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Review Article

Artificial Intelligence in Civil Engineering

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Artificial intelligence is a branch of computer science, involved in the research, design, and application of intelligent computer. Traditional methods for modeling and optimizing complex structure systems require huge amounts of computing resources, and artificial-intelligence-based solutions can often provide valuable alternatives for efficiently solving problems in the civil engineering. This paper summarizes recently developed methods and theories in the developing direction for applications of artificial intelligence in civil engineering, including evolutionary computation, neural networks, fuzzy systems, expert system, reasoning, classification, and learning, as well as others like chaos theory, cuckoo search, firefly algorithm, knowledge-based engineering, and simulated annealing. The main research trends are also pointed out in the end. The paper provides an overview of the advances of artificial intelligence applied in civil engineering.

1. Introduction

The research of artificial intelligence has been developed since 1956, when the term "Artificial Intelligence, AI" was used at the meeting hold in Dartmouth College. Artificial intelligence, a comprehensive discipline, was developed based on the interaction of several kinds of disciplines, such as computer science, cybernetics, information theory, psychology, linguistics, and neurophysiology. Artificial intelligence is a branch of computer science, involved in the research, design and application of intelligent computer [1, 2].

The goal of this field is to explore how to imitate and execute some of the intelligent function of human brain, so that people can develop technology products and establish relevant theories [3]. The first step: artificial intelligence's rise and fall in the 1950s. The second step: as the expert system emerging, a new upsurge of the research of artificial intelligence appeared from the end of 1960s to the 1970s. The third step: in the 1980s, artificial intelligence made a great progress with the development of the fifth generation computer.

The fourth step: in the 1990s, there is a new upsurge of the research of artificial intelligence: with the development of network technology, especially the international internet technology, artificial intelligence research by a single intelligent agent began to turn to the study of distributed artificial intelligence based on network environment. People study not only the same goal-based distributed problem solving, but also the multiply intelligent agents problem solving, which made the artificial intelligence more practical. Additionally, a thriving scene of artificial neural network research and application emerged and it had been deep into all areas of life as the Hopfield multilayer neural network model put forward. The main theories and methods of artificial intelligence are summarized as symbolism, behaviorism, and connectionism approach [4]. Since the appearance of artificial intelligence AI in the 1950s, a lot of hopes and dreams about it have been generated. Now we will elaborate the latest progress of artificial intelligence technology in all aspects of civil engineering and their relationship as follows.

The objective of this paper is to present highlights of references pertaining to artificial intelligence in civil engineering that have been published prior to 2012. Such papers will complement previously published literature survey articles that (1) would provide the theoretical foundation or may play an important role in the development of artificial intelligence in civil engineering; (2) would represent the levels and hotspots of current research of artificial intelligence in civil engineering; and (3) would facilitate continued research efforts. The rest of the paper is synthesized as follows: Section 2 describes artificial intelligence in civil engineering, Section 3 depicts reasoning classification, and learning of artificial intelligence in civil engineering, Section 4 introduces some other theories and methods. Finally we discuss some future trends in Section 5 and conclude in Section 6.

2. Intelligent Optimization Methods in Civil Engineering

Artificial intelligence is a science on the research and application of the law of the activities of human intelligence. It has been a far-reaching cross-frontier subject, after the 50 years' advancement. Nowadays, this technology is applied in many fields such as expert system, knowledge base system, intelligent database system, and intelligent robot system. Expert system is the earliest and most extensive, the most active and most fruitful area, which was named as "the knowledge management and decision-making technology of the 21 century." In the field of civil engineering, many problems, especially in engineering design, construction management, and program decision-making, were influenced by many uncertainties which could be solved not only in need of mathematics, physics, and mechanics calculations but also depend on the experience of practitioners. This knowledge and experience are illogically incomplete and imprecise, and they cannot be handled by traditional procedures. However, artificial intelligence has its own superiority. It can solve complex problems to the levels of experts by means of imitate experts. All in all, artificial intelligence has a broad application prospects in the practice of civil engineering.

Adam and Smith [5] presented progress in the field of adaptive civil-engineering structures. Self-diagnosis, multi-objective shape control, and reinforcement-learning processes were implemented within a control framework on an active tensegrity structure. Among artificial intelligence-based computational techniques, adaptive neuro-fuzzy inference systems were particularly suitable for modelling complex systems with known input-output data sets. Such systems can be efficient in modelling nonlinear, complex, and ambiguous behaviour of cement-based materials undergoing single, dual, or multiple damage factors of different forms in civil engineering. Bassuoni and Nehdi [6] developed neuro-fuzzy based prediction of the durability of self-consolidating concrete to various sodium sulfate exposure regimes. Prasad et al. [7] presented an artificial neural network (ANN) to predict a 28-day compressive strength of a normal and high strength self-compacting concrete (SCC) and high performance concrete (HPC) with high volume fly ash. Lee et al. [8] used an artificial intelligence technique of back-propagation neural networks to assess the slope failure. The numerical results demonstrate the effectiveness of artificial neural networks in the evaluation of slope failure potential. Shaheen et al. [9] presented a proposed methodology for extracting the information from experts to develop the fuzzy expert system rules, and a tunneling case study was used to illustrate the features of the integrated system. Das et al. [10] described two artificial intelligence techniques for prediction of maximum dry density (MDD) and unconfined compressive strength (UCS) of cement stabilized soil. Forcael et al. [11] presented the results of a study that incorporates computer simulations in teaching linear scheduling concepts and techniques, in a civil engineering course "Construction Planning and Scheduling." To assess the effect of incorporating computer simulation in teaching linear scheduling, the students' evaluations and answers to the questionnaire were statistically compared. Krcaronemen and Kouba [12] proposed a methodology for designing ontology-backed software applications that make the ontology possible to evolve while being exploited by one or more applications at the same time. The methodology relies on a contract between the ontology and the application that is formally expressed in terms of integrity constraints. In addition, a reference Java implementation of the methodology and the proof-of-concept application in the civil engineering domain was introduced.

Due to a lot of uncertain factors, complicated influence factors in civil engineering, each project has its individual character and generality; function of expert system in the special links and cases is a notable effect. Over the past 20 years, in the civil engineering field, development and application of the expert system have made a lot of achievements, mainly used in project evaluation, diagnosis, decision-making and prediction, building design and optimization, the project management construction technology, road and bridge health detection and some special field, and so forth.

2.1. Evolutionary Computation

Evolutionary computation (EC) is a subfield of artificial intelligence, which uses iterative process (often inspired by biological mechanisms of evolution) to evolve a population of solution to a desired end. EC has been applied to the domain of civil engineering for several decades, mainly served as an effective method for solving complex optimization problems.

2.1.1. Genetic Algorithms

Genetic algorithms (GAs) [13] are one of the famous evolutionary algorithms which simulate the Darwinian principle of evolution and the survival of the fittest in optimization. It has extensive application value in the civil engineering field, but in many aspects it needs to be further studied and improved.

According to the research progress above the genetic algorithm in civil engineering, due to genetic algorithm developed rapidly, so there are still a lot of improvement measures not included in this paper. In general, the improvement of genetic algorithm approaches include change the genetic algorithm component or the use of technology, the hybrid genetic algorithm, the dynamic adaptive technology, using nonstandard genetic operators, and the parallel genetic algorithm.

In recent years, the improvement of the genetic algorithm introduced many new mathematical tools and absorbed civil engineering as the latest achievement of applications. We can expect, along with the computer technology, the genetic algorithm in civil engineering application will be more general and more effective.

Senouci and Al-Derham [14] presented a genetic-algorithm-based multiobjective optimization model for the scheduling of linear construction projects. The model allows construction planners to generate and evaluate optimal/near-optimal construction scheduling plans that minimize both project time and cost.

2.1.2. Artificial Immune Systems

Provoked by the theoretical immunology, observed immune functions, principles, and models, artificial immune system (AIS) stimulates the adaptive immune system of a living creature to unravel the various complexities in real-world engineering optimization problems [15]. In this technique, a combination of the genetic algorithm and the least-squares method was used to find feasible structures and the appropriate constants for those structures. The new approach overcomes the shortcomings of the traditional and artificial neural network-based methods presented in the literature for the analysis of civil engineering systems.

Dessalegne and Nicklow employed an artificial life algorithm, derived from the artificial life paradigm [16]. The resulting multi-reservoir management model was successfully applied to a portion of the Illinois River Waterway.

According to characteristics of diversity of the immune system, a variety of immune algorithms have proposed by realization form. But since the immune system characteristics of the application exploration is still in its initial stage, the algorithm design has many aspects for improvement, such as the realization of the algorithm, parameter selection, the theory discussion, and the immune system in civil engineering application, still needing further development.

2.1.3. Genetic Programming

Genetic programming is a model of programming which uses the ideas of biological evolution to handle complex optimization problems [17]. Aminian et al. [18] presented a new empirical model to estimate the base shear of plane steel structures subjected to earthquake load using a hybrid method integrating genetic programming (GP) and simulated annealing (SA), called GP/SA. Hsie et al. [19] proposed a novel approach, called "LMGOT," that integrates two optimization techniques: the Levenberg Marquardt (LM) Method and the genetic operation tree (GOT). The GOT borrows the concept from the genetic algorithm, a famous algorithm for solving discrete optimization problems, to generate operation trees (OTs), which represent the structures of the formulas. Results show a concise formula for predicting the length of pavement transverse cracking and indicate that the LMGOT was an efficient approach to building an accurate crack model.

Cevik and Guzelbey [20] presented two plate strength formulations applicable to metals with nonlinear stress-strain curves, such as aluminum and stainless steel alloys, obtained by neural networks and Genetic Programming. The proposed formulations enable determination of the buckling strength of rectangular plates in terms of Ramberg-Osgood parameters.

2.1.4. Other Evolutionary Algorithms

Caicedo and Yun [21] proposed an evolutionary algorithm that was able to identify both global and local minima. The proposed methodology was validated with two numerical examples.

Khalafallah and Abdel-Raheem [22] developed a novel evolutionary algorithm named Electimize and applied it to solve a hard optimization problem in construction engineering. The algorithm mimics the behavior of electrons flowing, through electric circuit branches with the least electric resistance. On the test problem, solutions are represented by electric wires and are evaluated on two levels: a global level, using the objective function, and a local level, evaluating the potential of each generated value for every decision variable. The experimental results show that Electimize has good ability to search the solution space extensively, while converging toward optimality.

Ahangar-Asr et al. [23] presented a new approach, based on evolutionary polynomial regression (EPR), for analysis of stability of soil and rock slopes. Rezania et al. presented another method based on EPR for capturing nonlinear interaction between various parameters of civil engineering systems [24].

2.2. Swarm Intelligence

Metaheuristics based on swarm intelligence, which simulates a population of simple individuals evolving their solutions by interacting with one another and with the environment, have shown promising performance on many difficult problems and have become a very active research area in recent years.

2.2.1. Particle Swarm Optimization

Particle swarm optimization (PSO) is another population-based global optimization technique that enables a number of individual solutions, called particles, to move through a hyper dimensional search space to search for the optimum. Each particle has a position vector and a velocity vector, which are adjusted at iterations by learning from a local best found by the particle itself and a current global best found by the whole swarm. Modeling a system where multiple candidate solution coexists and collaborate simultaneously, PSO approaches embed problem-solving attempts in a social network and are suitable in nature for the optimization of very complex systems, and thus have been successfully applied. Solihin et al. [25] proposed a novel method for tuning PID controller of automatic gantry crane control using particle swarm optimization (PSO). This work presents in detail how to apply PSO method in finding the optimal PID gains of gantry crane system in the fashion of min-max optimization. The simulation results show that with proper tuning a satisfactory PID control performance can be achieved to drive nonlinear plant.

To overcome disadvantage, prove mathematical model accurate, and identify parameters full, Wang et al. used the group control. PSO algorithm was used to calculate the final value of every joint point [26]. The PD control based on the gravity compensation for concrete pump truck boom was used. Through the simulation examples analysis, the conclusion was that the method of combination PSO and gravity compensation was suitable for concrete pump truck boom control. Wang et al. [27] analyses and compares the solution performances of genetic algorithms (GA), particle swarm optimization (PSO), and ant colony algorithms (ACA) from the three aspects, respectively, convergence, speed, and complexity of algorithm. The research result shows that compared with the other two algorithms, the ACA manifests its superiority for better convergence, satisfactory speed, and relatively small algorithm complexity, which were very suitable for solving the problems of sewer optimal design. Shayeghi et al. [28] give the application of the Particle Swarm Optimization (PSO) to design and optimize the parameters of the Tuned Mass Damper (TMD) control scheme for achieving the best results in the reduction of the building response under earthquake excitations. The analysis results reveals that the designed PSO based TMD controller had an excellent capability in reduction of the seismically excited example building. Ali and Ramaswamy [29] presented an optimal fuzzy logic control algorithm for vibration mitigation of buildings using magneto-rheological (MR) dampers. A microgenetic algorithm (mu-GA) and a particle swarm optimization (PSO) were used to optimize the FLC parameters. The present approach provided a better vibration control for structures under earthquake excitations. Filiberto et al. [30] proposed a method that combines the methaheuristic Particle Swarm Optimization (PSO) with the Rough Set Theory (RST) to carry out the prediction of the resistant capacity of connectors (Q) in the branch of civil engineering. At the same time, the k-NN method was used to calculate this value. Experimental results show that the algorithm k-NN, PSO, and the method for calculating the weight of the attributes constitute an effective technique for the function approximation problem. Schmidt [31] presented the synthesis of an active control system using a modified particle swarm optimization method. The system's controller design was analyzed as a minimization of the building stories' acceleration. The proposed fitness function was computationally efficient and incorporates the constraints on the system's stability and the maximum output of actuators.

Zheng and Liu [32] analyzed the various impact factors of project progress, and developed the mathematical model of schedule control based on the quantitative description of the relationship between impact factors with the schedule control of the project. In order to improve the speed and accuracy of solving, authors used the particle swarm algorithm to solve the above model. The empirical research showed that the method is effective in the field of project schedule control.

To calculate appropriate network coefficients, Tsai [33] designed a center-unified particle swarm optimization (CUPSO) approach, composed of a center particle and global and local variants, which is quite effective for optimization tasks. Marinaki et al. [34] proposed particle swarm optimization (PSO) for the calculation of the free parameters in active control systems and tested. The usage of PSO with a combination of continuous and discrete variables for the optimal design of the controller was proposed. Numerical applications on smart piezoelastic beams were presented. Nejadfard et al. [35] introduced a novel approach based on multi-robot cooperation for inspection and repair of dome structures. The simulation results prove that there exists a stable path to fully sweep the surface of a dome. The experimental results on a small scale prototype validate these findings. Raju et al. [36] represented the development of dynamic model of flexible beam structure using finite difference (FD) method. The simulated model was validated by comparing the resonance modes with the theoretical values. A nature inspired intelligence method, the Particle Swarm Optimization (PSO), was used for the vibration control of the beam and the results were compared with genetic algorithm (GA) approach. The numerical simulation shows that sufficient vibration suppression can be achieved by means of these methods.

2.2.2. Ant Colony Optimization

Ant colony optimization (ACO) algorithm mimics the behavior of real ants living in colonies that communicate with each other using pheromones in order to accomplish complex tasks such as establishing a shortest path from the nest to food sources. In a very recent work, Moncayo-Martinez and Zhang studied the multi-objective ACO for supply chain optimization. They considered the problem for minimizing the total cost while keeping the total lead-times within required delivery due dates. They formulated the design problem into an ACO optimization form, and implemented a number of ant colonies in a sequence to explore the solution space and search for successively better non-dominated set of supply chain designs. Ant colony algorithm is proposed as a new bionic heuristic optimization algorithm. Although just a few years and, it is solving many complex combination optimization problems and showed obvious advantage.

Kaveh and Talatahari [37] presented an improved ant colony optimization (IACO) for constrained engineering design problems, and applied to optimal design of different engineering problems. Doerner et al. [38] introduced Pareto Ant Colony Optimization as an especially effective meta-heuristic for solving the portfolio selection problem and compares its performance to other heuristic approaches by means of computational experiments with random instances. Furthermore, authors provided a numerical example based on real world data.

Although ant colony algorithm has strong robustness, general parallel search and other advantages, but there is also search for a long time, in the algorithm model convergence and theoretical basis, and so forth have a lot of work remains to be further in-depth study. In addition, according combining optimization method of the ant colony algorithm and genetic algorithm and immune algorithm, it is effective way to improve the performance of ant colony algorithm. With the deepening of the research on ant colony algorithm, it will get more extensive application.

2.3. Neural Networks

Flood [39] applied artificial neural networks to stimulate interest within the civil engineering research community for developing the next generation results show that this approach requires the design of some very sophisticated genetic coding mechanisms in order to develop the required higher-order network structures and utilize development mechanisms observed in nature such as growth, self-organization, and multi-stage objective functions. Sharma and Das [40] used an artificial neural network (ANN) as a tool for backcalculation. Bendaña et al. [41] presents a fuzzy-logic-based system for selecting contractors. As part of the validation process, a neural network was developed to prove that the fuzzy-control tool has a behavior that can be recognized by a neural network. Bilgil and Altun [42] introduced an efficient approach to estimate the friction coefficient via an artificial neural network, which was a promising computational tool in civil engineering. The estimated value of the friction coefficient was used in Manning Equation to predict the open channel flows in order to carry out a comparison between the proposed neural networks based approach and the conventional ones. Results show that the proposed approach was in good agreement with the experimental results when compared to the conventional ones. Z. Q. Gu, and S. O. Gu [43] presented numerical studies of multiple degrees-of-freedom (MDOF) structural vibration control based on the approach of the back propagation algorithm to the DRNN control method. Research results show that the structural vibration responses of linear and nonlinear MDOF structures are reduced by between 78% and 86%, and between 52% and 80%, respectively, when they are subjected to El Centro, Kobe, Hachinohe, and Northridge earthquake processes. Laflamme and Connor [44] proposed an adaptive neural network composed of Gaussian radial functions for mapping the behavior of civil structures controlled with magnetorheological dampers. The proposed controller is simulated using three types of earthquakes. Lee et al. [45] used an artificial intelligence technique of back-propagation neural networks to assess the slope failure. The numerical results demonstrate the effectiveness of artificial neural networks in the evaluation of slope failure potential based on five major factors, such as the slope gradient angle, the slope height, the cumulative precipitation, daily rainfall, and strength of materials.

Xiao and Amirkhanian [46] develop a series of ANN models to simulate the resilient modulus of rubberized mixtures (ambient and cryogenic rubbers) using seven input variables including material components such as rubber and RAP percentages as well as the rheological properties of modified binders (i.e., viscosity, G*sin delta, stiffness, and *m*-values). The results indicated that ANN-based models were more effective than the regression models and can easily be implemented in a spreadsheet, thus making it easy to apply.

Flood [39] stimulated interest within the civil engineering research community for developing the next generation of applied artificial neural networks. In particular, it identifies what the next generation of these devices needs to achieve, and provides direction in terms of how their development may proceed.

Benchmark and Narasimhan [47] presented a direct adaptive control scheme for the active control of the nonlinear highway bridge benchmark. The control force was calculated using a single hidden layer nonlinearly parameterized neural network in conjunction with a proportional-derivative type controller. The results show that the proposed controller scheme can achieve good response reductions in the structure, without the need for the exact description of the nonlinearities, or extensive structural system information.

Zhang and Haghighat [48] described the development of an Artificial Neural Network based Heat Convection (ANN-HC) algorithm to predict local average Nusselt Numbers along the duct surfaces. It was shown that the method can very well simulate the interactions between an ETAHE and its environment. Yveras [49] explore the possibility of using a tool based on artificial intelligence and real-life data. The results of this study indicate that this was an approach that could usefully be developed and investigated further. The tool managed to predict smell 100%, mold 76%, and rot 92% correctly. Rahman et al. [50] outlined the application of the multi-layer perceptron artificial neural network (ANN), ordinary kriging (OK), and inverse distance weighting (IDW) models in the estimation of local scour depth around bridge piers. It was shown that the artificial neural network model predicts local scour depth more accurately than the kriging and inverse distance weighting models. It was found that the ANN with two hidden layers was the optimum model to predict local scour depth.

Based on the BP neural network, Wang et al. [51] set up the model of cost estimation of highway engineering. It shows the promising perspective of BP Neural Network in cost estimate of construction engineering. Parhi and Dash [52] analyses the dynamic behavior of a beam structure containing multiple transverse cracks using neural network controller. Results from neural controller have been presented for comparison with the output from theoretical, finite-element, and experimental analysis. From the evaluation of the performance of the neural network controller it was observed that the developed method can be used as a crack diagnostic tool in the domain of dynamically vibrating structures. Gui et al. [53] summarizes the structural optimization applications in civil engineering design and development of the situation based on the characteristics of the bridge structure design process was proposed for the bridge project to the genetic algorithm, neural network, expert system technology as the basis for combining automated design and optimization of structural design of the system. Alacali et al. [54] presented an application of Neural Network (NN) simulation in civil engineering science. The approach adapted in this study was shown to be capable of providing accurate estimates of lateral confinement coefficient, $K(s)$ by using the six design parameters.

Li et al. [55] presented a non-destructive, global, vibration-based damage identification method that utilizes damage pattern changes in frequency response functions (FRFs) and artificial neural networks (ANNs) to identify defects. Liu et al. [56] show possible applicability of artificial neural networks (ANN) to predict the compressive strength. The results showed that ANN is a feasible tool for predicting compressive strength. Cheng et al. [57] developed an evolutionary fuzzy hybrid neural network (EFHNN) to enhance the effectiveness of assessing subcontractor performance in the construction industry. The developed EFHNN combines neural networks (NN) and high order neural networks (HONN) into a hybrid neural network (HNN), which acts as the major inference engine and operates with alternating linear and nonlinear NN layer connections. Cachim [58] used artificial neural networks for predicting the temperatures in timber under fire loading. The artificial neural network model had been trained and tested using available numerical results obtained using design methods of Eurocode 5 for the calculation of temperatures in timber under fire loading. The training and testing results in the neural network model had shown that neural networks can accurately calculate the temperature in timber members subjected to fire. Arangio and Beck [59] used a historical overview of the probability logic approach and its application in the field of neural network models, the existing literature was revisited and reorganized according to the enunciated four levels. Then, this framework was applied to develop a two-step strategy for the assessment of the integrity of a long-suspension bridge under ambient vibrations.

As an analysis and solve complex problems, especially in the nonlinear problem, neural network is an important tool, and the neural network potential is realized more and more in engineering technology and information technology by the researchers. The neural network will be very broad used in the civil engineering field application prospect. The neural network still belongs to the new cross science, itself not perfect. As for neural network structure and algorithm, its improvement research has been in progress. And its application studies, there are still some problems, especially in the combination method of the neural network, fuzzy logic genetic algorithm, and expert system, and it will be a very attractive research field.

2.4. Fuzzy Systems

Zarandi et al. [60] develop fuzzy polynomial neural networks (FPNN) to predict the compressive strength of concrete. The results show that FPNN-Type1 has strong potential as a feasible tool for prediction of the compressive strength of concrete mix-design.

Hossain et al. presented an investigation into the comparative performance of intelligent system identification and control algorithms within the framework of an active vibration control (AVC) system [61]. A comparative performance of the algorithms in implementing system identification and corresponding AVC system using GAs and ANFIS is presented and discussed through a set of experiments.

Cheng et al. [62] developed an evolutionary fuzzy neural inference system (EFNIS) to imitate the decision-making processes in the human brain in order to facilitate geotechnical expert decision making.

Sobhani and Ramezanianpour [63] developed a soft computing system to estimate the service life of reinforced concrete bridge deck as one of the most important issues in the civil engineering. The proposed system utilizes four fuzzy interfaces to quantify the exposure condition, required cover thickness, corrosion current density, and pitting corrosion ratio. The results showed that the proposed system could effectively predict the service life; however, it estimated longer service life in comparison with the probabilistic method.

Guo et al. [64] proposed a fuzzy control strategy based on a neural network forecasting model of the building structure with MR dampers, in which a neural network forecasting model is developed to predict dynamic responses of the system with MR dampers and a fuzzy controller is then designed to determine control currents of MR dampers. Choi et al. [65] investigated the applicability of the magnetorheological (MR) damper-based smart passive control system with the electromagnetic induction (EMI) part to the seismic protection of base-isolated building structures with nonlinear isolation systems such as friction pendulum bearings and lead-rubber bearings. Omurlu et al. [66] introduced the application of cluster control on viaduct roads composed of flat parts. Analysis of the performance of cluster control along with the individual effects of the controller parameters on system frequency response is discussed and presented. Guclu and Yazici [67] designed fuzzy logic and PD controllers for a multi-degree-of freedom structure with active tuned mass damper (ATMD) to suppress earthquake-induced vibrations. Fuzzy logic controller (FLC) was preferred because of its robust character, superior performance and heuristic knowledge use effectively and easily in active control. The results of the simulations show a good performance by the fuzzy logic controllers for different loads and the earthquakes. Ozbulut and Hurlebaus [68] proposed a neuro-fuzzy model of NiTi shape memory alloy (SMA) wires that was capable of capturing behavior of superelastic SMAs at different temperatures and at various loading rates while remaining simple enough to realize numerical simulations. It was shown that SMA damping elements can effectively decrease peak deck displacement and the relative displacement between piers and superstructure in an isolated bridge while recovering all the deformations to their original position. Shaheen et al. [69] demonstrates how fuzzy expert systems can be integrated within discrete event simulation models to enhance their modeling and predictive capabilities for construction engineering applications. A proposed methodology was presented for extracting the information from experts to develop the fuzzy expert system rules. Chen et al. [70] examines the feasibility of applying adaptive fuzzy sliding mode control (AFSMC) strategies to reduce the dynamic responses of bridges constructed using a lead rubber bearing (LRB) isolation hybrid protective system. The results demonstrate the viability of the presented methods. The attractive control strategy derived there-from was applied to seismically excited bridges using LRB isolation.

Bianchini and Bandini [71] propose a neuro-fuzzy model to predict the performance of flexible pavements using the parameters routinely collected by agencies to characterize the condition of an existing pavement. The results of the neuro-fuzzy model were superior to those of the linear regression model in terms of accuracy in the approximation. The proposed neuro-fuzzy model showed good generalization capability, and the evaluation of the model performance produced satisfactory results, demonstrating the efficiency and potential of these new mathematical modeling techniques. Ozbulut and Hurlebaus [72] propose two fuzzy logic controllers (FLCs) for operating control force of piezoelectric friction dampers used for seismic protection of base-isolated buildings against various types of earthquake excitations. Results for several historical ground motions show that developed fuzzy logic controllers can effectively reduce isolation system deformations without the loss of potential advantages of seismic base isolation. Meng et al. [73] used a new fuzzy control arithmetic based on mode identification in semi-active control is put forward. Different fuzzy control strategy is applied. Nieto-Morote and Ruz-Vila [74] presented a risk assessment methodology based on the Fuzzy Sets Theory, which is an effective tool to deal with subjective judgment, and on the Analytic Hierarchy Process (AHP), which was used to structure a large number of risks. The proposed methodology incorporates knowledge and experience acquired from many experts, since they carry out the risks identification and their structuring, and also the subjective judgments of the parameters which are considered to assess the overall risk factor. Rosko [75] dealt with the structural topology optimization with fuzzy constraint. Presented study was applicable in engineering and civil engineering. Example demonstrates the presented theory. Gonzalez-Jorge et al. [76] proposed a methodology for extracting information about the presence of biological crusts on concrete structures using terrestrial laser scanners. The goal of this methodology was to integrate all the available information, range, intensity and color, into the extraction work-flow. The methodology is based primarily on two algorithms.

Yakut and Alli [77] designed neural based fuzzy sliding mode control algorithm by putting advantageous specifications of sliding mode control and artificial intelligence techniques and applied to 8 storey sample building with active tendon. The obtained results also show that the controller provides quite successful control under earthquake effects having different characteristics.

Mahjoobi et al. [78] presented alternative hindcast models based on Artificial Neural Networks (ANNs), Fuzzy Inference System (FIS), and Adaptive-Network-based Fuzzy Inference System (ANFIS). Wind speed, wind direction, fetch length, and wind duration were used as input variables, while significant wave height, peak spectral period, and mean wave direction were the output parameters. Results indicated that error statistics of soft computing models were similar, while ANFIS models were marginally more accurate than FIS and ANNs models.

According to above overview, research of the fuzzy system approximation theory is more than 10 years. From the initial approximation existence theorem to all kinds of sufficient conditions for the establishment of the necessary conditions, mechanism of fuzzy system approximation continuous function was revealed. The number of fuzzy rules is the universal approximation of the essence for fuzzy system. The fuzzy approximation theory has not been developed to the point of perfect, to be research work includes the following several aspects: fuzzy system approximation error analysis; the effective fuzzy system structure algorithm of suitable for the engineering application.

2.5. Expert System

An expert system is relying on human experts existing knowledge based on set up knowledge system; the expert system develops the earliest, the most effective in the artificial intelligence research field. The expert system is widely used in road and bridge, construction engineering, geotechnical engineering, underground engineering, disaster prevention project, material engineering, geological exploration and petroleum chemical industry, and so forth. An expert system is in a particular area, and it has the corresponding knowledge and it has the corresponding knowledge and experience in the programming system. The application of artificial intelligence simulates human experts in solving the problem of the thinking process in the field and reaches or approaches the level of experts.

Golroo and Tighe [79] develop performance models for PCP for the first time by using an integrated Markov chain technique (combination of homogenous and non-homogenous techniques) through incorporation of expert knowledge. Both deterministic and stochastic approaches are applied to build up Markov models by using expected values and the Latin hypercube simulation technique, respectively. Grau et al. [80] summarize research addressing the question of what, when, and how much on-site design is appropriate to favorably influence project performance. On the basis of the analysis of data representative of 115 capital facility projects with $9 billion in total installed costs, a database expert planning system was investigated to reliably compute the specific design activities that, when on-site executed, increase the chances for project success. In the civil engineering, the determination of concrete mix design is so difficult and usually results in imprecision. Fuzzy logic is a way to represent a sort of uncertainty which is understandable for human. Neshat and Adeli [81] is to design a Fuzzy Expert System to determine the concrete mix design. Sariyar and Ural [82] discussed soil-structure interaction (SSI) by using expert systems, namely, neural network (NN) approaches. This method provides a new point of view for evaluations of SSI and land use. Artificial neural networks (ANNs) have been applied to many civil engineering problems with some degree of success. Gupta et al. [83] used ANN as an attempt to obtain more accurate concrete strength prediction based on parameters like concrete mix design, size and shape of specimen, curing technique and period, environmental conditions, and so forth.

Chau and Albermani [84] describe a coupled knowledge-based system (KBS) for the design of liquid-retaining structures, which can handle both the symbolic knowledge processing based on engineering heuristics in the preliminary synthesis stage and the extensive numerical crunching involved in the detailed analysis stage. The prototype system is developed by employing blackboard architecture and a commercial shell VISUAL RULE STUDIO. Zain et al. [85] describes a prototype expert system called HPCMIX that provides proportion of trial mix of High Performance Concrete (HPC) and recommendations on mix adjustment. The knowledge was acquired from various textual sources and human experts. The system was developed using hybrid knowledge representation technique. Kazaz [86] considered the application of expert system as a sub-branch of the artificial intelligence systems. For overcoming this bottleneck as well as to enhance the knowledge of the supervisory staff, an expert-system on the fracture mechanics of concrete had been developed.

Expert system technology provides a new opportunity for organizing and system atising the available knowledge and experience in the structural selection domain. With the application of artificial intelligence method, the expert system in civil engineering application is also expanding. A civil engineering activity place will have intelligence technology including the application of expert system. The expert system will become construction management tools and assistant in civil engineering intelligent for 21st century humans.

3. Reasoning, Classification, and Learning

Göktepe et al. [87] presented the applicability of a fuzzy rule-based system for choosing swelling/shrinkage factors affecting the precision of earthwork optimization. This approach may assist in any highway alignment procedure to handle cut and fill volumes more accurately. Zanaganeh et al. [88] developed a hybrid genetic algorithm-adaptive network-based FIS (GA-ANFIS) model in which both clustering and rule base parameters were simultaneously optimized using GAs and artificial neural nets (ANNs). Results indicate that GA-ANFIS model is superior to ANFIS and Shore Protection Manual (SPM) methods in terms of their prediction accuracy. Bianchini and Bandini [89] proposed a neuro-fuzzy model to predict the performance of flexible pavements using the parameters routinely collected by agencies to characterize the condition of an existing pavement. The proposed neuro-fuzzy model showed good generalization capability, and the evaluation of the model performance produced satisfactory results, demonstrating the efficiency and potential of these new mathematical modeling techniques.

Eliseo et al. [90] presented a case study showing the potential of the ontology to reasoning about temporal changes in architectural space. This work shows a domain ontology with temporal relations to record changes in a building throughout time and shows how this ontology can be used as a support for learning in History of Architecture class to motivate students. Lee and Mita [91] proposed a moving sensor agent robot with accelerometers and a laser range finder LRF. To achieve this purpose the robot frame was modified to move down to the ground and to provide enough rigidity to obtain good data.

El-Sawalhi et al. introduced an evolved hybrid genetic algorithm and neural network (GNN) model [92]. The results revealed that there was a satisfactory relationship between the contractor attributes and the corresponding performance in terms of contractor's deviation from the client objectives. Lee and Bernold [93] presented the result of an effort to test the functionality of ubiquitous communication applications over a wireless fidelity infranet installed on an unfriendly construction site. Its value was the lessons learned and the outcome of a variety of field tests with the prototype system. Kovacevic et al. [94] developed a question-and-answer (Q-A) system (reported elsewhere). To support this system, authors developed an automated crawler that permits the establishment of a bank of relevant pages, and adopted to the needs of this particular industry-user community. O'Brien et al. [95] describes an architecture informed by a working first generation prototype. Details of the prototype, lessons learned, and specific advancements were detailed. Future commercial implementation of the architecture will make construction-specific visions for ubiquitous computing possible by enabling flexible and robust discovery and use of data in an ad hoc manner. Luna et al. [96] developed a geographic information system (GIS) learning tool using a series of learning objects. These learning objects were designed to support supplemental instruction in GIS and were integrated seamlessly into the course curriculum. Singh et al. [97] propose the use of a novel image-based machine-learning (IBML) approach to reduce the number of user interactions required to identify promising calibration solutions involving spatially distributed parameter fields. The IBML approach was tested and demonstrated on a groundwater calibration problem and was shown to lead to significant improvements, reducing the amount of user interaction by as much as half without compromising the solution quality of the IMOGA.

Civil engineering students need to learn how to deliver practical sustainable solutions for engineering projects. Thompson [98] demonstrated that applied assessment and award techniques can be usefully used as teaching tools. Overall the case study work certainly appears to fulfill the main learning objective of giving students an understanding of a breadth of practical solutions in sustainability. Obonyo [99] describe the deployment of an e-learning environment for construction courses based on enhancing virtual computing technologies using agent-based techniques. The proposed agent-oriented methodology and resulting application organizes construction knowledge into a structure that enables the students to undertake more self-directed, systematic and scientific exploration. Zhu et al. [100] explore the effectiveness of using simulation as a tool for enhancing classroom learning in the Civil Engineering Department of the University of Minnesota at Twin Cities. Findings in this research could have significant implications for future practice of simulation-based teaching strategy. Das et al. [101] describes two artificial intelligence techniques for prediction of maximum dry density (MDD) and unconfined compressive strength (UCS) of cement stabilized soil. Newson and Delatte [102] described the differences between two of the most familiar types: “case-histories” and “case-studies.” These methods are presented using the Kansas City Hyatt Regency walkway collapse as an exemplar.

4. Others

4.1. Chaos Theory

Lu et al. [103] develop conceptual frameworks that approach the current model methodologies and applications from the theoretical perspective provided by chaos theory. Though the proposed applications as well as the illustrative example are weighted towards phenomena suggesting chaos, there was no intent here to make a case for the relative importance between chaotic and traditional models. Authors do not propose to replace current approaches to theory generation by one based on chaos theory, rather authors suggest extending current theory by introducing a chaos layer. Kardashov et al. [104] proposed a unit analytical approach that could be associated with real ECG and pressure pulses signal processing. Results shows that analytical dynamic models coupled with the available signal processing methods could be used for describing the self-organization and chaos degree in the heartbeats propagation and pressure pulses in ventricular at ejection phase. Enterprise Architecture (EA) models capture the fundamental elements of organizations and their relationships to serve documentation, analysis and planning purposes. As the elements and their relationships change over time, EA planning becomes increasingly complex. An analysis of existing methods shows that the complexity of dynamics is not sufficiently addressed.

4.2. Cuckoo Search

Durgun and Yildiz [105] introduced a new optimization algorithm, called the Cuckoo Search (CS) algorithm, for solving structural design optimization problems. This research was the first application of the CS to the shape design optimization problems in the literature. The CS algorithm is applied to the structural design optimization of a vehicle component to illustrate how the present approach can be applied for solving structural design problems. Results show the ability of the CS to find better optimal structural design. A new robust optimization algorithm, which can be regarded as a modification of the recently developed cuckoo search by Walton et al. [106], was presented. The modification involves the addition of information exchange between the top eggs, or the best solutions. In particular the modified cuckoo search shows a high convergence rate to the true global minimum even at high numbers of dimensions. Li and Yin used an orthogonal learning cuckoo search algorithm used to estimate the parameters of chaotic systems [107]. This algorithm can combine the stochastic exploration of the cuckoo search and the exploitation capability of the orthogonal learning strategy. The proposed algorithm was used to estimate the parameters for these two systems.

4.3. Firefly Algorithm

Gandomi et al. [108] used a recently developed metaheuristic optimization algorithm, the Firefly Algorithm (FA), for solving mixed continuous/discrete structural optimization problems. FA mimics the social behavior of fireflies based on their flashing characteristics. The results of a trade study carried out on six classical structural optimization problems taken from literature confirm the validity of the proposed algorithm. Lukasik and Zak [109] provided an insight into the improved novel metaheuristics of the Firefly Algorithm for constrained continuous optimization tasks. Some concluding remarks on possible algorithm extensions are given, as well as some properties of the presented approach and comments on its performance in the constrained continuous optimization tasks. Xin-She [110] intend to formulate a new metaheuristic algorithm by combining L'evy flights with the search strategy via the Firefly Algorithm. Numerical studies and results suggest that the proposed L'evy-flight firefly algorithm is superior to existing metaheuristic algorithms. Implications for further research and wider applications were discussed.

4.4. Knowledge-Based Engineering

Sapuan [111] studies various work on the development of computerized material selection system. The importance of knowledge-based system ŽKBS. In the context of concurrent engineering was explained. The study of KBS in material selection in an engineering design process was described. Lovett et al. [112] describes a Knowledge Based Engineering (KBE) project currently in progress at Coventry University. The need for a methodology for KBE system development was examined, as are the differing requirements in this respect of small and large organizations. Chapman and Pinfold [113] discussed the current limitations of Computer Aided Design (CAD) tools and reports on the use of knowledge Based Engineering (KBE) in the creation of a concept development tool, to organize information flow and as an architecture for the effective implementation of rapid design solutions. These design solutions can then represent themselves in the correct form to the analysis systems. Kulon et al. developed a knowledge-based engineering (KBE) system for hot forging design using state-of-the-art technology and the Internet [114]. The benefits of a KBE approach over a traditional design process are emphasized. The aim of the proposed KBE system was to integrate the hot forging design process into a single framework for capturing knowledge and experience of design engineers.

4.5. Simulated Annealing

Mahfoud and Goldberg [115] introduced and analyzed a parallel method of simulated annealing. Borrowing from genetic algorithms, an effective combination of simulated annealing and genetic algorithms, called parallel recombinative simulated annealing, was developed. Dekkers and Aarts [116] presented a stochastic approach which was based on the simulated annealing algorithm. The approach closely follows the formulation of the simulated annealing algorithm as originally given for discrete optimization problems. The mathematical formulation was extended to continuous optimization problems, and we prove asymptotic convergence to the set of global optima. Bouleimen and Lecocq described new simulated annealing (SA) algorithms for the resource-constrained project scheduling problem (RCPSP) and its multiple mode version (MRCPSP) [117]. The objective function considered was minimization of the makespan. Chen and Aihara [118] proposed a neural network model with transient chaos, or a transiently chaotic neural network (TCNN) as an approximation method for combinatorial optimization problems, by introducing transiently chaotic dynamics into neural networks.

4.6. Synthetic Intelligence

Prada and Paiva [119] described a model to improve the believability of groups of autonomous synthetic characters in order to promote user collaboration with such groups. This model was successfully used in the context of a collaborative game. The experiment conducted in this scenario demonstrated the positive effect that the model can have on the user's interaction experience. The development of engineered systems having properties of autonomy and intelligence had been a visionary research goal of the twentieth century. These developments inspire the proposal of a paradigm of engineered synthetic intelligence as an alternative to artificial intelligence, in which intelligence is pursued in a bottom-up way from systems of molecular and cellular elements, designed and fabricated from the molecular level and up.

5. Future Trends

We have summarized the main bio-inspired methods for SCM system design and optimization. It is deserved to note that swarm-based methods and artificial immune systems are not yet mature and thus are expected to gain more research interests. In civil engineering field, in the present situation, the research and development of artificial intelligence is only just starting, so far failing to play its proper role. The combination including Artificial intelligence technology and object-oriented and the Internet is the artificial intelligence technology the general trend of development. Artificial intelligence is in its development for civil engineering in the following aspects.

(1) Fuzzy processing, integrated intelligent technology, intelligent emotion technology in the civil engineering.

(2) To deepen the understanding of the problems of uncertainty and to seek appropriate reasoning mechanism is the primary task. To develop practical artificial intelligence technology, only to be developed in the field of artificial intelligence technology, and the knowledge to have a thorough grasp.

(3) According to application requirements of civil engineering practical engineering, the research and development of artificial intelligence technology in civil engineering field were carried out continually. Many questions in civil engineering field need to used artificial intelligence technology. Due to the characteristics of civil engineering field, artificial intelligence technology was used in many areas for civil engineering field, such as civil building engineering, bridge engineering,

geotechnical engineering, underground engineering, road engineering, geological exploration and structure of health detection, and so forth.

(4) Hybrid intelligence system and a large civil expert system research.

(5) With the development of artificial intelligence technology, some early artificial intelligence technology need enhance and improve for knowledge, reasoning mechanism and man-machine interface optimization, and so forth.

(6) To some related problems, many single function of artificial intelligent system integration can carry out, integrated as a comprehensive system of artificial intelligence, and expand the artificial intelligence system to solve the question ability.

(7) Artificial intelligence technology was used in the actual application, only in the practical application of artificial intelligence technology, to test the reliability and give full play to the role of the artificial intelligence technology and to make artificial intelligence technology to get evolution and commercialize. In the commercialization of artificial intelligence technology, there are many successful examples abroad, for enterprise and socially brought considerable benefit.

6. Conclusion

This paper summarizes and introduces the intelligent technologies in civil engineering with recent research results and applications presented. All aspects of applications of the artificial intelligence technology in civil engineering were analyzed. On the basis of the above research results, prospects of the artificial intelligence technology in civil engineering field application and development trend were represented. Artificial intelligence can help inexperienced users solve engineering problems, can also help experienced users to improve the work efficiency, and also in the team through the artificial intelligence technology to share the experience of each member. Artificial intelligence technology will change with each passing day, as the computer is applied more and more popularly, and in civil engineering field will have a broad prospect.

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