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The Effects of Artificial Intelligence Applications in Natural Resource Management

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Keywords	Abstract
Artificial Neural Network Genetic Algorithm Fuzzy System Multi-Agent System Swarm İntelligence	Artificial intelligence methods have been increasingly used in natural resource management as an alternative to classical methods. Three computational challenges in natural resource management are data management and communication, data analysis, and optimization and control. Artificial intelligence methods can be a solution to these problems due to their ability to manage dynamic activities in natural resources. There are several artificial intelligence algorithms that have found various applications in various fields. In this article, some artificial intelligence methods, including artificial neural networks, fuzzy models, genetic algorithms, cellular automata, multi-agent systems, collective intelligence, and hybrid systems, are introduced, and some of their applications in natural resource management are listed.

1. INTRODUCTION

Various definitions of artificial intelligence have been proposed so far. In general, artificial intelligence can be defined as enabling computers to perform intellectual tasks performed by humans. Many of today's world problems, such as computational problems, information search and analysis, have been solved by computers in this way.

The basic idea of artificial intelligence is to understand the nature of human thinking and intelligence and provide software that models how they work. But in applied fields, engineers sought to create algorithms that perform tasks like humans. Natural resource management is a field that attempts to manage natural resources such as water, oil, plants and animals, and is of great importance due to the impact of management on the quality of life of current and future generations.

Natural resource management focuses on the scientific and technical understanding of resources and ecology and the capacity of resources required for survival. Three computational challenges in natural

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resource management are data management and communications, data analysis, and optimization and control.

One way to implement computational tools to address the challenges of natural resource management is to use artificial intelligence methods because they have the flexibility to deal with the inherent dynamics of natural resources. There are many artificial intelligence methods that have been used in various fields.

In this article, several artificial intelligence algorithms, including artificial neural networks, fuzzy models, genetic algorithms, cellular automata, multi-agent systems, collective intelligence, and hybrid systems, are introduced and some of their applications in natural resource management are listed.

2. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are inspired by the way the human brain processes information. An ANN consists of a large number of processing units called neurons or nodes that act as a unit. They are connected to each other by a series of weighted connections. The network can have one input layer, one output layer, and any number of hidden layers. Each neuron in one layer is connected to all neurons in the next layer (Chen et al., 2008).

Artificial neural networks can be applied to seven categories of problems: pattern classification, clustering, function estimation, prediction, optimization, content-based retrieval, and process control. Pattern classification assigns an input pattern to one of the predefined classes, for example, sewage odor classification.(Onkal-Engin, et al.2005).

Clustering is an unsupervised pattern classification method, for example, input patterns for predicting the ecological status of streams.(Vellido et al. 2007). Function estimation, also called regression, produces a function from the provided learning patterns.

For example, modeling river sedimentation (Cigizoglu and Alp, 2006) or watershed water supply (Iliadis and Maris, 2007), predicting ozone concentration (Sousa et al., 2007), modeling leachate flow rates (Karaca and Özkaya, 2006), or estimating nitrate distribution in groundwater (Almasri and Kaluarachchi, 2005). Forecasting takes the output from previous examples in a time series, e.g., climate (Kim and Barros, 2001) and air quality. (Agirre-Basurko, et al., 2006).

Optimization maximizes or minimizes a cost function given its constraints, e.g., calibrating the infiltration equation (Jain and Kumar, 2006). Content-based retrieval invokes memory, even if the input is partial or distorted, e.g., proxies for water quality measurements from Satellite imagery.(Pozdnyakov et al. 2005).

3. GENETIC ALGORITHMS

A Genetic Algorithm (GA) is a search method that mimics natural selection. The algorithm evolves until it solves the problem satisfactorily. Of the solutions produced by this algorithm in each round, the best solutions survive and pass on their characteristics to their offspring, replacing the weakest solutions. Each possible solution is encoded, for example, as a binary string called a chromosome. Successive populations of productive solutions are called populations (Chen et al. 2008).

GA methods are often used to optimize model parameters or resource management. Some examples of their application include parameter estimation of a watershed vegetation model (Kumar et al. 2012), groundwater management (Moharram et al. 2012), and stochastic optimization model for air quality management under uncertainty (Qin et al. 2010). (Babazadeh and Tabrizi,2013) also investigated the combined optimization of water productivity (WP) and crop yield under irrigation management defects using a multi-objective GA optimization algorithm.

4. CELLULAR AUTOMATA

Cellular Automata (CA) are dynamic models, discrete in space, time, and state. They consist of a regular network of cells that interact with their neighbors. The state of the cells is synchronous in time according to rules Local updates are performed to calculate the new state of a cell at time +1t using its current state and the neighboring cells at time. Neighbors are cells that are located near the cell of interest, (Chen et al.2008). Applications of cellular automata include modeling urban landscape dynamics (He et al. (2013), modeling land use and population density and economic activities (White et al. (2012), and simulating population dynamics of plant species (Jie et al. 2010).

In these examples, it is clear how the state of a cell is affected by the previous state of its neighbors. In (Hualin et al. 2012), by setting up a natural development scenario, an object-oriented scenario, and an environmental priority scenario, a model using CA is presented to simulate the underlying environmental evolutionary pattern.

5. FUZZY SYSTEMS

Fuzzy systems (or FS) use fuzzy sets to deal with imprecise and incomplete data. In conventional set theory, an object can be a member of a set or not, but the membership of a fuzzy set can take any value between zero and one. Therefore, fuzzy models can Describe ambiguous situations. (Chen et al. 2008).

Fuzzy systems handle incomplete and imprecise data in applications such as function estimation, classification or clustering, control, and prediction. For example, we can mention the characterization and quantification of vegetative drought (Rulinda et al. 2012), estimation of agricultural crop yield (Wieland, et al. 2013), monitoring of sensitive environmental ecosystems in a dynamic semi-arid landscape from satellite images (Meng-Lung, and Cheng- Wu,2010), estimation of agricultural and plant breeding parameters (Pandey et al.2013), modeling of fish habitat preferences (Fukuda et al. 2012), classification of fishing areas (Sylaios et al. 2010), assessment of land environmental security (Su et al. 2010), assessment of habitat suitability (Lu et al. 2012), detection of ocean oil spills in SAR images (Liu et al. 2010)) and modeling of rainfall runoff (Talei et al. 2010).

6. MULTI-AGENT SYSTEMS

A Multi-Agent System (MAS) consists of a network of agents that interact to achieve a goal. An agent is a software component that contains code and data. Agents communicate with each other using a high-level language called Agent Communication Language (ACL), share information, receive requests, and negotiate with each other (Chen et al. 2008).

Recently, MASs have been widely used in natural resource management. For example, they can be used in supply chain risk management (Giannakis and Louis,2011), assessing the impacts of land-use policies (Le et al. 2010), modeling climate adaptation and mitigation options in agriculture (Berger and Troost,2013), expert system for diagnosing fish diseases (Dongping and Ming,2012), forest fires (Elmas and Sönmez,2011)). regional-scale land use change modeling (Valbuena et al. 2010), water dynamics and demand modeling at the watershed level (Farolfi et al. 2010), and human-environment interaction modeling in agricultural systems (Schreinemachers and Berger,2011).

7. SWARM INTELLIGENCE

Swarm Intelligence (SI) is a form of agent-based modeling inspired by colonies of social animals such as ants or schools of fish. While individual agents are simple, as part of a collective, they exhibit higher intelligence. Self-organization is a key property by which general patterns emerge from local interactions without central control or a general model. These interactions can occur during direct (agent-to-agent) or indirect (through the environment) communication, (Chen et al. 2008).

Ant behavior is the basis for Ant Colony Optimization (ACO), one of the main types of swarm intelligence algorithms. Individual ants move randomly until they encounter a pheromone trail, which they are likely to follow and subsequently deposit their own pheromone on that trail, reinforcing the trail. Ants tend to choose a route with a stronger pheromone concentration, so the route that has received more traffic is more likely to be chosen.

Shorter routes, because they are traveled faster, are more reinforced and have more pheromone. So after a short period of time, all ants will choose the same route to find food. Over time, the evaporation of the pheromone causes less frequented or random routes to be less popular. Another widely used swarm intelligence algorithm is the Particle Swarm Optimization (PSO) algorithm, which is inspired by the coordination of bird populations and schools of fish.(Singh,et al.2012)

The system is initialized with a random population of solutions or particles that fly around an N-dimensional problem space, where each solution is represented by a point. At each iteration, the particles evaluate their fitness (their position relative to the goal) and share their information about the best position among the population. Each particle subsequently updates its velocity and position with respect to its previous best position and the position of the best particle in the population. The algorithm also includes random functions in the range [1 0,] to avoid falling into local optima.

Environmental applications of ACO include spatial assessment of land use suitability (Yu et al.2011) optimal management of coastal aquifers (Ataie-Ashtiani and Ketabchi 2011), environmental flow management for rivers, wetlands, and floodplains (Szemis et al.2012). The PSO algorithm was developed for general minimization but, like ACO, has found wide applications.

Environmental applications include water resources optimization (Cyriac and Rastogi,2013), oil and gas field development (Onwunalu and Durlofsky 2010), groundwater management (Gaur et al. 2011), and rainfall-runoff model parameter estimation (Bardolle et al. 2014).

8 HYBRID SYSTEMS

Hybrid systems combine two or more methods to achieve greater power and overcome shortcomings. There are three main types of combinatory methods based on how they are combined: sequential, auxiliary, and embedded. In the sequential method, the first method feeds its output to the second method to produce the final output.

In the auxiliary combination method, the first method produces some of the information needed to produce the output by the second method. In the embedded hybrid method, the two methods are combined (Chen et al.2008). The following examples of hybrid systems can be mentioned:

1 Combination of FS with ANN: Estimation of heavy metal concentrations in rice, (Liu et al. 2011) and environmental risk representation in rivers, (Ocampo-Duque, et al. 2012).

2 Combination of FS and CA: Dynamic modeling of complex spatial systems, (Dragićević, 2010).

3 Combination of GA and ANN: Forecasting ozone concentrations, (Pires et al.2012) and Forecasting pollen concentrations, (Voukantsis et al. 2010).

4 Combination of PSO and GA: Multi-objective calibration of large-scale water quality models, (Afshar and Kazemi,2012).

9. CONCLUSIONS

The suitability of AI methods for natural resource management depends on the case. In complex and incomprehensible processes, black-box methods such as ANN and GA may be suitable. ANNs are trained on learning data and derive relationships between data. ANNs have many applications, including environmental applications for classification, function estimation, optimization, and prediction. GAs evolve a set of solutions towards a global optimum. ACO and PSO methods also perform population-based optimization.

SI methods evolve simple agents to collectively solve problems with local interactions. CA and MAS methods are often used to simulate complex systems. CA models systems in space, time, and discrete states that have local interactions. They are used to understanding and predict behavior. MASs employ agents that interact with each other to solve problems. They are often suitable for natural resource management and the study of management strategies.

In contrast, FSs have been applied to many environmental problems, because they can handle incomplete and imprecise data. FSs are often combined with other methods to create hybrid methods. Given the introduction of new methods in artificial intelligence, it is expected that more applications of these methods will be seen in natural resource management and new methods will also be used in this field.

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