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A review on the integration of artificial intelligence into coastal modeling

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ABSTRACT

With the development of computing technology, mechanistic models are often employed to simulate coastal processes in coastal environments. However, these predictive tools are inevitably highly specialized, involving certain assumptions and/or limitations, and can be manipulated only by experienced engineers who have a thorough understanding of the underlying theories. This results in significant constraints on their manipulation as well as large gaps in understanding and expectations between the developers and practitioners of a model. The recent advancements in artificial intelligence (AI) technologies are making it possible to integrate machine learning capabilities into numerical modeling systems in order to bridge the gaps and lessen the demands on human experts. The objective of this paper is to review the state-of-the-art in the integration of different AI technologies into coastal modeling. The algorithms and methods studied include knowledge-based systems, genetic algorithms, artificial neural networks, and fuzzy inference systems. More focus is given to knowledge-based systems, which has apparent advantages over the others in allowing more transparent transfers of knowledge in the use of models and in furnishing the intelligent manipulation of calibration parameters. Of course, the other AI methods also have their individual contributions towards accurate and reliable predictions of coastal processes. The resulting tool might be very powerful, since the advantages of each technique can be combined.

INTRODUCTION

In the analysis of the coastal water process, numerical models are frequently used to simulate the flow and water quality problems. The rapid development of computing technology has provided a large number of models to be used in engineering or environmental problems. To date, a variety of coastal models are available and the modeling techniques have become quite mature. The numerical technique can be based on the finite element method, finite difference method, boundary element method, and Eulerian-Lagrangian method. The time-stepping algorithm can be implicit, explicit, or characteristic-based. The shape function can be of the first order, second order, or a higher order. The modeling can be simplified into different spatial dimensions, i.e., a one-dimensional model, two-dimensional depth-averaged model, two-dimensional layered model, three-dimensional model, and so forth [1-8]. An analysis of coastal hydraulics and water quality generally involves heuristics and empirical experience, and is effected through some simplifications and modeling techniques on the basis of the experience of specialists [9]. However, the accuracy of the prediction is to a great extent dependent on open boundary conditions, model parameters, and the numerical scheme [10].

The selection of an appropriate numerical model for a practical coastal problem is a highly specialized task. Ragas et al. [11] compared eleven U.K. and U.S.A. water quality models used to determine the levels and kinds of discharge to be permitted and found that model selection is a complicated process of matching model features with the particular situation.

These predictive tools inevitably involve certain assumptions and/or limitations, and can be applied only by experienced engineers who have a thorough understanding of the underlying theories. This results in significant constraints on the use of models and large gaps in understanding and expectations between the developers and practitioners of a model.

Over the past decade, there has been a widespread interest in the field of artificial intelligence (AI) [11-17]. The recent advancements in AI technologies are making it possible to integrate machine learning capabilities into numerical modeling systems in order to bridge the gaps between developers and practitioners of a model and lessen the demands on human experts. The development of these intelligent management systems is facilitated by employing some shells under the established development platforms such as MathLab, Visual Basic, C++, and so forth. Due to the complexity of the numerical simulation of flow and/or water quality, there is an increasing demand to integrate AI with these mathematical models in order to incorporate more and more features based on advanced computer technology.

In this paper, the development and current progress of integration of different AI technologies into coastal modeling are reviewed and discussed. The algorithms and methods studied include knowledge-based systems (KBSs), genetic algorithms (GAs), artificial neural networks (ANNs), and fuzzy inference systems. More focus is given to KBSs, which have apparent advantages over the other systems in allowing more transparent transfers of knowledge in the use of models and in furnishing intelligent manipulation of calibration parameters. This paper may provide some useful advice to some inexperienced engineers on how to establish a numerical model, although an understanding of the underlying theories is still necessary.

NUMERICAL MODELING

Numerical modeling can be defined as a process that transforms knowledge on physical phenomena into digital formats, simulates for the actual behaviors, and translates the numerical results back to a comprehensible knowledge format [17]. In mechanistic models, the equation for the transport of pollutants can be expressed as:

$$\frac{\partial SD}{\partial t}+\frac{\partial SUD}{\partial x}+\frac{\partial SVD}{\partial y}+\frac{\partial S\omega}{\partial \sigma}=\frac{\partial}{\partial x}(A_S H\frac{\partial S}{\partial x})+\frac{\partial}{\partial y}(A_S H\frac{\partial S}{\partial y})+\frac{\partial}{\partial \sigma}\left[\frac{K_H}{D}\frac{\partial S}{\partial \sigma}\right]-K_S DS+S_S\ , \qquad (1)$$

where (U,V,ω) are mean fluid velocities in the (x,y,σ) direction; S is the density of the pollutant; $D=\eta+H$, η is the elevation of the sea surface above the undisturbed level; H is the undisturbed mean depth of the water; and K_H is the vertical turbulent flux coefficient, which can be derived from the second moment $q^2 \sim q^2 l$ turbulence energy model [18]. K_s is the decay rate of pollutant; S_s is the source of the pollutant; and A_s is the horizontal turbulent coefficient. Pollutant transport equations can then be written in discretized forms, depending on which algorithm is used.

Model Manipulation

Model manipulation is always required, particularly during the setting up of the model, since a slight change in the parameters may lead to quite different results. The procedure is a mixed one of feedback and modification. Knowledge of model manipulation includes real physical observations, mathematical descriptions of water movement or water quality, the discretization of governing equations for physical and chemical processes, schemes to solve the discretized equations effectively and accurately, and an analysis of output. Experienced modelers can determine the failure of a model based on a comparison of the simulated results with real data as well as a heuristic judgment of key environmental behavior. The knowledge mentioned above may be used unconsciously. However, many model users do not possess the requisite knowledge to glean their input data, build algorithmic models, and evaluate their results. The result may be inferior designs, leading to the under-utilization, or even the total failure, of these models.

The ultimate goal of model manipulation in coastal engineering is to acquire satisfactory simulation. Hence, a balance should be struck between modeling accuracy and speed. It is noticeable that modelers usually keep certain fundamental parameters unchanged during the manipulation process. For instance, when researchers were used to two-dimensional coastal modeling, they varied only the bottom friction coefficient [19]. In water quality modeling, Baird and Whitelaw [20] reported that the algal behavior was related intimately not only to its respiration rate but also the water temperature. Model users will consider variations in the intensity of sunlight within the water column when simulating the phenomenon of eutrophication [21]. These examples reflect that human intelligence uses existing knowledge to reduce the number of choices in order to raise the effectiveness of model manipulation. Each time, they tend to alter merely one or two parameters. This is because if they modify many parameters at the same time, they may easily become lost as to the direction of the manipulation. To this end, AI techniques are capable of mimicking this behaviour as well as of complementing the deficiency.

Generations of modeling

The notion of “generations” of modeling to describe the trend of development was introduced by Abbott [17] and Cunge [22]. The so-called third generation modeling, being a system to solve specific domain problems, can only be apprehended by the modeler and special users well trained over a long period. It has incorporated very few features to facilitate other users and to handle other problems. Typical examples are some sophisticated convection-dispersion models of the Eulerian-Lagrangian type [2], two-dimensional or three-dimensional finite difference numerical models on tidal flow [4,5] and on a specific water quality phenomenon such as eutrophication [21], finite-element modeling of floodplain flow [6], the depth-averaged turbulence k-e model [9], and so on.

Previous efforts have been devoted to accommodating a much wider range of end-users. The fourth generation of modeling has become much more useful to a much wider range of end-users. It provides a menu of parameter specifications, automatic grid formation, pre-processing and post-processing features, and features for the management of real collected data for modeling, etc. These tools act as intelligent front-ends to support the handling of the simulation models for specific hydraulic [23] or water quality [24] problems. Yet they do not address the core problem of the elicitation and transfer of knowledge. In the modern era, characterized by a boom in knowledge, the fourth generation of modeling starts the technological research to transform the knowledge of hydrodynamic and water quality computation into the products.

INCORPORATION OF AI INTO MODELING

During the past decade, the general availability of sophisticated personal computers with ever-expanding capabilities has given rise to increasing complexity in terms of computational ability in the storage, retrieval, and manipulation of information flows. With the recent advancements in AI technology, there has been an increasing demand for a more integrated approach in addition to the need for better models. Justification for this claim comes from the relatively low utilization of models in the industry when compared to the number of reported and improved models. It is expected that this enhanced capability will both increase the value of the decision-making tool to users and expedite the water resources planning and control process.

Knowledge-based systems (KBSs)

Conventionally, in solving coastal problems, the emphasis has been on algorithmic procedures. These mechanistic models, being insufficiently user-friendly, lack knowledge transfers in model interpretation. It is a difficult task for novice application users to select an appropriate numerical model due to varying factors, such as the water depth, water velocity, grid spacing, etc. For non-expert users in particular, it is usual for the length of the procedures for model manipulation to depend largely on their experience. As a result, it is highly desirable to establish a bridge between model developers and application users. Therefore as a design aid or training tool for engineers or students, it is necessary to include some features to provide help in selecting models. In this regard, KBSs can address the problem by incorporating a repository of heuristic knowledge provided by human experts.

It can be seen that more and more software systems are being accompanied by a “usage wizard” to provide guidance for the use of such systems. The “wizard” integration in the system is usually related to AI technology. After comparing a number of U.K. and U.S.A. models, Ragas et al. [11] suggested, although they did not actually implement, the development of a KBS for model selection in order to deal with uncertainty in model predictions. The fifth generation of modeling system [17,25,26] is acknowledged to have the features to allow AI technology and computational hydrodynamics to be integrated into a single system to furnish assistance for non-experienced users.

KBSs are interactive computer programs that mimic and automate the decision-making and reasoning processes of human experts. The schematic view of a typical KBS is shown in Figure 1. The knowledge base is a collection of general facts, rules of thumb, and causal models of the behavior specific to the problem domain. The inference mechanism guides the decision-making process by using the knowledge base to manipulate the context. The context contains facts that reflect the current state of the problem, constructed dynamically by the inference mechanism from the information provided by the user and the knowledge base. The knowledge acquisition module serves as an interface between the experts and the KBS and provides a means for entering domain-specific knowledge into the knowledge base. The user interface is responsible for translating the interactive input as specified by the user to the form used by the KBS. The explanation module provides explanations of the inferences used by the KBS, namely, why a certain fact is requested and how a conclusion was reached. KBSs are considered suitable for solving problems that demand considerable expertise, judgment, or rules of thumb. KBSs have widespread applications in different fields and are able to accomplish a level of performance comparable to that of a human expert [27-31].

The feasibility of integrating KBS with numerical modeling has recently been studied [29-30]. Chau and Yang [31] implemented an integrated expert system for fluvial hydrodynamics. Jamieson and Fedra [32] developed a decision-support system for efficient river basin planning and management. Bobba et al. [33] applied environmental models through an intelligent system to different hydrological systems. Most of this fifth generation of numerical coastal models only refer to a one-dimensional system for river network or river planning due to the simplicity of the knowledge and selection procedures. Their knowledge bases include heuristic rules for model selection but not for model manipulation. However, even for that simplest case, the symbolic programming for the knowledge representation and selection procedure required enormous effort. For two or three-dimensional modeling, the integration of a KBS and problem solutions in a single system will become much more complex. The basic requirement is that the system should be able to provide expert advice on the selection of the most appropriate model as well as the relevant model parameters under that particular scenario. Since numerical modeling programs have often been developed in some traditional programming languages such as Fortran, Pascal, C, etc., it is considered not cost-effective to re-write and replace these well-proven and validated programs whose development involved long hours of concerted effort.

To introduce KBS technology into the modeling system requires a method to make the system capable of providing advice on the selection of parameters or models, and to make the system have the intelligent features of a “usage wizard” if the program is written in some embedded forms of code. The architecture of a prototype integrated system [34] is shown in Figure 2. The expert system shell, Visual Rule Studio [35], which runs as an ActiveX Designer under the windows-based programming language environment Microsoft Visual Basic 6.0, was employed. The Visual Rule Studio is a hybrid expert system shell that couples the advantage of both production rules and object-oriented programming paradigm. All the usual objects of control of the common interface under a Windows environment such as a command button, picture box, and so forth, are furnished.

As an example, the KBS is employed to select and manipulate numerical models on addressing the problem of eutrophication for Tolo Harbour in Hong Kong [36]. Figure 3 shows an example of the inference direction from the user’s specifications through the inference engine. Figure 4 displays a sample interactive screen of model selection for the application example. After the inputted data have been entered, a summary of the input requirements is shown in the left frame of the questionnaires as shown in Figure 4. When the command button **INFER** is clicked, the process of model selection can be automatically attained on the basis of the rule sets in the knowledge base. The right frame shows the inference results on the features of the suggested model for this example, which are verified with the decision made by the expert modeler.

The principal advantage of integrating KBS into the numerical coastal modeling is that it is capable of producing a more intelligent, interactive, and user-friendly system to furnish assistance on selecting a model and its pertinent parameters. Explanations of the reasoning process, options, procedures, various specific provisions, and expert comments regarding coastal modeling are effected via the explanation module. This can significantly narrow the gap between the numerical modelers and the users of the application. Moreover, the rule sets and the knowledge bases are tailored to be transparent to facilitate updating with new knowledge when available.

One disadvantage of a KBS is the difficulty of gleaning the experiences of various expert modelers in the world, who may have different treatments for the same problem. Hence, it is imperative to incorporate more heuristic experiences of numerical modeling experts. A KBS should be further developed and updated constantly through frequent usage and feedback from the users as well as through the validation of personal conclusions and experiences from previous studies on numerical modeling for coastal water processes. In this regard, hybrid integration with other AI technologies, taking advantage of the characteristics of each, may supplement the current deficiencies of a KBS.

Genetic algorithms (GAs)

GAs, being search techniques based on the mechanism of natural genetics and biologically-inspired operations, can be employed as an optimization method to minimize or maximize an objective function [37]. They apply the concept of the artificial survival of the fittest coupled with a structured exchange of information using randomized genetic operators taken from nature to compose an efficient search mechanism. This form of search evolves throughout iterative generations by improving the features of potential solutions and mimicking the natural population of biological creatures. Through a variety of operations to generate an enhanced population of strings from an old population, GAs exploit useful information subsumed in a population of solutions. Various genetic operators that have been identified and used in GAs include crossover, deletion, dominance, intra-chromosomal duplication, inversion, migration, mutation, selection, segregation, sharing, and translocation. Figure 5 shows a typical flow chart delineating the steps by which GAs generate their solutions.

A variety of applications has been presented since the early studies on the subject, and GAs have clearly demonstrated their capability to yield good solutions even in cases of highly complex, multiple-parameter problems [38-39]. GAs can help in determining the patterns, regularities and relationships that exist and drive a certain phenomenon, such as algal abundance. Mulligan and Brown [40] used genetic algorithms to calibrate water quality models. Bobbin and Recknagel [41] used GA to build inducing explanatory rules for the prediction of algal blooms. Ng and Perera [42] calibrated a river water quality model by GAs. Cho et al. [43] utilized GAs to undertake the optimization of regional wastewater treatment in a river water quality management model.

As an example of its implementation on coastal modeling, a GA is employed to determine an appropriate combination of parameter values [44]. The inappropriate use of any model parameters, which cannot be directly acquired from measurements, may introduce large errors or result in numerical instability. The percentage errors of peak value, peak time, and total volume of coastal constituents are important performance measures for model predictions. The calibration of parameters is based on field data on tidal as well as water quality constituents collected over a five-year span from 1991 to 1995 in the Pearl River. Another two-year record from 1996 to 1997 is utilized to verify these parameters. A sensitivity analysis on crossover probability, mutation probability, population size, and maximum number of generations is also performed to determine the most fitting algorithm parameters. The results demonstrate that the application of GA can mimic the key features of the coastal process and that the calibration of models is efficient and robust. More details can be found in [44].

A major advantage of GA is its capability to locate global optimizations. However, GA is an algorithmic process and cannot help much with user-friendly interactions with the system. Many GA parameters, such as crossover probability, mutation probability, population size, and maximum number of generations, have a significant impact on the accuracy of a prediction. It is necessary to carefully choose these parameters in order to attain a reliable prediction. Moreover, a GA cannot extrapolate beyond the range of the training data.

Nevertheless, a comprehensive investigation on the application of GAs to coastal modeling has yet to be conducted, but the early indications of the use of GA in this way are promising.

Artificial neural networks (ANNs)

A definition of an ANN is “a computational mechanism able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping” [16]. Maier and Dandy [45] gave an excellent review on the use of neural network models for the prediction and forecasting of water resources variables. ANNs are based on our present understanding of the brain and its associated nervous systems. They use processing elements connected by links of variable weights to form black box representations of systems. A typical ANN is comprised of several layers of interconnected neurons, each of which is connected to other neurons in the ensuing layer. Data are presented to the neural network via an input layer, while an output layer holds the response of the network to the input. One or more hidden layers may exist between the input layer and the output layer. All hidden and output neurons process their inputs by multiplying each input by its weight, summing the product, and then processing the sum using a nonlinear transfer function to generate a result. Among others, the S-shaped sigmoid curve is a commonly used transfer function [46]. The data-driven models have the ability to learn complex model functions from examples.

The greatest advantage of ANNs over other modeling techniques is their capability to model complex, non-linear processes without having to assume the form of the relationship between input and output variables. Learning in ANNs involves adjusting the weights of interconnections. Areas addressed by ANN techniques include pattern matching, combinatorial optimization, data compression, and function optimization. As a developing and promising technology, ANNs have become extremely popular for prediction and forecasting. The capability of an ANN to cope with uncertainty in complex situations has been seized upon for wide-ranging applications in recent years [47-48].

ANNs have found applications in the forecasting of water quality variables such as phosphorus [49], algal concentrations [50], cyanobacterial concentrations [51], salinity levels [52], ecological modeling [53], and so forth. Kralisch et al. [54] employed an ANN approach for the optimization of watershed management to maintain a reasonable balance between water quality demands and the consequent restrictions for the farming industry. Maier et al. [55] used ANNs to predict optimal alum doses and treated water quality parameters. However, most of the studies were undertaken for limnological systems [56-58] or riverine systems [59-60], while reports on ANN modeling of coastal systems have been very scarce [61]. Moreover, in most of the studies, the effectiveness of ANN as a predictive tool has not been fully addressed. For example, the water quality dynamics at the current time were often linked via the model with other environmental variables at the same time, which rendered them useless for real predictions. Most studies employed almost all possible environmental parameters as input variables without considering the optimal choice among them. As an illustrative example, a three-layer feedforward back-propagation ANN was used to simulate the relationship between the parameters and the steady-state response of a mechanistic total phosphorus model for a period of 1,095 days spanning from 1993 to 1995 [49]. Figure 6 shows the architecture of this ANN, in which the input layer contains three nodes: settling velocity, recycling velocity, and burial velocity. The hidden layer consists of six hidden nodes while the only node in the output layer is the concentration of phosphorus. It is demonstrated, in the case of the total phosphorus model of the Triadelphia Reservoir, that the

ANN technique is capable of accurately approximating the input-output response of a water quality model and that the ANN-predicted concentrations of phosphorus match the concentrations predicted by the mechanistic model well for both the training and testing sets.

In the process of building an ANN model, many options are available [45]: the choice of performance criteria, the division and pre-processing of the available data, the determination of appropriate model inputs and network architecture, the optimization of the connection weights, and the validation of the model. All of these parameters have a significant impact on the accuracy of a prediction. Moreover, ANNs cannot extrapolate beyond the range of the training data and, thus, they may not be able to account for trends and heteroscedasticity in the data. Thus, careful choices of various parameters in different steps as well as a thorough understanding of the boundaries of applicability are entailed if ANNs are to play a meaningful role in coastal modeling. Another weakness is that the most popular gradient-based back propagation algorithms of ANNs are vulnerable to getting stuck in a local minimum. Moreover, insufficient attention has been given to extracting some knowledge from the learning process. More efforts can be given to the application of this technique to coastal modeling.

Fuzzy inference systems

Fuzzy logic is very useful in modeling complex and imprecise systems [62]. Under the fuzzy set theory, elements of a fuzzy set are mapped to a universe of membership values using a function-theoretic form belonging to the close interval from 0 to 1. An important step in applying fuzzy methods is the assessment of the membership function of a variable, which parallels the estimation of probability in stochastic models. Membership functions in fuzzy set theory, which are appropriate for modeling the preferences of the decision maker, can be obtained on the basis of actual statistical surveys. Modeling based on fuzzy logic is a simple approach, which operates on an "if-then" principle, where "if" is a vector of fuzzy explanatory variables or premises in the form of fuzzy sets with membership functions and "then" is a consequence also in the form of a fuzzy set.

If the objective or the constraints of an optimization problem are vague, then the problem can be referred to as a fuzzy optimization problem. Fuzzy logic has been used in a number of applications, but generally as a refinement to conventional optimization techniques in which the usual crisp objective and some or all of the constraints are replaced by fuzzy constraints [38,63]. Fuzzy set theory concepts can be useful in ecological impact classifications [64], as they can provide an alternative approach to dealing with those problems in which the objectives and constraints are not well defined or the information about them is not precise. Chang et al. [65] used the fuzzy synthetic evaluation approach to identify the quality of river water. Chen and Mynett [66] employed data mining techniques and heuristic knowledge in modeling the fuzzy logic of eutrophication in Taihu Lake. Liou et al. [67] applied a two-stage fuzzy set theory to evaluate river quality in Taiwan. Marsili-Libelli [68] described the design of a bloom predictor based on the daily fluctuations of simple parameters for water quality such as dissolved oxygen, oxidation–reduction potential, pH, and temperature.

An example of the application of fuzzy logic is a comparison between the simulated results and the real observation of flow or water quality. Improvements in estimating the results of modeling depend on the technology of pattern recognition. The normalized root-mean-square error (NRMSE) between key field data and the results of the model is computed to evaluate the performance of the model and its associated model parameters. The NRMSE covers cases with a time series of data at a single point within the model domain, or instantaneous measurements at many locations, or a combination of both. Let N be the number of data locations for comparison, n be the number of time intervals in a time series of data for comparison, $T_{i,t}$, $O_{i,t}$ be the target values and the computed value of the i^{th} data location and t^{th} time step respectively, and $\overline{T}$ be the average target value. Then, the definition of the above-mentioned statistical quantity is as follows:

$$NRMSE = \frac{\sum_{i=1}^{N}\sum_{t=1}^{n}(T_{i,t} - O_{i,t})^2}{\sum_{i=1}^{N}\sum_{t=1}^{n}(T_{i,t} - \overline{T})^2}. \qquad (2)$$

Figure 7 shows the membership functions for NRMSE, which represent the fuzzy logic of literal classification into very small, small, large, and very large. Another application of fuzzy inference is in the representation of rule sets within the knowledge base of a KBS by using a more human-like fuzzy format, instead of a crisp threshold format.

In water quality problems, many indicators may conflict with each other, significant observations may be lacking, and potentially valuable information may be non-quantitative in nature. An advantage of fuzzy inference methods is their capability to represent real-life water quality problems, which are sometimes difficult to address by standard mathematical and statistical approaches. However, fuzzy logic by itself cannot help much with user-friendly interactions with the system. Many parameters, such as the number of categories, shape of the membership function, and method of combining partial memberships, have a significant impact on the results. The proper choice of these parameters and rigorous validation are necessary for accurate representations.

It is observed that most of the above studies have been undertaken for fresh water riverine systems and applications to coastal systems have been very scarce. More works can be undertaken to find applications of AI in this area to a fuller extent.

FUTURE DIRECTIONS

To date, individual applications of these innovative AI techniques have been recorded in the literature, yet they have often adopted for specific situations in an isolated manner. Since the application of different AI technologies is not mutually exclusive, one of the promising directions is the hybrid combination of two or more of the methods discussed above to produce an even more versatile coastal modeling system. For example, the use of a hybrid algorithm integrating KBS and ANN is feasible for establishing rules in the KBS on the basis of implicit relationships derived from the ANN. In fact, there is a great deal of potential in extracting the knowledge that is contained in the connection weights of trained ANN models, as well as in the highly transparent knowledge representation paradigm of KBS. Similarly, it is also feasible to use GA to locate the global optimization in ANNs as well as the fuzzy representation of rule sets in KBSs. It is believed that the integration of AI modules will enhance the applicability of modelling systems in real practice.

CONCLUSIONS

Existing coastal models are inevitably highly specialized, involve certain assumptions and/or limitations, and are usable only by experienced engineers who have a thorough understanding of the underlying theories. The recent advancements in AI technologies have made it possible to integrate machine learning capabilities into numerical modeling systems in order to bridge the gaps in understanding and expectations and lessen the demands on human experts. This study has reviewed the state-of-the-art and progress in the integration of AI into coastal modeling. Attempts to integrate various AI technologies, including KBSs, GAs, ANNs, and fuzzy inference systems, into numerical modeling systems have been discussed. More focus has been given to KBS, which has apparent advantages over the others in allowing more transparent transfers of knowledge in the use of models and in furnishing the intelligent manipulation of calibration parameters. KBS may provide some useful advice to some inexperienced engineers how to establish a numerical model, although they still need to have an understanding of the underlying theories. Of course, the other AI methods also have their individual contributions towards accurate and reliable coastal predictions. It is believed, as AI technologies grow in capability, that the resulting tool might be very powerful, since advantages of each technique can be combined.

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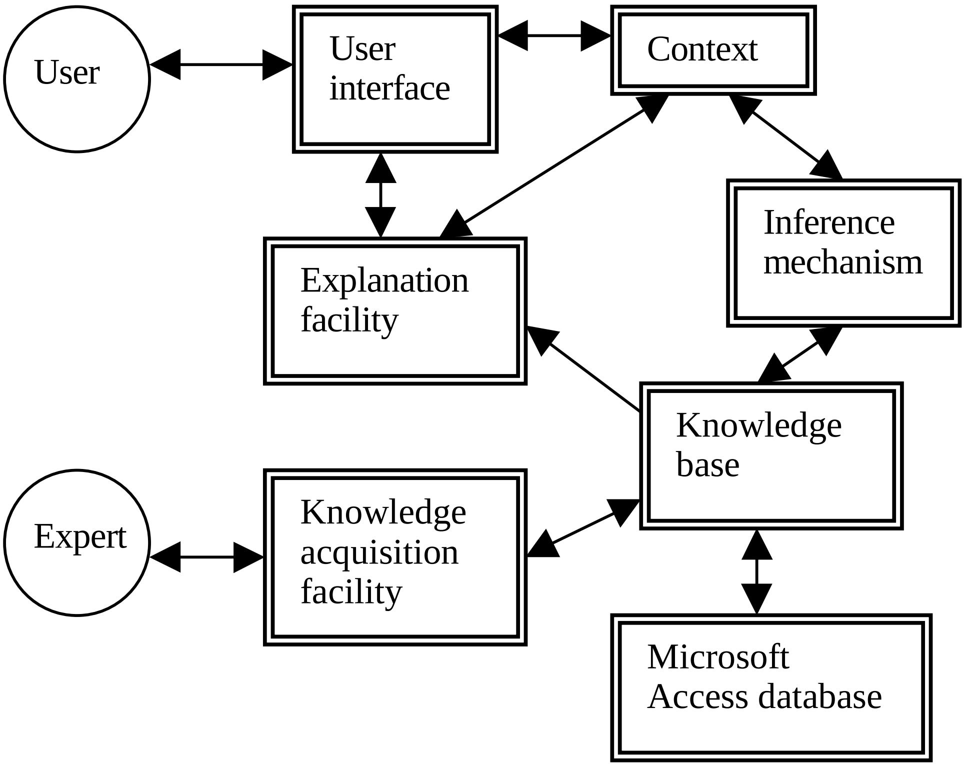

Figure 1. Schematic view of a typical KBS

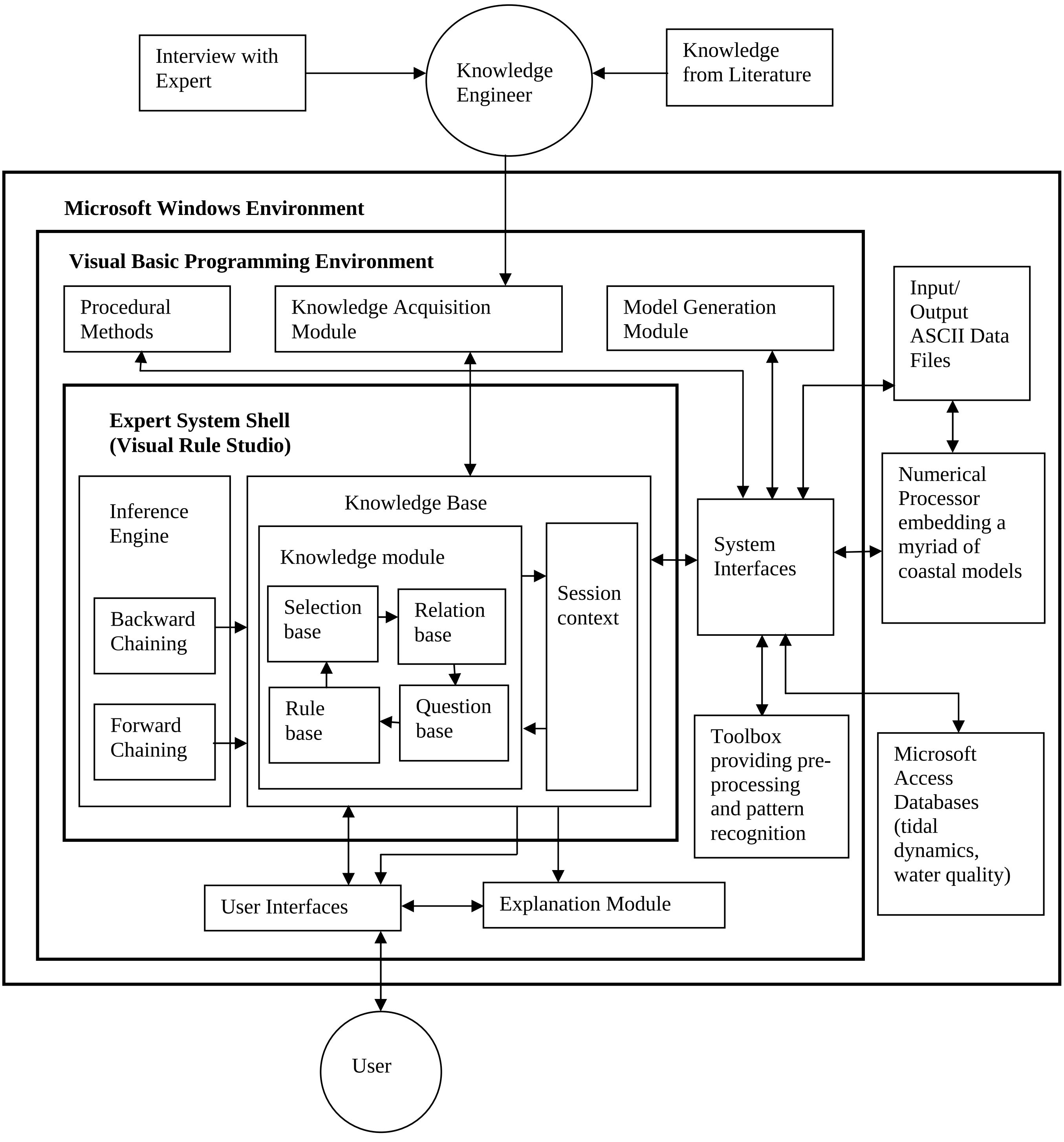

Figure 2 Architecture of a prototype KBS on the manipulation of a numerical coastal model

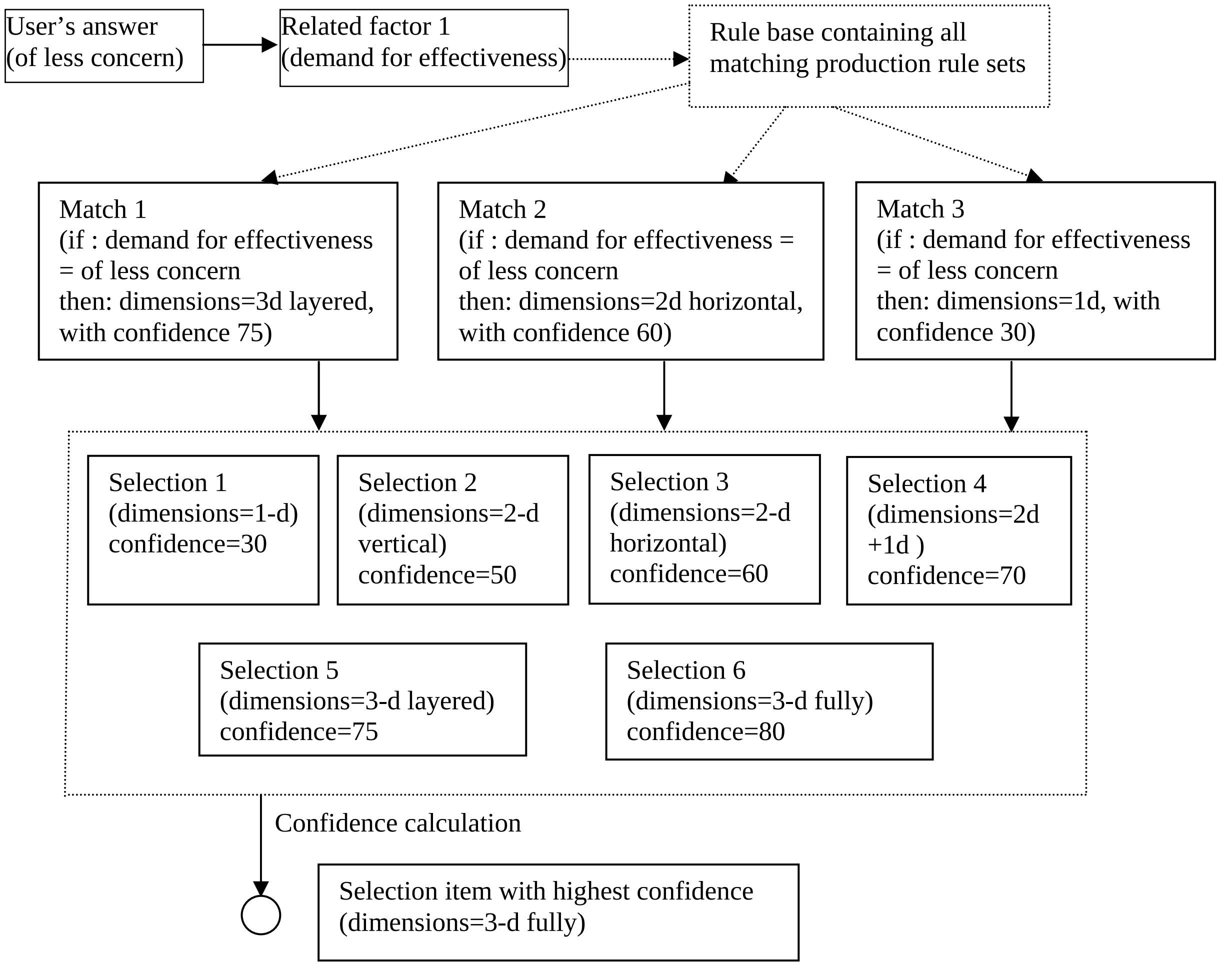

Figure 3. An example of the inference direction from the user's specifications through the inference engine

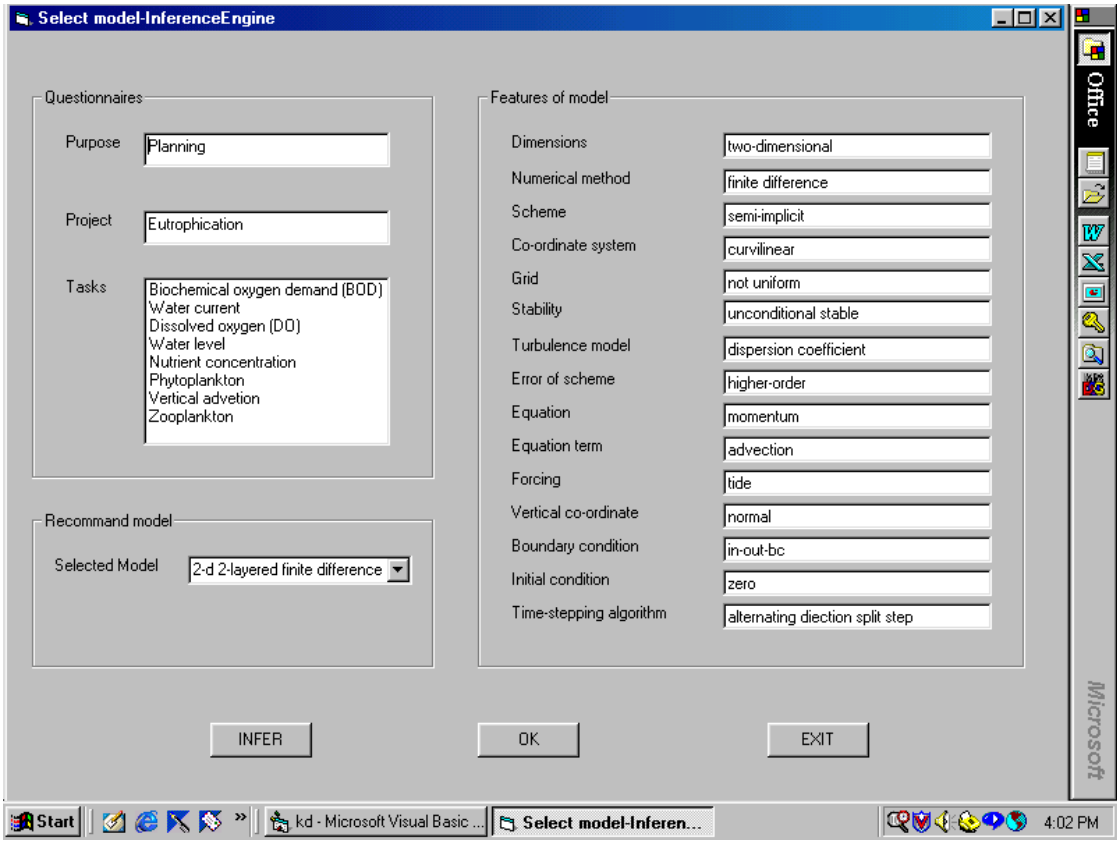

Figure 4. Sample screen of model selection for the application example

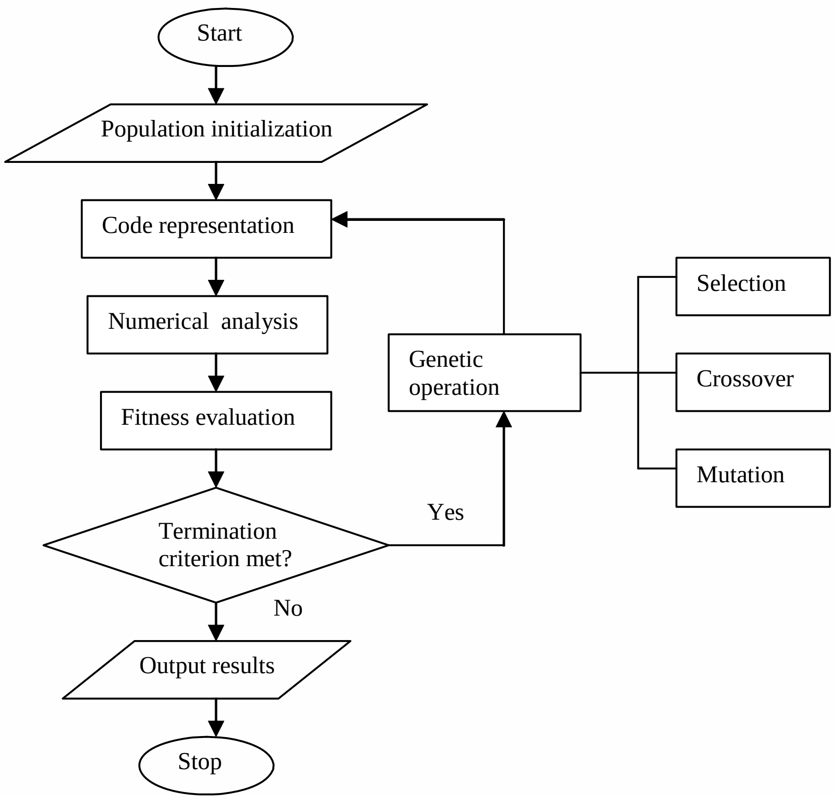

Figure 5. Flow chart of GA

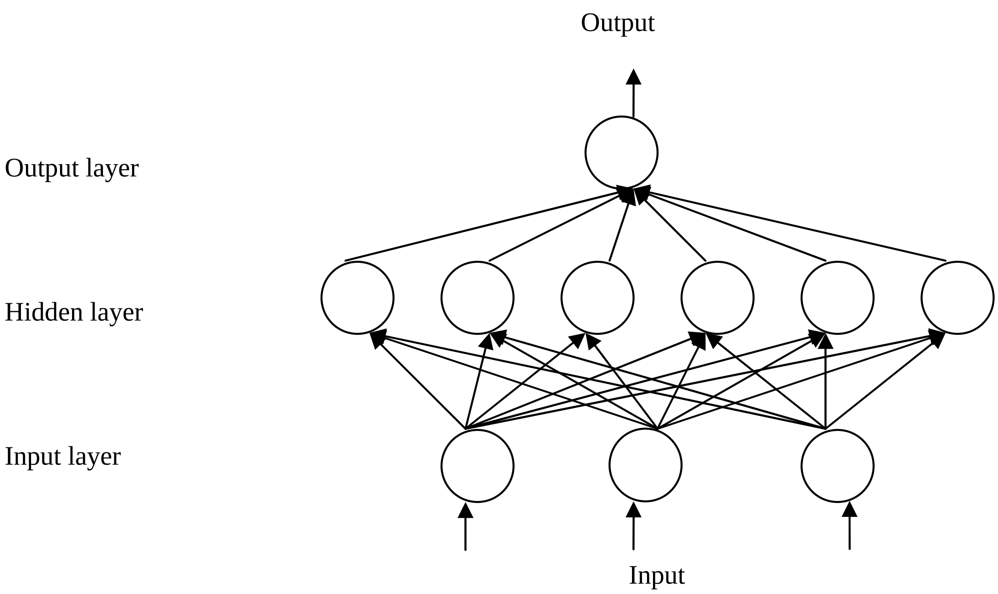

Figure 6. Architecture of a three-layer feedforward back-propagation ANN in modeling the total concentration of phosphorus

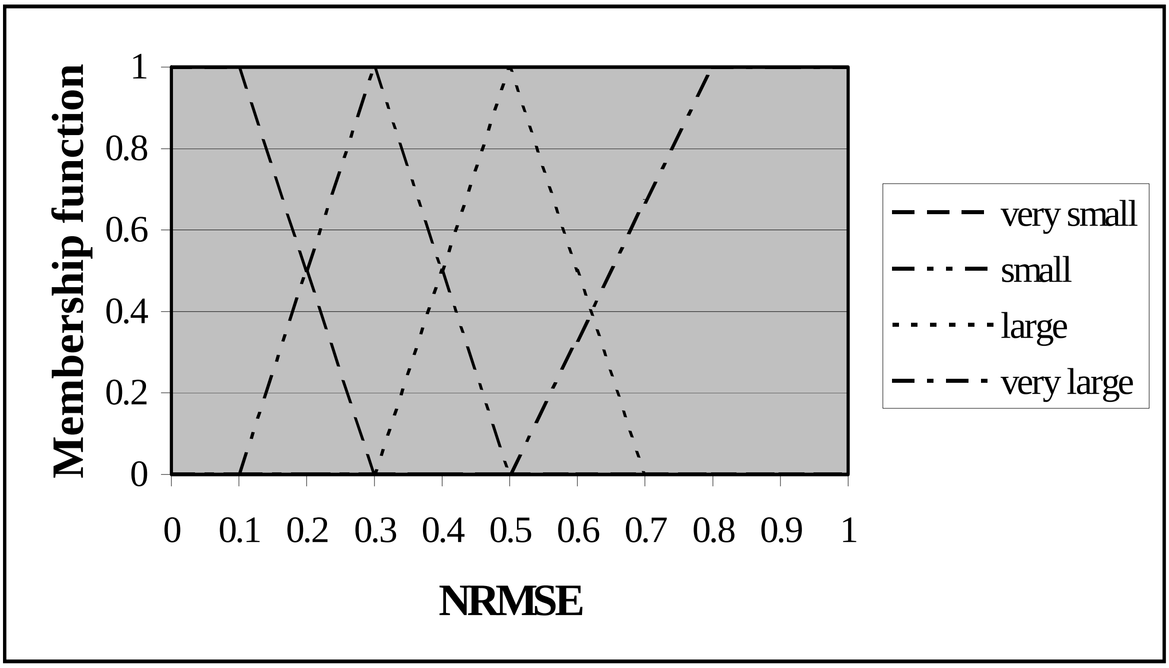

Figure 7. Membership functions for the normalized root-mean-square error (NRMSE), representing the fuzzy logic of the literal classifications of very small, small, large, and very large