programs provide supporting information. The first expert system evaluates the composting raw materials and initial conditions.

It assists the operator in setting control parameters for the DAS and established criteria for evaluating process data. The second expert system assesses the status of the process from the data returned by the DAS. It does this at 3-h intervals and more thoroughly at 24-h intervals. It produces a report which summarizes the process status and lists any potential or apparent problems. At the 24-h evaluation stage, it automatically adjusts control parameters as necessary.

The basic programs perform tasks which are cumbersome for the expert system such as obtaining numerical information, performing calculations, and accessing data files. The control program was tested by supplying it with process data from the computer keyboard and from an electronic instrument panel, which simulates the sensors of the control system. The data were intended to produce predictable results, which could be compared to the control program's results. In nearly all cases, the control program produces results consistent with those expected. Its performance was satisfactory in that all components of the system were activated properly and information was successfully transferred among the programs. Based on the performance and capability of the control program, it was indicated that expert systems could potentially play a beneficial role in control systems for composting processes. Their utility for this purpose depends on the specific needs of each composting facility. Large facilities with inexperienced staff and a reliance on a high level of technology are most likely to benefit from an expert system.

Betts (1998) described an Expert Process Advisory System (EPAS), which is an advisory system that supports designers in pollution prevention by informing them about environmental ramifications of their designs. The EPAS system ranks the alternative designs based on how they rate on the five factors of technical adequacy, health and safety, environmental ramifications, regulatory requirements, and cost. The system consists of information on the environmental, regulatory, health and safety, and cost factors of a design. The EPAS improved upon the software packages available at Boeing, which provided users with primarily descriptive information about a product's potential environmental impacts. The EPAS, on the other hand, provided more analytical solutions.

Chen et al. (1999) described a decision support system that assists decision-makers in determining optimal daily loads of various pollutants in order to satisfy water quality requirements in a water basin. There can be multiple water quality limited sections (WQLS) in a river basin. For each section from the most upstream to the most downstream, the total maximum daily loads (TMDLs) need to be calculated. There can be many combinations of point source and non-point source loads that can meet the water quality criteria, and the many feasible solutions provide an opportunity for the stakeholders to determine the optimal TMDLs. The decision support system for total maximum daily load can calculate the total maximum daily loads of various pollutants for the WQLS. The system includes a watershed simulation model, a database, a consensus-building module, and a TMDL module that provides a worksheet for the calculations. The system can generate multiple combinations of point-source and non-point-source allocations to meet the water quality criteria for the intended uses of the WQLS. Based on the various possible solutions suggested by the system, the regulatory agency and local stakeholders can negotiate an option most agreeable to all parties.

Jankowski and ZumBrunnen (1993) presented a modeling support system (MSS) for simulation of water quality. The objective of the system is to provide modeling support to the user in deriving and simulating a water quality model to predict changes in water quality for a given aquatic system. The MSS provides a single software environment for modeling, and is composed of three parts: the knowledge base, the model base and the simulation engine. It is implemented through representation and manipulation of modeling constructs, called atomic models, which describe the dynamic behavior of structural components of an aquatic system. A knowledge representation scheme called the system entity structure (SES) is employed to express three relationships. The first relationship is that of decomposition. That is, how the system is hierarchically decomposed into components. The second relationship is that of taxonomy, that is, how admissible variants of the components can be classified. The third relationship is that of coupling, that is, how these components can be linked to reconstitute the original system.

The MSS for simulation of water quality consists of two kinds of knowledge stored in the knowledge base: structural modeling knowledge and procedural modeling knowledge. The model base includes the atomic models and coupled models. The simulation engine for the MSS functions as follows. A user initiates the model simulation by sending a message to the coordinator, which triggers the simulation. The coordinator sends a message to the simulation controller, generator, and coupled models and their components or atomic models. The input values are stored in a file in the generator and can represent, for example, various conditions of water quality. The input values are sequentially transmitted from the coordinator through the input/output ports to the coupled model. The outputs are sent from the coupled model to the co-ordinator, which simultaneously transmits them to a log-file as well as sends a message to the simulation controller to update the simulation clock. The MSS is built on the SES, which serves as a generative framework for model representation, retrieval, and manipulation. A modeler provides the system with information regarding the specific problems of the site such as physical and biochemical aspects of the aquatic system. The information is matched with the production rules in the rule base, and recommendations about the proper selection of entities from the entity structure tree are generated. The modeler uses these recommendations during pruning of the entity structure tree. The basic structural elements or atomic models are the primitives. When the retrieved atomic models are linked into a model instance, it is called a coupling process. A coupled model is subsequently simulated after initialization of the input data.

Kao and Liebman (1991) described the use of a computer-aided system to support decision-making in groundwater resources management (GRM), which involves multiple objectives to (i) allocate ground-water resources among competing water demands, (ii) control ground-water quality, (iii) prevent undesirable overdraft of the ground-water basin, (iv) analyze the impact of hydraulic and other characteristics of ground water, and (v) maximize the benefits of the available resources. Due to the complexity of the problem, a single-objective approach is insufficient to address the inter-relationships among these issues, and a multi-criteria technique is adopted. To support this difficult decision-making process, the decision support system makes use of several mathematical techniques such as a finite-element method for ground-water simulation modeling, linear programming, multi-criteria optimization, and a modeling-to-generate-alternatives (MGA) approach for generating potential alternatives. In addition, the system includes a modeling language to represent the mathematical models in a human-understandable form, and a graphic interface that can support presentation of comparisons among the different solution options.

Patry and Barnett (1992) presented an integrated modeling system for water resource management. The principal component of the integrated system is the General Purpose Simulator (GPS), which is a comprehensive software package for simulation, analysis and control of wastewater treatment plants. The software has been applied to several large-scale wastewater treatment plants in North America and elsewhere. The other components in the integrated modeling system include a knowledge-based expert system that has been implemented as a model-based reasoning system complemented with object-oriented programming. The knowledge-based expert system includes a model that describes effects propagating among objects representing system components to establish causal chains. The linguistic model also has the advantage of being able to represent incomplete and qualitative knowledge. ANN are also considered in the paper and they were found to be useful for real-time control because of their adaptive characteristics. Each of these techniques in isolation may not be sufficient for making the system robust. However, working together as components of an integrated system, they can combine to make an effective system for operational control of wastewater treatment.

Gilbert (1999) discussed how an organization should tackle the task of selecting and implementing an environmental management information system. The paper indicated that environment, health and safety management is a natural candidate for automation because of the extensive documentation needed to demonstrate compliance. However, there are substantial challenges in successfully implementing such a system. Therefore, an organization needs to carefully evaluate the situation before deciding to embark on a project on developing an environmental management information system (EMIS). The paper suggested that an organization needs to ask the three basic questions: (1) What is an EMIS. (2) Why implement such a system. (3) How to select and implement a system. The last question can be further refined into ten considerations: (i) What are the overall objectives of the organization? (ii) How ready is the organization? (iii) What type of high-level functionality is desired? (iv) Will the EMIS be integrated or interfaced with other systems? (v) Who is the user community and what are their specific needs? (vi) What are the organization's technical requirements? (vii) How much customization is needed to achieve project goals? (viii) What is the desired timing of the project? (ix) What are the resources needed to implement the system? (x) What is the justification for the system? These issues were raised in the paper to caution organizations on the need for careful assessment on whether an EMIS is necessary and right for them.

4. Neural networks

A number of researchers have been working on modeling of various environmental processes for supporting further process control studies. A model is a useful engineering tool if it is able to predict reaction conditions and rates (Steven, 1998). Simplifying assumptions associated with the modeling efforts may lead to loss of relevant information and thus affect the simulation accuracy. Techniques of neural networks are alternatives for mitigating such deficiencies.

Neural computing is one of the fastest growing areas of AI. There are two key differences between neural computers and digital computers. First, neural networks are inherently parallel machines and as a result they can solve problems much faster than a serial digital computer. Secondly, many neural nets have the ability to "learn". The most frequently used algorithm for neural networks is back propagation. According to Bhat and McAvoy (1990), back propagation is an example of a mapping neural net that develops an approximation to the function $y = f(x)$ from sample x, y pairs. Back propagation is distinctive because of its ability to identify non-linear relationships and utilize parallel processing. This algorithm has been applied to a wide variety of practical problems and has been proven successful in its ability to model non-linear relationships. The traditional models are equivalent to two-layered linear back-propagation networks, and as such, they are more limited in their ability than the complete back-propagation algorithm. Sometimes a momentum term is adapted to a modified gradient rule so that oscillation is avoided in the convergence process (Reich et al., 1999). Applications of back-propagation neural network (BPNN) can be found in Bhat and McAvoy (1990), De Veaux et al. (1999), Melas et al. (2000), and Reich et al. (1999).

Kavchak and Budman (1999) used another type of neural networks called radial basis function. The accuracy of a model is strongly affected by the choice of the basis function dilation. The paper presents two algorithms. The first one allows the network to adapt to dilation. Because the dilation enters into reconstruction of the function in a non-linear fashion, a Lyapunov stability proof requires the imposition of hard constraints on the adapted parameters. For a function with a known optimal dilation, convergence was demonstrated, but the actual speed of dilation adaptation was necessarily slow. Since the use of a single dilation may not be optimal for any given function, the second algorithm with a different strategy was proposed. It uses a multi-resolution neural network representation. This structure uses a collection of wavelets of different dilations, which allows the estimator to account for multiple dominant frequencies in the function being estimated. Two sets of adaptation laws were proposed for this multi-resolution network, for which stability is better guaranteed. The first bases the adaptation of the multi-resolution network coefficients on a separate error for each layer of the network, and the second adapts by means of an overall prediction error. The latter approach has the advantage that the Lyapunov stability proof does not require imposition of hard constraints on the coefficients. However, using the overall error also slows down the adaptation process as compared to the adaptation process based on the error at each layer.

The neural networks that involve back propagation, recurrent or radial basis functions often result in long training time, local minima and lack of self-tuning ability in on-line applications. Due to these reasons, Ye et al. (1998) adopted a Bayesian–Gaussian neural network (BGNN) for predicting dynamic behavior of a non-linear single-input single-output system and for predicting the static performance and dynamic behavior of circulating fluidized bed boilers. A comparison of the performance of Bayesian–Gaussian BGNN versus BPNN in terms of both the static performance and dynamic behavior predictions of the two circulating fluidized bed (CFB) boilers is given in the paper. On the positive side, BGNN gives reasonably good predictions and takes less training time than the BPNN. On the negative side, BGNN requires longer execution time than the BPNN does, possibly due to the large topology of BGNN. One disadvantage of BGNN is that problems can occur when the training data set is large, because this network stores all the training data into its topology from the beginning. By contrast, the BPNNs 'compress' the training data set into the connection weights and thresholds. When new training data are introduced, the topology of the BGNN does not grow because of its self-tuning ability. On the other hand, when new samples are available to retrain the BPNNs, they must be carefully screened to select the ones that contain innovative information. If a large amount of new samples containing little innovative information were used in retraining, the new samples may overwhelm the existing ones that are smaller in number but which represent crucial characteristics of some aspects of the process, thereby attenuating prediction ability of these networks.

Neural networks have been frequently applied for environmental process modeling and control. Melas et al. (2000) presented a BPNN model developed for 24-h prediction of photochemical pollutant levels. The model relates peak pollutant concentrations to meteorological and emission variables and indices, as well as maximum hourly pollutant concentrations during the three previous days of the week. An experiment was used to investigate sensitivity of model predictions to uncertainty in the input data. The experiment shows an agreement between observed and predicted concentrations. However, the results of the BPNN model were only marginally better than those obtained by regression models in the literature, possibly due to inadequacy of input parameters (i.e. some important predictors were either not included in the analysis because they were unavailable or under-represented) and inadequate representation of the data used (i.e. only local measurements of some data were obtained and they may not be representative of a larger area).

Reich et al. (1999) proposed a BPNN with momentum to identify the apportionment of a small number of sources from a data set of ambient concentrations of a given pollutant. The trained network was able to identify the most likely emission parameters of an unknown source, and hence, to determine the relative allocation of the point sources involved. The real case is a noisy generation with a higher uncertainty than the given examples. The neural network was able to solve the inverse source–receptor problem in the presence of noisy or ambiguous data. However, it was unable to adapt to data outside the validation region of the selected set of examples.

Kavchak and Budman (1999) reported on an adaptive controller for a continuous stirred tank reactor (CSTR). The controller was implemented with adaptive radial basis function neural networks based on dilation adaptation with a multi-resolution network structure using an overall prediction error. The controller outperformed the original controller that used a fixed dilation. The improvement obtained with the dilation adaptation technique as compared to the original technique is marginal in most situations tested in the case study. On the other hand, the controller that used the multi-resolution network structure most closely resembled the input–output linearizing controller, and the improvement in accuracy with respect to the original Cannon's method is significant.

De Veaux et al. (1999) proposed a model that includes both first principle differential equations and an ANN to forecast and control biological treatment for water contamination. ANN modeling of the growth rate of the biomass is used in conjunction with the assumed known part of the model. The neural network estimates the unobservable kinetics parameters from the state at time t. This information plus the estimated kinetics parameters at time t is then fed into the known model to obtain the state at time $t+1$. The hybrid neural network can be trained with fewer data and extrapolate better than pure neural networks.

Bhat and McAvoy (1990) and Zhang and Stanley (1999) introduced model-based process control systems. Bhat and McAvoy (1990) modeled a pH CSTR with pseudo-random binary sequence (PRBS) input, while Zhang and Stanley (1999) proposed a system for the coagulation, flocculation, and sedimentation processes. Both systems consist of (1) a process model to predict the effect of the manipulated variables on the output and (2) an inverse model to compute future values of the manipulated variables. The internal model control (IMC) model-based control system introduced in Zhang and Stanley (1999) also includes a filter to control the feedback into the inverse model. The IMC with neural network is divided into direct, indirect, and hybrid IMC. In the direct IMC, the inverse model of the process is replaced by a neural network model, which drives the system to a target state given current state. In the indirect IMC, the process model is replaced by a neural network, which predicts the process output given a set of input parameters. If both the forward and inverse models are replaced with neural networks, the control system is called a hybrid IMC system. In Zhang and Stanley (1999), the first neural network is trained using both good operation cases and cases in which underdose or overdose occurred. The second neural network is trained with good cases only. Both models converge and generalize well. The plant reference model is far less accurate than the inverse model because it is trained with both good and poor operational conditions.

Hussain (1999) provided an extensive review of the various applications of neural networks for chemical process control, which shows that the technique has been used in both simulation and online implementations. The majority of the neural networks adopted are of the multi-layered feed-forward type, and three major control schemes are implemented in these applications:

(i) *Neural networks for model-predictive control*: Using neural networks for model-predictive control is the most commonly found control technique. In this scheme, the controller determines a variable profile that optimizes open-loop performance during a specific time interval. The objective of the controller is to minimize future output deviations from the set point while taking into consideration the constraints as well as the control sequence necessary to achieve the objective.
(ii) Neural networks for inverse-model-based techniques: Two approaches using neural networks in the inverse-model-based strategy are the direct inverse control and the IMC techniques. In the direct inverse control technique, the controller is implemented as a neural network model and works in parallel with the system under control. The controller has to learn to supply the appropriate values for the control parameters. A more robust and stable strategy is the non-linear IMC technique.
(iii) Neural network in adaptive control techniques: Neural networks can also be adopted in the conventional adaptive control structures of non-linear dynamic systems. These conventional adaptive methods can belong to either the direct adaptive or indirect adaptive schemes.

Neural-network-based control strategies are also adopted for online applications. The majority of these utilize the multi-layered feed forward network with sigmoidal or hyperbolic activation functions. However, while many online chemical process control applications have been reported in the literature, they are mostly for miniature laboratory-scale equipment only.

Psichogios and Ungar (1991) reported on ANN that are used in model-based control, both as process models and as controllers. In process control applications, neural networks can be incorporated into the controllers using either direct or indirect control methods. In the direct method, a neural network is trained with observed input–output data from the system so that the neural network models the inverse dynamics of the system. The resulting neural network model can then be used as a feed forward controller. In the indirect method, the neural network is trained with input–output data from the dynamic system so that the neural network model represents the forward dynamics of the system. The process model can then be used by the control algorithm to calculate the control action. This paper discussed control of the output concentration of a non-linear chemical reactor using the direct control approach. The behavior of the controller and useful features of the control architecture were discussed. This paper shows that when only historical input–output data are available and model equations are not known, neural networks can work as a feasible alternative that provides good non-linear control.

Syu and Chen (1998) discussed implementation of an online estimation and control system undertaken as part of a response to the environmental regulations introduced in Taiwan in 1998. The system implements a BPNN adaptive controller on a continuous wastewater treatment process. The BPNN adaptive controller regulates pump rates for addition of hydrogen peroxide (H_2O_2) and ferrous chloride to treat the chemical oxygen demands (COD) of the process. After completion of the oxidation process, an anion resin was added to coagulate and settle the suspended particles. The pH value was a major factor for determining the coagulation condition of the suspended particles and a value of 5.0 was considered the best pH for coagulation. An online control system was used to provide the minimum amount of reagents to reach the required COD.

The neural network structure consisted of seven input nodes, four hidden nodes and one output node, and was of a time-delayed type. The seven input nodes are $\mathrm{COD}(t)$, $\mathrm{COD}(t-3)$, $\mathrm{COD}i(t-3)$, $\mathrm{COD}i(t-2)$, $\mathrm{COD}i(t-1)$, $H_2O_2(t-1)$ and $H_2O_2(t-2)$, and the only output node was the predicted amount of H_2O_2 that should be added at current control time. The back-propagation network learns by calculating an error between desired and actual output and propagating this error information back to each node in the network. The neural network was trained in a dynamic mode. For each learning cycle, a moving window of learning data with a fixed size was provided. An analysis of the reaction time, the pH value and concentrations of reagents reveal that a network structure of 7-4-1 and a data window size of 15 gives the best control performance.

Boger (1992) presented a survey of applications of neural networks to industrial plants operation, especially water and wastewater treatment plant operations. Compared with other AI techniques such as expert systems and fuzzy logic, neural networks offer the advantage of being able to learn from historical data on the plant. Hence, neither a human expert nor an explicitly developed process model are needed. The resulting neural network developed from the data is robust against process noise or instrument bias and models plant-specific behavior.

A review of several applications of neural networks in waste water treatment plants reveal that the process begins with modeling of process variables or the control actions. Boger (1992) modeled the behavior of the Shafdan wastewater treatment plant by training a neural network from a database that contained weekly averages of 106 variables from the first 2 years of operation. Once the neural network is trained, the rules describing system behavior can be extracted through neural network analysis.

Internal checks are necessary in the neural network system to compensate for erroneous inputs. This can be implemented as a modular neural network system which checks inputs against measured values, or as an external program that compares input values against the range of input values in the training data set. If a significant deviation from the range of learning data is detected, a flag is raised. A retraining schedule can be established as a periodic check on validity of the neural network.

Sefiner (1997) reviewed neural network applications for environmental control of greenhouse gas, and discussed four salient points:

(i) *Greenhouse gas modeling with neural networks*: Traditional greenhouse gas models are based on energy and mass balances, such as quasi-steady-state energy-balance models. While the traditional model is sufficient for design purposes, it has substantial residual error because it oversimplifies the actual system. To address the inadequacy of the traditional model, Sefiner (1997) proposed greenhouse gas modeling using neural networks for two purposes: first, a more accurate modeling of existing greenhouses gas phenomena for environmental control; and secondly, a benchmark for development of improved physical models.

(ii) *Input reduction methods*: Reducing the number of inputs to a neural network without adversely affecting the result can decrease estimation errors due to unchecked extrapolations. However, this reduction process is not desirable because it only serves to lessen future measurement efforts. The same effect can be achieved with elimination of weaker inputs. Among the input variables that cannot be eliminated, the weights of the trained neural networks can sometimes provide clues to their relative importance. The importance of a variable is measured by the loss of goodness of fit when it is eliminated from the input. Sefiner (1997) presented his experience on deciding the weights for the input variables of a greenhouse gas control model.

(iii) *Model reduction with neural networks*: Models based on a large state vector need to be reduced especially in optimal control problems, where a complete solution for a large-scale model requires prohibitively significant computing effort. In greenhouse gas control problems, the crop model may contain a large number of state variables, many of which are inter-correlated under normal conditions. Sefiner

(1997) presented two general approaches for reducing the state–space: (a) by understanding the system, reduction is achieved by aggregating variables, and (b) statistical reduction that satisfies some optimization criterion results in new variables which are combinations of the old ones.

(iv) *Optimal control applications*: A control algorithm that recommends control actions can be either model-based or rule-based. The control algorithm can also be mimicked by a neural network, which requires considerably less computing effort in real-time operations. Sefiner (1997) suggested that mimicking expert decision-making with neural network modeling requires large amounts of data which may be difficult to obtain. But if the data are available, a neural network approach can extract policy decisions which are likely to be more objective than those obtained by means of traditional or manual knowledge acquisition approaches. In this context, a significant advantage of neural networks is that they have the flexibility to adapt to non-linear and non-physical data. But a major disadvantage is that proper training of neural networks requires large multi-dimensional sets of data to reduce possible errors due to extrapolation. Therefore, it is important if possible to reduce dimensionality of the problem.

Tendulkar et.al. (1998) developed an ANN model for non-linear identification and variable prediction for the phenol hydroxylation process. The experimental objective of the phenol hydroxylation reaction was to optimize conditions with respect to formation of dihydroxybenzen isomers. Catechol and hydroquinone are two of the many phenolic derivatives of high value. Hydroxylation of phenol using a hydrogen peroxide oxidant and titanium to five catechol and hydroquinone has been extensively studied. Within this context, the flow rate of phenol and the reactor temperature constitute the manipulated and controlled variables of the experiment.

The dynamic error back-propagation network (EBPN) model was used with a total of 123 data points acquired at 5-min intervals. The data were collected and separated into the training set and the test set. The former was used to update the network weights, the latter was used to evaluate the generalization ability of the network model. The input layer of EBPN consisted of four nodes representing the current and lagged values of the process input and output. The process model was used and tested within the framework of neural model prediction control (NMPC). The advantage of the NMPC methodology is that all the control computations are performed in the domain of a single network working as a forward process model, thereby avoiding the need to train a separate neural network to act as a controller.

More recently, Liang (2001) examined the effects of the environmental variables (temperature and moisture content) and time on microbial activity during biosolids composting, and quantifies the relationships among environmental variables and time and microbial activity during biosolids composting by developing ANN models. Controlled composting experiments were conducted using 2-factor factorial design with six temperature levels (22°C, 29°C, 36°C, 43°C, 50°C, and 57°C) and five moisture contents (30%, 40%, 50%, 60%, and 70%). The ANN models are then used to estimate the dynamic microbial activities over time during biosolids composting. These models are further incorporated within a decision support system for composting management, and are used for optimizing the composting process and reducing operation costs.

5. Fuzzy set theory

Systems involving fuzzy logic are distinct from "non-fuzzy" expert systems in that the former typically involve (1) linguistic rather than numeric variables and (2) "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 industrial process control situations.

The fuzzy logic controller is pre-programmed with a flexible set of rules and can adapt to changing conditions. It is made up of three basic elements: a fuzzifier, an inference engine, and a de-fuzzifier. The fuzzifier and de-fuzzifier translate the literal language of sensors into linguistic terms understandable by the inference engine, where the control decisions are made. The most interesting use of fuzzy logic in the process industries is to control a process that is non-linear and multi-variable in its makeup.

Enbutsu et al. (1991) combined fuzzy logic with neural networks and obtained more detailed expert rules. Dynamic forecasting was also studied in the chemical industry where a moving window of process variables is used to train a neural network from past records to predict the value of a variable in the immediate future.

Bastian (1995) proposed a flexible fuzzy controller based on the concept of a flexibly defined linguistic variable. That is, the meaning of variables in the rule base can be changed according to predetermined conditions. A simulation study showed that this controller can support easy modification and simplification of the comprehensive rule base.

Tay and Zhang (1999) adopted advanced neural fuzzy technology to develop a conceptual adaptive model for anaerobic treatment systems. Modeling anaerobic biological wastewater treatment systems is difficult because their performance is complex and highly dependent on the configurations of the different reactors, influent characteristics, and operational conditions. Instead of conventional kinetic modeling, the model developed by Tay and Zhang combines the robustness of fuzzy systems with the learning ability of neural networks, and can adapt to various situations. The advantage of combined neural fuzzy systems is that fuzzy systems are enhanced with the automatic tuning abilities of neural networks. However, a weakness in the neural fuzzy model is that its performance is highly dependent on the quality of training data.

An anaerobic biological wastewater treatment system consists of the three phases of biological, liquid and gas treatment. Different substances are exchanged among the three phases, and products of the microbial conversion process are carried away by the effluent discharge gas. To avoid conducting the difficult analysis that such a complex system would require, the system is often treated as a "black box". The proposed model consists of several key components, including inputs and outputs, database and pre-processor, a fuzzy system generator, a fuzzy inference system, and an adaptive neural network representing the fuzzy system. Since it is difficult to manually pre-process the redundant and conflicting data, a fuzzy clustering method is utilized to automatically carry out the task.

More recently, Chang et al. (2001) and Chen et al. (2001) proposed a fuzzy controller for managing industrial wastewater treatment processes. In these studies, the authors employed techniques of fuzzy set theory, optimization and genetic algorithm for dealing with uncertainty and non-linearity in such control systems. The results indicate that, with the consideration of uncertainties through the fuzzy set approaches, more effective process control could be realized. The authors also applied the similar concepts to the control of municipal incinerators (Chang and Chen, 2000; Chang et al., 2002).

6. Hybrid intelligent systems

Many environmental systems are complex, non-linear, and uncertain, leading to difficulties in simulating and controlling them through a single methodology. Often, hybrid technologies are desired to enhance robustness of the decision support. For example, both expert system and fuzzy logic try to emulate the reasoning process of an expert, or a set of experts, in a particular field. However, implementing fuzzy logic control as a set of rules in a knowledge base represents a significant investment in time and resources. On the other hand, neural networks can be an excellent tool for making sense out of data. Whenever knowledge is felt to be lacking, a neural network can be applied to extract from the data the inherent relationships. Therefore, in many industrial applications, expert systems, fuzzy logic and neural networks are integrated in a system to support optimized process control and management. In this section, some applications that adopt a hybrid approach to developing intelligent systems in the process industries are discussed.

De la Rosa et al. (1999) described modeling of soil erosion by water, which is an important environmental problem in southern Spain. The objective of the study was to relate soil erosion vulnerability to biophysical factors and agricultural management practices. The paper discusses formulation, calibration, sensitivity and validation analysis of a hybrid model of expert decision trees and ANN to evaluate the soil erosion process. The hybrid model is called ImpelERO, which captures relationships among land and management qualities and their associated characteristics using expert decision trees. To capture the interactions among the qualities affecting the erosion vulnerability index, an ANN was developed. The ImpelERO consists of two parts. The first part of the model considers the land qualities, land characteristics, management qualities and management characteristics and these factors form the decision trees. ANN analysis was used to develop the second part of the ImpelERO model which predicts the actual field vulnerability. In order to train the ANN, the Cascase-correlation algorithm was used. According to the sensitivity and validation analysis, ImpelERO was able to recognize the main interrelationships of the input parameters, and reproduce the soil erosion vulnerability accurately. In addition to prediction of soil loss by water erosion, this system can be used as an optimization tool for selecting the land use and management practices that satisfy optimum environmental protection such as reduction of soil loss.

Abuelgasim et al. (1999) proposed a method to assess the environmental effects of the Gulf War on the desert surface of Kuwait using a change detection method that combines a neural network classification architecture with fuzzy logic. Field data were collected from January to February 1993. The data for each test site include information on the soil type, vegetation cover and its density, degree of oil pollutants, presence of oil lakes, sand dunes, or mobilized sand sheets. The data pre-processing involved the three phases of geometric registration, radiometric normalization, and data scaling.

To assess the environmental impact of the Gulf War, a system for change detection was implemented which can identify two types of categorical changes: (i) a new landcover class that has emerged and (ii) changes between known classes. The change detection adaptive fuzzy (CDAF) network can be used to first derive a set of category representations that could be successfully employed to detect changes between known landcover classes. Secondly, the network can establish new category representations for unknown landcover classes, and then, it provides quantitative measures of the probability of changes in terms of category likelihood, as well as of the magnitude of changes in terms of intensity.

The application of the CDAF network to assess change resulting from the Gulf War involves the following procedure: (i) *training*, i.e. the network is trained with spectral data for each pixel in the training set from the 1989 image along with the corresponding land cover class; (ii) *classification*, i.e. the trained neural network produced in step 1 was used in three ways, where the performance of the trained neural network is validated using an independent "unseen" test data set, the trained network was used to classify the entire 1989 image, and the trained network of 1989 was used to classify the 1991 image; (iii) *change detection*, i.e. fuzzy membership values for each land class for each pixel are obtained for both 1989 and 1991 classifications and are used in the detection of change. The results showed that this neural network approach gave good results compared to analysis using other methods.

Huang and Fan (1993) developed a hybrid intelligent system called HIDEN to synthesize material and energy recovery processes (MERPs) for minimizing hazardous or toxic waste streams and recovering waste energy in a process plant. The system HIDEN consists of three subsystems: a knowledge-based subsystem KBDEN, a fuzzy logic subsystem FLDEN, and a neural network subsystem NNDEN. The subsystem KBDEN is the core of HIDEN. This subsystem accepts the process data on the material and energy recovery processes or MERPs, and the data are divided into the two classes of data and imprecise data. The subsystems FKDEN and NNDEN are designed to provide a series of recommendations on critical stream matching derived from the second class of data. To demonstrate the applicability of the HIDEN system, two design problems, one for material recovery and the other for energy recovery, are described.

The hierarchical expert system is structured into the lower and upper layers, with the former consisting of a number of rule bases. To perform the task of scheduling, both deep and shallow knowledge are included in the knowledge base. The deep knowledge includes the first principles of reaction kinetics, thermodynamics, and mass and energy balances, as well as process models derived from first principles. The process models can evaluate process operations. The shallow knowledge is expressed as heuristic rules and functions. Since the available information is imprecise, the heuristic rules are fuzzy in nature and are called fuzzy heuristic rules or simply fuzzy rules.

Scheduling decisions are made in two stages. First, each subsystem in the lower layer makes a locally optimal decision. Secondly, by coordinating the subsystems, the local decisions are modified to satisfy the criterion of global optimality. The rules in the rule base at the lower layer are weighted. By co-ordinating and balancing trade-offs among the local decisions according to a number of constraints, a set of globally optimal decisions is made. The constraints include scheduling criteria, the minimum total idle time of process units in a day, satisfaction of a production plan, and waste minimization.

The expert system PS-BATCH is developed for the scheduling of the batch chemical process. PS-BATCH is a question–answer system which poses a set of questions on the operating conditions of each process unit to the user. Among the variety of wastes generated in the metal finishing industry, the waste solution of electroplating plants consists of cyanide and is of particular concern because it is highly toxic. In a typical electroplating process, each work piece is cleansed to remove dirt and oil prior to plating or stripping. This involves electro-cleaning, alkaline cleaning, acid cleaning and rinsing. A fuzzy expert system has been constructed to facilitate the source reduction of cyanide-waste solutions and to train plant operators in the techniques of cyanide minimization. The knowledge base of the system includes the detailed cyanide minimization strategies, which are expressed as both fuzzy and crisp (i.e. non-fuzzy) rules.

The fuzzy expert system MIN-CYANIDE evaluates and prioritizes the minimization options, which include drag-out minimization, bath-life extension, rinse water reduction, replacement with a non-cyanide solution, use of an alternative plating technique, and improvement of the operating procedure. Based on the ranking, the system makes a recommendation on the most effective minimization strategy.

Simutis et al. (1997) described a hybrid or integrated system approach used in biochemical engineering to increase the cost–benefit ratio of model-supported optimization and control. A comparison between classical and hybrid modeling approaches clearly indicates that the latter performs better than the former for process optimization and control. The advantage lies in the amount of a priori knowledge incorporated into the hybrid model as compared to the mathematical model. The hybrid models enables direct use of knowledge as it becomes available and avoids loss of information in the transformation process. Also adopting the hybrid approach is more effective in terms of development time, and hence cost.

Since hybrid models take advantage of the combination of knowledge and information from different sources, they are more complex than classical models. This may cause problems with classical optimization procedures, like dynamic programming or the application of Pontryagin's maximum principle for process optimization. These difficulties might in practice reduce the applicability of the model and consequently its benefit. The HYBNET software package is a development system for hybrid structure definition and optimization. HYBNET can combine differential equation systems, analytical mathematical relations, ANN, fuzzy expert systems or fuzzy neural networks and their variants. These become individual components in a modular model which is organized in a network structure. The novelty of HYBNET is that the entire model assumes a network structure, which implies ideas of network training developed for simple ANN can be applied at a higher level. From a practical point of view, the advantage of HYBNET is that it supports flexibility in arranging partial process models so that they can work together in solving a particular problem.

The paper emphasizes that the cost–benefit ratio is a key determinant in the acceptance of model-supported process supervision, optimization and control in industrial scale production processes. Combining ANN, fuzzy rule systems and classical model approaches in a hybrid model can usually enhance its performance. An additional reason that hybrid modeling is particularly suited for production process automation is that in this application, there is usually enough data to conduct data analysis in combination with classical mathematical modeling.

Efstathiou (1993) presented a survey of the evolving system architectures that apply AI techniques to process control. There are altogether three architectures presented:

(i) *Blackboard and layered architectures*: The blackboard architecture permits several components of a knowledge-based system to communicate by means of a shared space in memory known as the blackboard. The blackboard architecture could be augmented by addition of a manager that controls the data written to the blackboard and the order in which expert modules use scarce resources to perform their tasks. The layered architectural design specifies the tasks of the expert system to be layered according to the time-scale at which events occur.

(ii) *Coping with real time interruption*: Coping with real-time processes can be difficult. While there are a few strategies that can be adopted to improve real-time performance, none of them can guarantee adequacy of the performance. To do so, it is necessary to investigate performance profiles of the reasoning processes, to determine how much the results of the reasoning can be improved with allocating more processing time.

(iii) *Distributed architectures*: In a distributed architecture, the blackboard or layered architectures would distribute the knowledge sources to different processors, with each one managing its own data exchange. This in fact describes the multi-agent architecture that consists of several, possibly physically distributed expert modules, each of which is capable of some control over its communication and decision-making. In a process control system, these agents would likely have the same goal, namely the safe and efficient production of some manufactured goods. However, at a lower level, it is possible that conflicts would arise among the agents.

In these three types of architectures, a variety of AI methods can be incorporated. One of the earliest successes in the application of AI to process control involved the use of a fuzzy rule-based expert system. Many knowledge-based systems for process control use rule-based inference or fuzzy logic to cope with at least part of their control strategy. In addition, the neural network approach has recently emerged as a process control method. Current work in Japan and the United States is seeking to combine fuzzy control with neural networks.

De Veaux et al. (1999) presented work on integrating differential equations based on first principle with an ANN to forecast and control an environmental process. This approach overcomes the problem of unavailability of some important parameters required by a mathematical model of some process control system. The hybrid model substantially improves upon reliability of the model predictions.

For the biological treatment process for contaminated water, some knowledge about the inherent biochemistry of the process is usually available, either in the form of energy balances or other equations describing development of the process. However, these equations often involve variables that are not quantifiable. Therefore, a feed-forward neural network is used in conjunction with the 'specifiable' part of the model. The neural network estimates the unobservable kinetic parameters from the state at time t. This information plus the estimated kinetic parameters at time t is then fed into the known model to obtain the state at time $t+1$. Hybrid neural networks, sometimes called 'gray box models', can be trained with fewer data and extrapolate better than pure neural networks.

The experiments demonstrated the potential for using a hybrid model for forecast and simulation of an environmental process. When sufficiently large training sets of data are available, pure neural networks give an accurate model of the process. However, when limited data are available, as frequently happens in real life, the hybrid model gives significantly better accuracy, particularly on extrapolation. The part of the model that is assumed known acts as a constraint on the estimation, producing extrapolation far more reliable than those generated using a purely empirical model.

Adding more constraints to the model is generally beneficial.

Lippmann et al. (1997) described a software package called LNKnet that simplifies the task of applying neural network, statistical, and machine-learning pattern-classification algorithms in new application areas. The purpose of a pattern classifier is to assign every input pattern to one of a small number of discrete classes or groups. There are three major approaches to developing pattern classifiers: the probability-density-function (PDF), posterior-probability, and boundary-forming strategies.

The five most common types of neural network classifiers are PDF, global and local neural network, nearest neighbor and rule forming. PDF classifiers provide good performance when the PDF of the input features are known and when there is sufficient training data. Global and local neural network classifiers are both suitable for applications in which probabilistic outputs are desired. Nearest-neighbor classifiers are best suited for problems in which fast training and adaptation are essential. Finally, rule-based classifiers and decision trees are most suitable when a minimal-sized classifier is desired and when simple explanations for classifier decisions are desired.

LNKnet integrates all of these methods. The software can be used at any of the three levels described as follows. The point-and-click graphical user interface can facilitate rapid experimentation and interaction with the various classifiers on new databases. Users who want to execute long batch jobs can edit and run the shell scripts produced by the point-and-click interface. Finally, users with knowledge of C programming can work at the source-code level. At this level, C source code of LNKnet can be embedded in a user application program. LNKnet contains more than 20 neural network, pattern-classification, and feature-selection algorithms. The algorithms can be trained and tested on separate data or tested with automatic cross-validation. The software is written in C and runs under the UNIX operating system. A number of research laboratories including the Lincoln Laboratory of Massachussettes Institute of Technology have used LNKnet successfully for many diverse applications, including talker identification, talker–gender classification, hand-printed character recognition, underwater and environmental sound classification, image spotting, seismic-signal classification, medical diagnosis, galaxy classification, and fault detection.

More recently, Rodrigo et al. (1999) described a fuzzy proportion-integral-differential (PID) controller for a non-linear sludge aeration process developed based on expert knowledge. The controller incorporated fuzzy neural networks that were applied to modify the fuzzy functions and fuzzy rules in the controllers. Molina et al. (2000) used expert systems and neural networks to construct a predictive maintenance system for a hydroelectric power plant. The expert system was built based on a rule-based diagnostic model, and a neural network predictive model was developed based on historical data to produce process predictions.

Neural network models are often considered 'black boxes' due to their inability to provide explanations. To compensate for this weakness, De Veaux et al. (1999) proposed a hybrid system of neural network and first principle differential equation. This combination is sometimes called a 'grey box'. The inclusion of first principle knowledge in this hybrid model is shown to improve substantially the stability of the model predictions. When sufficiently large training sets of data are available, pure neural networks give an accurate model of the process. However, when only limited data are available, as typically is the case in real life, the hybrid model gives significantly better accuracy, particularly on extrapolation. The part of the model that is assumed known acts as a constraint on the estimation, producing extrapolation far more reliable than those generated using a purely empirical model of neural networks.

7. Research perspectives on AI-aided process control

Process control for environmental systems is an interdisciplinary concept, involving a variety of factors with multi-component, multi-phase, multi-period, and multi-criterion characteristics. The goal is to obtain desired environmental targets with minimized capital and operating costs. However, the possibility for accomplishing this goal could be affected by many constraints, limitations and complexities that exist in the pollution control systems. Facing these challenges, it is essential to identify effective approaches for realizing the desired targets. In the following, the detailed perspectives will be discussed.

(1) *Data availability*: The insufficiency of information about pollution sources, minimization and mitigation measures, water quality records and economic data often hinder the development of effective models or expert systems. In many situations, information of scaled and field works was insufficient for supporting the AI-aided process modeling and control studies. Thus, researchers have to work within limited scopes where the required data are available, constraining the adoption of techniques of comprehensive analysis, integrated modeling, global optimization, and systematic consideration. It is suggested that improvement in data availability and quality is pre-requisite for useful process control studies.

(2) *Data reliability*: Many environmental data are subject to significant problems of uncertainties, inconsistencies, and errors. In fact, reliability and uncertainty

are direct opposites of each other. That is, high reliability usually corresponds to low uncertainty, but it is, in fact, difficult to achieve both high reliability and low uncertainty at the same time. However, it is well recognized that high uncertainty means high system complexity, and low reliability could be worse than no data. To obtain improved reliability and certainty, solid works on validation of input data before they are used for further AI-related studies are desired.

(3) *Validity of methodology*: A variety of techniques have been developed for supporting missions of environmental process management and control. However, problems of reliability and suitability exist. In process simulation and prediction, due to the existence of uncertainties and the lack of quantified economic information, most of neural network models can only reflect part of the impact factors. These affect accuracy of the prediction. Therefore, when neural network models are used for providing decision support, the researchers have to conduct solid on-site works to gain as much insight of the study system as the process managers before claiming that they are wiser and can do better jobs. Simply staying in offices and conducting modeling computations and theoretical imaginations based on documented reports and data will not work.

(4) *System complexity*: Environmental processes generally have interactive, dynamic and uncertain features. Complexities exist in determination of system parameters, reflection of interactive relationships, formulation of AI-aided modeling approaches, interpretation of research outputs, and implementation of recommended activities. Often, to quantify and control such systems, a number of simplifications were made by adopting, for example linear, continuous, static, and/or deterministic assumptions. These simplifications, however, are subject to risks of system errors and failures. How to effectively reflect these complexities without taking these risks has been a challenging question facing the modeling researchers. Obviously, using any single technique to solve such problems could be subject to risks. Therefore, whenever possible, it is recommended to use an integration of more than one tool to tackle different aspects of these complexities. This paper has presented some hybrid approaches that incorporate diverse techniques. These can be more flexibly adopted to address more open-ended investigations. For example, the ANN technique can be integrated with fuzzy logic to tackle more complex problems. The ability of fuzzy logic to model qualitative knowledge and represent knowledge in a logical form can compensate for the weakness in ANN of embedding knowledge implicitly in their structural parameters (Zhou, 2002). Applications of the hybrid approaches to pollution minimization and mitigation processes would be a fruitful direction of future research.

8. Conclusions

Several demanding areas for enhanced research efforts are discussed, including issues of data availability and reliability, methodology validity, and system complexity. In general, expert systems and AI techniques can be categorized according to problem solving or task types. Along this dimension, the majority of AI applications for pollution mitigation and minimization fall into four broad task groups: (i) process control, (ii) prediction or estimation, (iii) process modeling or simulation, and (iv) process management that involves some comparison and evaluation of cost–benefit ratios of different solution scenarios. Among these, the most frequently tackled tasks are process control, prescription, and prediction. When sufficient data are available, the neural network technique often generates good results for system prediction. On the other hand, expert systems are often used for the task of prescription and control which involve process modeling and optimization. However, many environmental processes are complex with interactive, dynamic and uncertain features, leading to difficulties in using a single technique to solve such problems. Therefore, integrated or hybrid approaches are desired for reflecting such complexities and accomplishing the desired targets.

Problems of environmental pollution have caused severe stress on the human society and economic progress. Pollution abatement through minimization and mitigation measures is an important approach for addressing such a challenge, where effective process control would be essential for obtaining desired efficiencies. Recently, AI technologies have been found to excel in environmental systems that are complex, non-linear, and uncertain. This study investigates and analyzes some recent advancement of these technologies. In particular, technologies of expert systems, fuzzy logic, and neural networks have emerged as the most frequently employed approaches for realizing process control. The results not only provide an overview of progress in the study field but also, more importantly, reveal opportunities for research in order to realize more effective environmental process control through incorporation of AI technologies.

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