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REVIEW ARTICLE

Neural Networks in Civil Engineering: 1989–2000

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Abstract: *The first journal article on neural network application in civil/structural engineering was published in this journal in 1989. This article reviews neural network articles published in archival research journals since then. The emphasis of the review is on the two fields of structural engineering and construction engineering and management. Neural networks articles published in other civil engineering areas are also reviewed, including environmental and water resources engineering, traffic engineering, highway engineering, and geotechnical engineering. The great majority of civil engineering applications of neural networks are based on the simple backpropagation algorithm. Applications of other recent, more powerful and efficient neural networks models are also reviewed. Recent works on integration of neural networks with other computing paradigms such as genetic algorithm, fuzzy logic, and wavelet to enhance the performance of neural network models are presented.*

1 INTRODUCTION

Artificial neural networks (ANNs) are a functional abstraction of the biologic neural structures of the central nervous system (Aleksander and Morton, 1993; Rudomin et al., 1993; Arbib, 1995; Anderson, 1995). They are powerful pattern recognizers and classifiers. They operate as black-box, model-free, and adaptive tools to capture and learn significant structures in data. Their computing abilities have been proven in the fields of prediction and estimation, pattern recognition, and optimization (Adeli and Hung, 1995; Golden, 1996; Mehrotra et al., 1997; Adeli and Park, 1998; Haykin, 1999). They are suitable particularly for problems too complex to be modeled and solved by classical mathematics and traditional procedures.

The first journal article on civil/structural engineering applications of neural networks was published by Adeli and Yeh (1989) in this journal. Since then, a large number of articles have been published on civil engineering applications of neural networks. Most of these articles deal with some type of *pattern-recognition* or *learning* problem. A neural network can be trained to learn to perform a particular task. The approach is particularly attractive for *hard-to-learn* problems and when there is no formal underlying theory for the solution of the problem. Engineering design and image recognition are two such problems (Adeli and Hung, 1995).

One of the reasons for popularity of the neural network is the development of the simple error backpropagation (BP) training algorithm (Rumelhart et al., 1986), which is based on a gradient-descent optimization technique. The BP algorithm is now described in many textbooks (Adeli and Hung, 1995; Mehrotra et al., 1997; Topping and Bahreininejad, 1997; Haykin, 1999), and unfamiliar readers can refer to any one of them. A review of the BP algorithm with suggestions on how to develop practical neural network applications is presented by Hegazy et al. (1994). The great majority of the civil engineering application of neural networks is based on use of the BP algorithm primarily because of its simplicity. Training of a neural network with a supervised learning algorithm such as BP means finding the weights of the links connecting the nodes using a set of training examples. An error function in the form of the sum of the squares of the errors between the actual outputs from the training set and the computed outputs is minimized iteratively. The learning or training rule specifies how the weights are modified in each iteration.

2 STRUCTURAL ENGINEERING

2.1 Pattern recognition and machine learning in structural analysis and design

Adeli and Yeh (1989) present a model of machine learning in engineering design based on the concept of internal

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control parameters and perceptron (Rosenblatt, 1962). A *perceptron* is defined as a four-tuple entity (sensors to receive inputs, weights to be multiplied by the sensors, a function collecting all the weighted data to produce a proper measurement on the impact of the observed phenomenon, and a constant threshold), and the structural design problem is formulated as a perceptron without hidden units. Adeli and Yeh apply the model to the design of steel beams.

Vanluchene and Sun (1990) demonstrate potential applications of the BP algorithm (Rumelhart et al., 1986) in structural engineering by presenting its application to three problems—a simple beam load location problem involving pattern recognition, the cross-section selection of reinforced-concrete beams involving typical design decisions, and analysis of a simply supported plate—showing how numerically complex solutions can be estimated quickly with the neural network approach.

Hajela and Berke (1991) demonstrate that neural networks can be used for rapid reanalysis for structural optimization. Hung and Adeli (1991a) present a model of machine learning in engineering design, called PERHID, based on the concept of the perceptron learning algorithm (Rosenblatt, 1962; Adeli and Yeh, 1989) with a two-layer neural network. PERHID has been constructed by combining a perceptron with a single-layer AND neural net. Extending this research, Hung and Adeli (1994a) present a neural network machine learning development environment using the object-oriented programming paradigm (Yu and Adeli, 1991, 1993).

Adeli and Zhang (1993) present an improved perceptron learning algorithm by introducing an adjustment factor in each self-modification iteration of the original perceptron learning model. The adjustment factor in each iteration is determined such that the domain error is reduced in the subsequent iterations. This leads to global improvement in the iterative process toward finding the final weight vector. The application of the new algorithm to the steel beam design problem demonstrates that the number of iterations needed for convergence of the vector is substantially fewer than that using the original perceptron algorithm.

Theocaris and Panagiotopoulos (1993) describe the parameter identification problem in fracture mechanics as a neural network learning problem. Gunaratnam and Gero (1994) study the effect of representation on the performance of neural networks in structural engineering applications using the the BP algorithm. They suggest that dimensional analysis provides a suitable representation framework for training the input-output pattern pairs. Messner et al. (1994) describe a neural network system for preliminary selection of the most appropriate structural members (beams, columns, and slabs) given a building project's attributes such as available site space, budget, and height.

The BP algorithm is used by Yeh et al. (1993) as a knowledge-acquisition tool for a knowledge-based system for diagnosing damage to prestressed concrete piles (such as spalling of concrete and transverse cracking or breaking of the pile); by Kang and Yoon (1994) for design of simple trusses; by Hoit et al. (1994) for equation renumbering in finite element analysis of structures to improve profile and wavefront characteristics; by Rogers (1994) for fast approximate structural analysis in a structural optimization program; by Mukherjee and Deshpande (1995a, 1995b) for the preliminary design of structures; by Abdalla and Stavroulakis (1995) to predict the behavior of semirigid connections in steel structures from experimental moment rotation curves for single-angle and single-plate beam-column connections; by Turkkan and Srivastava (1995) to predict the steady-state wind pressure profile for air-supported cylindrical and hemispherical membrane structures; by Mukherjee et al. (1996) to predict the buckling load of axially loaded columns based on experimental data; by Papadrakakis et al. (1996) for structural reliability analysis in connection with the Monte Carlo simulation; by Anderson et al. (1997) to predict the bilinear moment-rotation characteristics of the minor-axis beam-to-column connections based on experimental results; by Szewczyk and Noor (1996, 1997) for sensitivity and nonlinear analysis of structures; by Kushida et al. (1997) to develop a concrete bridge rating system; by Hegazy et al. (1998) to model the load-deflection behavior, concrete strain distribution at failure, reinforcing steel strain distribution at failure, and crack-pattern formation of concrete slabs; by Chuang et al. (1998) to predict the ultimate load capacity of pin ended reinforced concrete columns; by Stavroulakis and Antes (1998) for crack identification in steady-state elastodynamics; by Cao et al. (1998) to identify loads on aircraft wings modeled approximately as a cantilever beam subjected to a set of concentrated loads; by Mathew et al. (1999) for analysis of masonry panels under biaxial bending; and by Jenkins (1999) for structural re-analysis of two-dimensional trusses.

Biedermann (1997) investigates the use of the BP neural networks to represent heuristic design knowledge such as how to classify the members of a multistory frame into a limited number of groups for practical purposes (design fabrication groups). Cattan and Mohammadi (1997) use the BP algorithm to relate the subjective rating of bridges based on visual inspection of experienced bridge inspectors to the analytical rating based on detailed structural analyses under standard live loads as well as the bridge parameters. They conclude that "neural networks can be trained and used successfully in estimating a rating based on bridge parameters."

Adeli and Park (1995c) present application of counter-propagation neural networks (CPNs) with competition and interpolation layers (Hecht-Nielsen, 1987a, 1987b, 1988) in structural engineering. A problem with the CPN algorithm is the arbitrary trial-and-error selection of the learning coefficients encountered in the algorithm. The authors propose a simple formula for the learning coefficients as a function of the iteration number and report excellent convergence results. The CPN algorithm is used to predict elastic critical lateral torsional buckling moment of wide-flange steel beams (W shapes) and the moment-gradient coefficient for doubly and singly symmetric steel beams subjected to end moments. The latter is a complex stability analysis problem requiring a large neural network with 4224 links, extensive numerical analysis, and management of a large amount of data. It took less than 30 iterations to train the large CPN network in both competition and interpolation layers using 528 training instances. Compared with the BP algorithm, the authors found superior convergence property and a substantial decrease in the processing time for the CPN algorithm with the proposed formula for the learning coefficients.

The computation of an effective length factor, K, is complicated but essential for design of members in compression in steel-frame structures. The present AISC codes for design of steel structures (AISC, 1995, 1998) present simplified alignment charts for determining the effective length factor. Duan and Chen (1989) and Kishi et al. (1997) have pointed out the gross underestimation (leading to an unsafe design) and overestimation (leading to an overly conservative design) of the alignment charts for different boundary conditions. Hung and Jan (1999a) describe a variation of the cerebellar model articulation controller (CMAC), used mostly in the control domain, for predicting the effective length factor, K for columns in unbraced frames. They conclude that the results obtained from the neural network model are more accurate than those obtained from the AISC alignment charts.

In the finite element analysis of structures, the relationship between the loads and displacements is represented by the structure or global stiffness matrix. A neural network can be trained to perform the same task. Solution of the simultaneous linear equations including the stiffness matrix is the most time-consuming part of any large-scale finite element analysis. To speed up this step of the finite element analysis, neural networks can be used to create domain-specific equation solvers using the knowledge of a particular domain such as highway bridges. However, neural networks can provide only an approximate solution where an "exact" solution is usually required. Consolazio (2000) proposes combining neural networks with iterative equation-solving techniques such as a preconditioned conjugate gradient algorithm (PCG) (Adeli and Kumar, 1999). In particular, he uses the BP neural network algorithm to compute approximate displacements at each iteration, whereas the overall PCG steers convergence to the exact solution. The neural network part of the algorithm improves the efficiency of the algorithm by (1) providing a good initial solution and (2) playing the role of the preconditioner in the PCG algorithm. Consolazio applies the method to finite element analysis of flat-slab highway bridges and concludes the neural network to be an effective method for accelerating the convergence of iterative methods. Use of neural networks in finite element analysis is also discussed by Li (2000).

2.2 Design automation and optimization

Automation of design of large one-of-a-kind civil engineering systems is a challenging problem due partly to the open-ended nature of the problem and partly to the highly nonlinear constraints that can baffle optimization algorithms (Adeli, 1994). Optimization of large and complex engineering systems is particularly challenging in terms of convergence, stability, and efficiency. Most of the neural network research has been done in the area of pattern recognition and machine learning (Adeli and Hung, 1995). Neural network computing also can be used for optimization (Berke et al., 1993).

Adeli and Park (1995a) present a neural dynamics model for optimal design of structures by integrating the penalty function method, the Lyapunov stability theorem, Kuhn-Tucker conditions, and the neural dynamics concept. A pseudo-objective function in the form of a Lyapunov energy functional is defined using the exterior penalty function method. The Lyapunov stability theorem guarantees that solutions of the corresponding dynamic system (trajectories) for arbitrarily given starting points approach an equilibrium point without increasing the value of the objective function. The robustness of the model was first verified by application to a linear structural optimization problem, the minimum-weight plastic design of low-rise planar steel frames (Park and Adeli, 1995). Optimization algorithms are known to deteriorate with increases in size and complexity of the problem. The significance of the new optimization model is that it provides the optimal design of large structures with thousands of members subjected to complicated and discontinuous constraints with excellent convergence results.

In order to achieve automated optimal design of realistic structures subjected to actual constraints of commonly used design codes such as the American Institute of Steel Construction (AISC) allowable stress design (ASD) and load and resistance factor design (LRFD) specifications (AISC, 1995, 1998), Adeli and Park (1995b, 1996) developed a hybrid CPN–neural dynamics model for discrete optimization of structures consisting of commercially available sections such as the wide-flange (W) shapes used in steel structures. The computational models are shown to be highly stable and robust and particularly suitable for design automation and optimization of large structures no matter how large the size of the problem is, how irregular the structure is, or how complicated the constraints are. For their innovative work, the authors were awarded a patent by the U.S. Patent and Trademark Office on September 29, 1998 (United States Patent Number 5,815,394).

An important advantage of cold-formed steel is the greater flexibility of cross-sectional shapes and sizes available to the structural steel designer. The lack of standard optimized shapes, however, makes selection of the most economical shape very difficult, if not impossible. This task is further complicated by the complex and highly nonlinear nature of the rules that govern their design. Adeli and Karim (1997a) present a general mathematical formulation and computational model for optimization of cold-formed steel beams. The nonlinear optimization problem is solved by adapting the robust neural dynamics model of Adeli and Park (1996). The basis of design can be the AISI ASD or LRFD specifications (AISI, 1996, 1997). The computational model is applied to three different commonly used types of cross-sectional shapes: hat, I, and Z shapes. The computational model was used to perform extensive parametric studies to obtain the global optimal design curves for cold-formed hat- , I- , and Z-shaped steel beams based on the AISI code to be used directly by practicing design engineers (Karim and Adeli, 1999a, 1999b, 2000).

Optimization of space structures made of cold-formed steel is complicated because an effective reduced area must be calculated for members in compression to take into account the nonuniform distribution of stresses in thin cold-formed members due to torsional/flexural buckling. The effective area varies not only with the level of the applied compressive stress but also with its width-to-thickness ratio. Tashakori and Adeli (2001) present optimal (minimum weight) design of space trusses made of cold-formed steel shapes in accordance with the AISI specifications (AISI, 1996, 1997) using the neural dynamics model of Adeli and Park (1996). The model has been used to find the minimum-weight design for several space trusses commonly used as roof structures in long-span commercial buildings and canopies, including a large structure with 1548 members, with excellent convergence results.

Arslan and Hajela (1997) discuss counterpropagation neural networks in decomposition-based optimal design. Parvin and Serpen (1999) discuss a procedure to solve an optimization problem with a single-layer, relaxation-type recurrent neural network but do not present a solution to any significant structural design problem.

2.3 Structural system identification

Masri et al. (1993) describe neural networks as a powerful tool for identification of structural dynamic systems. Chen et al. (1995b) use the BP algorithm for identification of structural dynamic models. The authors indicate "great promise in structural dynamic model identification by using neural networks" based on simulation results for a real multistory building subjected to earthquake ground motions. The BP algorithm is used by Yun and Bahng (2000) for substructural identification and estimating the stiffness parameters of two-dimensional trusses and frames. Huang and Loh (2001) propose a neural network–based model for modeling and identification of a discrete-time nonlinear hysteretic system during strong earthquakes. They use two-dimensional models of a three-story frame and a real bridge in Taiwan subjected to several earthquake accelerograms to validate the feasibility and reliability of the method for estimating the changes in structural response under different earthquake events.

2.4 Structural condition assessment and monitoring

Wu et al. (1992) discuss use of the BP algorithm for detection of structural damage in a three-story frame with rigid floors. The damage is defined as a reduction in the member stiffness. Elkordy et al. (1994) question the reliability of the traditional methods for structural damage diagnosis and monitoring that rely primarily on visual inspection and simple on-site tests. They propose a structural damage monitoring system for identifying the damage associated with changes in structural signatures using the BP algorithm. For training, they used experimental results from a shaking table as well as numerical results from a finite element analysis of the structure for strain-mode shapes as the vibrational signatures. They point out that "analyzing the data obtained from different types of sensors to detect damage is a very complex problem, particularly because of the noise associated with the signals," and suggest that neural networks can diagnose complicated damage patterns and "can handle noisy and partially incomplete data sets." Stephens and Vanluchene (1994) describe an approach for assessing the safety condition of structures after the occurrence of a damaging earthquake using multiple quantitative indices and the BP algorithm. They conclude that the neural network model "generated more reliable assessments than could be obtained using any single indicator or from a linear regression model that utilized all indicators."

Defining damage as a reduction in the stiffness of structural members, Szewczyk and Hajela (1994) use a CPN for damage detection in truss and frame structures. They describe the problem as an inverse static analysis problem where the elements of the structure stiffness matrix are found based on experimentally observed response data. Pandey and Barai (1995) describe use of the BP algorithm for damage detection of steel-truss bridge structures. A similar study for vibration signature analysis of steel trusses is discussed in Barai and Pandey (1995). Masri et al. (1996) explore the use of neural networks to detect changes in structural parameters during vibrations. Masri et al. (2000) describe application of neural networks to a nonparametric structural damage detection methodology based on nonlinear system identification approaches.

High-strength bolts in spliced joints of steel bridges may become loose gradually during their lifetime. This problem has to be detected and corrected during periodic inspection and maintenance of the bridge. Mikami et al. (1998) present a system based on the BP algorithm to estimate the residual axial forces of high-strength bolts in steel bridges using the reaction and acceleration waveforms collected by an automatic hammer or looseness detector. An important issue in structural health monitoring is selection of the members and locations of the structure to be monitored. Feng and Bahng (1999) use the BP algorithm to estimate the change in stiffness based on the measured vibration characteristics for damage assessment of reinforced concrete columns retrofitted by advanced composite jackets. Kim et al. (2000b) describe a two-stage procedure where in the first stage traditional sensitivity analysis is used to rank and select critical members. In the second stage, the results of the sensitivity analysis and a trained neural network are used to identify the optimal numbers and locations of monitoring sensors. The method is applied to two-dimensional trusses and multistory frames.

2.5 Structural control

Active control of structures has been an active area of research in recent years (Adeli and Saleh, 1999). Ghaboussi and Joghataie (1995) present application of neural networks in structural control. A neural network training algorithm, a modified BP algorithm in this case, performs the role of the control algorithm. The structure's response, measured at a selected number of points by sensors, and the actuator signals are the input to the *neurocontroller*. Its output is the subsequent value of the actuator signal to produce the desired actuator forces. The neurocontroller learns to control the structure after being trained by an emulator neural network. The authors suggest that neurocontrollers are a potentially powerful tool in structural control problems based on simulation results for a three-story frame with one actuator.

Chen et al. (1995a) also describe use of the BP algorithm in structural control and present simulation results based on the model of an actual multistory apartment building subjected to recorded earthquake ground motions. The BP algorithm is also used by Tang (1996a) for active control of a single-degree-of-freedom system and by Yen (1996) for vibration control in flexible multibody dynamics. Nikzad et al. (1996) compare the performances of a conventional feedforward controller and a neurocontroller based on a modified BP algorithm in compensating the effects of the actuator dynamics and computational phase delay using a two-degree-of-freedom dynamic system and report the latter is "far more effective." Most control algorithms are based on the availability of a complete state vector from measurement. Tang (1996b) uses the BP algorithm as the state-vector estimator when only a limited number of sensors are installed in the structure, and consequently, a complete state vector is not available. Bani-Hani and Ghaboussi (1998) discuss nonlinear structural control using neural networks through numerical simulations on a two-dimensional three-story steel frame considering its inelastic material behavior.

Ankireddi and Yang (1999) investigate the use of neural networks for failure detection and accommodation in structural control problems. They propose a failure detection neural network for monitoring structural responses and detecting performance-reducing sensor failures and a failure accommodation neural network to account for the failed sensors using the Widrow-Hoff (Widrow and Lehr, 1995) training rule. Kim et al. (2000a) propose an optimal control algorithm using neural networks through minimization of the instantaneous cost function for a single-degree-of-freedom system. Hung et al. (2000) describe an active pulse structural control using neural networks with a training algorithm that does not require the trial-and-error selection of the learning ratio needed in the BP algorithm and present simulation results for a small frame.

2.6 Finite element mesh generation

In finite element analysis of structures, creating the right mesh is a tedious trial-and-error process often requiring a high level of human expertise. The accuracy and efficiency of the method rely heavily on the selected mesh. Automatic creation of an effective finite element mesh for a given problem has been an active area of research. Different approaches have been explored in the literature, including neural networks. For a given number of nodes and mesh topology, Manevitz et al. (1997) use the self-organizing algorithm of Kohonen (1988) to create a near-optimal finite element mesh for a two-dimensional domain using a combination of different types of elements. Bahreininejad et al. (1996) explore application of the BP and Hopfield neural networks for finite element mesh partitioning. Pain et al. (1999) present a neural network graph-partitioning algorithm for partitioning unstructured finite element meshes. First, an automatic graph coarsening method is used to create a coarse mesh, followed by a mean field theorem neural network to perform partitioning optimization.

2.7 Structural material characterization and modeling

Ghaboussi et al. (1991) describe use of the BP neural network for modeling behavior of conventional materials such as concrete in the state of plane stress under monotonic biaxial loading. Brown et al. (1991) demonstrate the applicability of neural networks to composite material characterization. They use the BP algorithm to predict hygral, thermal, and mechanical properties of composite-ply materials. The BP algorithm also has been used for constitutive modeling of concrete (Sankarasubramanian and Rajasekaran, 1996) and viscoplastic materials (Furukawa and Yagawa, 1998).

Ghaboussi et al. (1998) present *autoprogressive* training of neural network constitutive models using the global load-deflection response measured in a structural test with application to laminated composites. In their approach, a partially trained neural network generates its own training cases through an iterative nonlinear finite element analysis of the test specimen. Yeh (1999) uses the BP algorithm to model the concrete workability in the design of a high-performance concrete mixture. Neural networks are also used to model generalized hardening plasticity (Theocaris and Panagiotopoulos, 1995), the alkali-silica reaction of concrete with admixtures (Li et al., 2000), and elastoplasticity (Daoheng et al., 2000).

2.8 Parallel neural network algorithms for large-scale problems

The convergence speed of neural network learning models is slow. For large networks, several hours or even days of computer time may be required using the conventional serial workstations. A parallel BP learning algorithm has been developed by Hung and Adeli (1993) and implemented on the Cray YMP supercomputer. A parallel-processing implementation of the BP algorithm on a Transputer network with application to finite element mesh generation is also presented by Topping et al. (1997).

Optimization of large structures with thousands of members subjected to actual constraints of commonly used codes requires an inordinate amount of computer processing time and high-performance computing resources (Adeli and Kamal, 1993; Adeli, 1992a, 1992b; Adeli and Soegiarso, 1999). Park and Adeli (1997a) present a data parallel neural dynamics model for discrete optimization of large steel structures implemented on a distributed-memory multiprocessor, the massively parallel Connection Machine CM-5 system. The parallel algorithm has been applied to optimization of several high-rise and super-high-rise building structures, including a 144-story steel super-high-rise building structure with 20,096 members in accordance with the AISC ASD and LRFD codes (AISC, 1995, 1998) and subjected to multiple loading conditions including wind loading according to the *Uniform Building Code* (UBC, 1997). This is by far the largest structural optimization problem subjected to actual constraints of a widely used design code ever solved and reported in the literature. Park and Adeli (1997b) present distributed neural dynamics algorithms on the Cray T3D multiprocessor employing the work-sharing programming paradigm.

3 CONSTRUCTION ENGINEERING

3.1 Construction scheduling and management

Adeli and Karim (1997b) present a general mathematical formulation for scheduling of construction projects and apply it to the problem of highway construction scheduling. Repetitive and nonrepetitive tasks, work-continuity considerations, multiple-crew strategies, and the effects of varying job conditions on the performance of a crew can be modeled. An optimization formulation is presented for the construction project scheduling problem with the goal of minimizing the direct construction cost. The nonlinear optimization is then solved by the neural dynamics model of Adeli and Park (1996). For any given construction duration, the model yields the optimal construction schedule for minimum construction cost automatically. By varying the construction duration, one can solve the cost-duration tradeoff problem and obtain the global optimal schedule and the corresponding minimum construction cost. Karim and Adeli (1999c) present an object-oriented information model for construction scheduling, cost optimization, and change-order management based on the new neural network–based construction scheduling model of Adeli and Karim (1997b). The model can be used by the owner/client who has to approve any change-order requests made by the contractor, as well as by the contractor. The model provides support for schedule generation and review, cost estimation, and cost-time tradeoff analysis. The model has been implemented in a prototype software system called *CONSCOM* (CONstruction Scheduling, Cost Optimization, and Change-Order Management) using Microsoft Foundation Classes under the Windows environment (Karim and Adeli, 1999d).

3.2 Construction cost estimation

Williams (1994) attempts to use the BP algorithm for predicting changes in construction cost indexes for 1 and 6 months ahead but concludes that "the movement of the cost indexes is a complex problem that cannot be predicted accurately by a BP neural network model." Automating the process of construction cost estimation based on objective data is highly desirable not only for improving the efficiency but also for removing the subjective questionable human factors as much as possible. The costs of construction materials, equipment, and labor depend on numerous factors with no explicit mathematical model or rule for price prediction. Adeli and Wu (1998) point out that "highway construction costs are very noisy, and the noise is the result of many unpredictable factors such as human judgment factors, random market fluctuations, and weather conditions." They also discuss the problem of overfitting data, noting that "because of the noise in the data, a perfect fit usually is not the best fit," and underfitting results in poor generalization. Adeli and Wu (1998) present a regularization neural network model and architecture for estimating the cost of construction projects. The model is applied to estimate the cost of reinforced concrete pavements as an example. The new computational model is based on a solid mathematical foundation, making the cost estimation consistently more reliable and predictable. Moreover, the problem of noise in the data is taken into account in a rational manner.

3.3 Resource allocation and scheduling

Mohammad et al. (1995) formulate the problem of optimally allocating available yearly budget to bridge rehabilitation and replacement projects among a number of alternatives as an optimization problem using the Hopfield network (Hopfield, 1982, 1984). Savin et al. (1996, 1998) also discuss the use of a discrete-time Hopfield net in conjunction with an augmented Lagrangian multiplier optimization algorithm for construction resource leveling. Elazouni et al. (1997) use the BP algorithm to estimate the construction resource requirements at the conceptual design stage and apply the model to the construction of concrete silo walls.

Senouci and Adeli (2001) present a mathematical model for resource scheduling considering project scheduling characteristics generally ignored in prior research, including precedence relationships, multiple-crew strategies, and the time-cost tradeoff. Previous resource scheduling formulations traditionally have focused on project-duration minimization. The new model considers the total project cost minimization. Furthermore, resource leveling and resource-constrained scheduling are performed simultaneously. The model is solved using the neural dynamics optimization model of Adeli and Park (1996).

3.4 Construction litigation

Disputes and disagreements between the contractor and the owner for reasons such as misinterpretation of the contract, changes made by the owner or the contractor, differing site and weather conditions, labor problems, and unexpected delays can lead to litigation. Arditi et al. (1998) use neural networks to predict the outcome of construction litigation. They use the outcomes of circuit and appellate court decisions to train the network and report a successful prediction rate of 67 percent for the "extremely complex data structure of court proceedings." A comparison of the neural network approach with case-based reasoning (CBR) for the same problem is presented by Arditi and Tokdemir (1999).

3.5 Other applications of BP and other neural network models in construction engineering and management

Moselhi et al. (1991) were among the first to realize the potential applications of neural networks in construction engineering. They present an application of the BP algorithm for optimal markup estimation under different bid conditions. They use a small set of 10 bid situations to train the system but report up to 30,000 iterations for the BP algorithm to converge with a small error. The BP algorithm also has been used for selection of vertical concrete formwork supporting walls and columns for a building site (Kamarthi et al., 1992), for estimating construction productivity (Chao and Skibniewski, 1994; Sonmez and Rowings, 1998), for markup estimation using knowledge acquired from contractors in Canada and the United States (Hegazy and Moselhi, 1994), for evaluation of new construction technology acceptability (Chao and Skibniewski, 1995), for selection of horizontal concrete formwork to support slabs and roofs (Hanna and Senouci, 1995), and for measuring the level of organization effectiveness in a construction firm.

Murtaza and Fisher (1994) describe the use of neural networks for decision making about construction modularization. Yeh (1995) uses a combination of simulated annealing (Kirkpatrick et al., 1983) and a Hopfield neural network (Hopfield, 1982, 1984) to solve the construction-site layout problem. Kartam (1996) uses neural networks to determine optimal equipment combinations for earthmoving operations. Pompe and Feelders (1997) use neural networks to predict corporate bankruptcy. Li et al. (1999) discuss rule extractions from a neural network trained by the BP algorithm for construction markup estimation in order to explain how a particular recommendation is made.

4 NEURAL NETWORK APPLICATIONS IN OTHER CIVIL ENGINEERING FIELDS

4.1 Environmental and water resources engineering

Karunanithi et al. (1994) demonstrate the use of neural networks for river flow prediction using the cascade-correlation algorithm. The BP algorithm is used by Du et al. (1994) to predict the level of solubilization of six heavy metals from sewage sludge using the bioleaching process, by Grubert (1995) to predict the flow conditions at the interface of stratified estuaries and fjords, by Kao and Liao (1996) to facilitate the selection of an appropriate facility combination for municipal solid-waste incineration, by Tawfik et al. (1997) to model stage-discharge relationships at stream gauging locations at the Nile River, by Deo et al. (1997) to interpolate the ocean wave heights over short intervals (weekly mean wave heights) from the values obtained by remote sensing techniques and satellites over long durations (a month), and by Liong et al. (2000) for water-level forecasting in Dhaka, Bangladesh.

Crespo and Mora (1995) describe neural network learning for river streamflow estimation, prediction of carbon dioxide concentration from a gas furnace, and a feed-water control system in a boiling water reactor. Basheer and Najjar (1996) use neural networks to model fixed-bed adsorber dynamics. Rodriguez and Serodes (1996) use the BP neural network to estimate the disinfectant dose adjustments required during water rechlorination in storage tanks based on representative operational and water-quality historical data and conclude that the model "can adequately mimic an operator's know-how in the control of the water quality within distribution systems." Maier and Dandy (1997) discuss the use of neural networks for multivariate forecasting problems encountered in the field of water resources engineering, including estimation of salinity in a river. Thirumalaiah and Deo (1998) present neural networks for real-time forecasting of stream flows. Flood values during storms are forecast with a lead time of 1 hour or more using the data from past flood values at a specific location. Deo and Chaudhari (1998) use neural networks to predict tides at a station located in the interior of an estuary or bay.

Gangopadhyay et al. (1999) integrate the BP algorithm with a Geographic Information System (GIS) for generation of subsurface profiles and for identification of the distribution of subsurface materials. The model is applied to find the aquifer extent and its parameters for the multiaquifer system under the city of Bangkok, Thailand. Coulibaly et al. (2000) use feedforward and recurrent neural networks for long-term forecasting of potential energy inflows for hydropower operations planning. This is one of the few articles addressing the problem of overfitting in neural network pattern recognition. The authors conclude that "the neural network–based models provide more accurate forecasts than traditional stochastic models." Liu and James (2000) use the BP algorithm to estimate the discharge capacity in meandering compound (or two-stage) channels consisting of a main channel flanked by floodplains on one or both sides. Guo (2001) presents a semivirtual watershed model for small urban watersheds with a drainage area of less than 150 acres using neural networks where the network training and the determination of the matrix of time-dependent weights to rainfall and runoff vectors is guided by the kinematic wave theory.

4.2 Traffic engineering

Cheu and Ritchie (1995) use three different neural network architectures—multilayer perceptron, self-organizing feature map, and adaptive resonance theory (ART) model two (ART2)—for the identification of incident patterns in traffic data. Faghri and Hua (1995) use ART model one (ART1) to estimate the average annual daily traffic (AADT) including the seasonal factors and compare its performance with clustering and regression methods. They conclude that the neural network model yields better results than the other two approaches. Dia and Rose (1997) use field data to test a multilayer perceptron neural network as an incident-detection classifier. Eskandarian and Thiriez (1998) use neural networks to simulate a driver's function of steering and braking and develop a controller on a moving platform (vehicle) encountering obstacles of various shapes. The system can generalize its learned patterns to avoid obstacles and collisions. The BP neural network is used by Lingras and Adamo (1996) to estimate average and peak hourly traffic volumes, by Ivan and Sethi (1998) for traffic incident detection, by Sayed and Abdelwahab (1998) for classification of road accidents for road improvements, and by Park and Rilett (1999) to predict the freeway link travel times for one through five time periods into the future.

Saito and Fan (2000) present an optimal traffic signal timing model that uses the BP algorithm to conduct an analysis of the level of service at a signalized intersection by learning the complicated relationship between the traffic delay and traffic environment at signalized intersections.

4.3 Highway engineering

Gagarin et al. (1994) discuss the use of a radial-Gaussian-based neural network for determining truck attributes such as axle loads, axle spacing, and velocity from strain-response readings taken from the bridges over which the truck is traveling. Eldin and Senouci (1995) describe the use of a BP algorithm for condition rating of roadway pavements. They report very low average error when compared with a human expert determination. Cal (1995) uses the BP algorithm for soil classification based on three primary factors: plastic index, liquid limit water capacity, and clay content. Razaqpur et al. (1996) present a combined dynamic programming and Hopfield neural network (Hopfield, 1982, 1984) bridge-management model for efficient allocation of a limited budget to bridge projects over a given period of time. The time dimension is modeled by dynamic programming, and the bridge network is simulated by the neural network. Roberts and Attoh-Okine (1998) use a combination of supervised and self-organizing neural networks to predict the performance of pavements as defined by the International Roughness Index. The BP algorithm is used by Owusu-Ababio (1998) for predicting flexible pavement cracking and by Alsugair and Al-Qudrah (1998) to develop a pavement-management decision support system for selecting an appropriate maintenance and repair action for a damaged pavement. Attoh-Okine (2001) uses the self-organizing map or competitive unsupervised learning model of Kohonen (1988) for grouping of pavement-condition variables (such as the thickness and age of pavement, average annual daily traffic, alligator cracking, wide cracking, potholing, and rut depth) to develop a model for evaluation of pavement conditions.

4.4 Geotechnical engineering

A common method for evaluation of elastic moduli and layer thicknesses of soils and pavements is the seismic spectral analysis of surface waves (SASW). Williams and Gucunski (1995) use the BP algorithm to perform the inversion of SASW test results. Core penetration test (CPT) measurements are frequently used to find soil strength and stiffness parameters needed in design of foundations. Goh (1995) demonstrates application of the BP algorithm for correlating various experimental parameters and evaluating the CPT calibration chamber test data. The BP algorithm is used by Chikata et al. (1998) to develop a system for aesthetic evaluation of concrete retaining walls and by Teh et al. (1997) to estimate static capacity of precast reinforced concrete piles from dynamic stress wave data. Juang and Chen (1999) present neural network models for evaluating the liquefaction potential of sandy soils. Use of neural networks to predict the collapse potential of soils is discussed by Juang et al. (1999).

After pointing out that "classical constitutive modeling of geomaterials based on the elasticity and plasticity theories suffers from limitations pertaining to formulation complexity, idealization of behavior, and excessive empirical parameters," Basheer (2000) proposes neural networks as an alternative for modeling the constitutive hysteresis behavior of soils. He examines several mapping techniques to be used as frameworks for creating neural network models for constitutive response of soils, including a hybrid approach that provides high accuracy.

5 SHORTCOMINGS OF THE BP ALGORITHMS AND OTHER RECENT APPROACHES

5.1 Shortcomings of the BP algorithm

The momentum BP learning algorithm (Rumelhart et al., 1986, Adeli and Hung, 1995) is widely used for training multilayer neural networks for classification problems. This algorithm, however, has a slow rate of learning. The number of iterations for learning an example is often in the order of thousands and sometimes more than one hundred thousands (Carpenter and Barthelemy, 1994). Moreover, the convergence rate is highly dependent on the choice of the values of learning and momentum ratios encountered in this algorithm. The proper values of these two parameters depend on the type of the problem (Adeli and Hung, 1994; Yeh, 1998). As such, a number of other neural network learning models have been proposed in recent years. Some of them with applications in civil engineering are reviewed briefly in this section.

5.2 Adaptive conjugate gradient neural network algorithm

In an attempt to overcome the shortcomings of the BP algorithm, Adeli and Hung (1994) have developed an adaptive conjugate gradient learning algorithm for training of multilayer feedforward neural networks. Powell's modified conjugate gradient algorithm has been used with an approximate line search for minimizing the system error. The problem of arbitrary trial-and-error selection of the learning and momentum ratios encountered in the momentum backpropagation algorithm is circumvented in the new adaptive algorithm. Instead of constant learning and momentum ratios, the step length in the inexact line search is adapted during the learning process through a mathematical approach. Thus the new adaptive algorithm provides a more solid mathematical foundation for neural network learning. The algorithm has been applied to the domain of image recognition. It is shown that the adaptive neural networks algorithm has a superior convergence property compared with the momentum BP algorithm.

5.3 Radial basis function neural networks

The radial basis function neural network (RBFNN) learns an input-output mapping by covering the input space with basis functions that transform a vector from the input space to the output space (Moody and Darken, 1989; Poggio and Girosi, 1990). Conceptually, the RBFNN is an abstraction of the observation that biologic neurons exhibit a receptive field of activation such that the output is large when the input is closer to the center of the field and small when the input moves away from the center. Structurally, the RBFNN has a simple topology with a hidden layer of nodes having nonlinear basis transfer functions and an output layer of nodes with linear transfer functions (Adeli and Karim, 2000). The most common type of the basis function is Gaussian. Yen (1994) proposes the use of radial basis function networks as a neurocontroller for vibration suppression. Amin et al. (1998) use the RBFNN to predict the flow of traffic. Jayawardena and Fernando (1998) present application of the RBFNN for hydrologic modeling and runoff simulation in a small catchment and report that it is more efficient computationally than the BP algorithm.

5.4 Other approaches

Masri et al. (1999) propose a stochastic optimization algorithm based on adaptive random search techniques for training neural networks in applied mechanics applications.

Castillo et al. (2000a) present functional networks where neural functions are learned instead of weights but apply the concept to simple problems such as predicting the behavior of a cantilever beam and approximating the differential equation for vibration of a simple single-degree-of-freedom system with spring and viscous damping. Some learning methods in functional networks are presented in Castillo et al. (2000b).

6 INTEGRATING NEURAL NETWORKS WITH OTHER COMPUTING PARADIGMS

6.1 Genetic algorithms

Hung and Adeli (1991b) present a hybrid learning algorithm by integrating a genetic algorithm with error backpropagation multilayer neural networks. The algorithm consists of two learning stages. The first learning stage is to accelerate the learning process by using a genetic algorithm with the feedforward step of the BP algorithm. In this stage, the weights of the neural network are encoded on chromosomes as decision variables. The objective function for the genetic algorithm is defined as the average squared system error. After performing several iterations and meeting the stopping criterion, the first learning stage is terminated, and the chromosome returning the minimum objective function is considered as the initial weights of the neural network in the second stage. Next, the BP algorithm performs the second learning process until the terminal condition is satisfied.

Moselhi et al. (1993) use the BP neural networks and the genetic algorithm (Adeli and Hung, 1995) to develop a decision support system to aid contractors in preparing bids. A parallel genetic–neural network algorithm is also presented by Hung and Adeli (1994b). Jinghui et al. (1996), Hajela and Lee (1997), and Papadrakakis et al. (1998) use the BP algorithm to improve the efficiency of genetic algorithms for structural optimization problems. Topping et al. (1998) present parallel finite element analysis on a MIMD distributed computer. They describe a mesh partitioning technique for planar finite element meshes where a BP neural network is used to find the approximate number of elements within a coarse mesh. The coarse mesh is then divided into several subdomains using a genetic algorithm optimization approach.

6.2 Fuzzy logic

Adeli and Hung (1993) present a fuzzy neural network learning model by integrating an unsupervised fuzzy neural network classification algorithm with a genetic algorithm and the adaptive conjugate gradient neural network learning algorithm. The learning model consists of three major stages. The first stage is used to classify the given training instances into a small number of clusters using the unsupervised fuzzy neural network classification algorithm. The second stage is a supervised neural network learning model using the classified clusters as training instances. The genetic algorithm is used in this stage to accelerate the whole learning process in the hybrid learning algorithm. The third stage is the process of defuzzification. The hybrid fuzzy neural network learning model has been applied to the domain of image recognition. The performance of the model has been evaluated by applying it to a large-scale training example with 2304 training instances.

Hurson et al. (1994) discuss the use of fuzzy logic in automating knowledge acquisition in a neural network–based decision support system. Anantha Ramu and Johnson (1995) present a fuzzy logic–BP neural network approach to detect, classify, and estimate the extent of damage from the measured vibration response of composite laminates. Kasperkiewicz et al. (1995) use a fuzzy ART neural network (Carpenter et al., 1991) to predict strength properties of high-performance concrete mixes as a factor of six components: cement, silica, superplasticizer, water, fine aggregate, and coarse aggregate.

Furuta et al. (1996) describe a fuzzy expert system for damage assessment of reinforced concrete bridge decks using genetic algorithms and neural networks. The goal is to automatically acquire fuzzy production rules through use of the genetic algorithm and the BP neural networks. The weights of the links obtained from the neural networks are used in the genetic algorithm evaluation function to obtain the optimal combination of rules to be used in the knowledge base of the expert system (Adeli, 1988; Adeli and Balasubramanyam, 1988; Adeli, 1990a, 1990b).

Ni et al. (1996) present a fuzzy neural network approach for evaluating the stability of natural slopes considering the geologic, topographic, meteorologic, and environmental conditions that can be described mostly in linguistic terms. Parameters of the neural networks are represented by fuzzy sets (Zadeh, 1970, 1978). Faravelli and Yao (1996) discuss the use of neural networks in fuzzy control of structures. Rajasekaran et al. (1996) describe the integration of fuzzy logic and neural networks for a prestressed concrete pile diagnosis problem and concrete mix design. Hung and Jan (1999b) present a fuzzy neural network learning model consisting of both supervised and unsupervised learning and apply it to simply supported concrete and steel beam design problems. Sayed and Razavi (2000) combine fuzzy logic with an adaptive B-spline network to model the behavioral mode choice in the area of transportation planning. They apply the model to a bimodal example for shipment of commodities (rail and Interstate Commerce Commission–regulated motor carriers for shipments over 500 lb).

6.3 Wavelets

Neural network models can lose their effectiveness when the patterns are very complicated or noisy. Traffic data collected from loop detectors installed in a freeway system and transmitted to a central station present such patterns. Neural networks have been used to detect incident patterns from nonincident patterns with limited success. The dimensionality of the training input data is high, and the embedded incident characteristics are not easily detectable. Adeli and Samant (2000) present a computational model for automatic traffic incident detection using the discrete wavelet transform (Samant and Adeli, 2000) and neural networks. The wavelet transform is used for feature extraction, denoising, and effective preprocessing of data before the adaptive conjugate gradient neural network model of Adeli and Hung (1994) is used to make the traffic incident detection. The authors show that for incidents with a duration of more than 5 minutes, the incident-detection model yields a detection rate of nearly 100 percent and false-alarm rate of about 1 percent for two- or three-lane freeways.

Adeli and Karim (2000) present a new multiparadigm intelligent system approach to the traffic incident-detection problem through integration of fuzzy, wavelet, and neural computing techniques to improve reliability and robustness. A wavelet-based denoising technique is employed to eliminate undesirable fluctuations in observed data from traffic sensors. Fuzzy c-mean clustering is used to extract significant information from the observed data and to reduce its dimensionality. A radial basis function neural network is developed to classify the denoised and clustered observed data. The authors report excellent incident-detection rates with no false alarms when tested using both real and simulated data.

Liew and Wang (1998) describe application of wavelets for crack identification in structures. Marwala (2000) uses the wavelet transform and neural networks for damage identification in structures.

7 FINAL COMMENTS

The neural networks articles reviewed in this article have been published mostly in the following journals (the first number in the parentheses refers to the year when the first article on neural networks was published in that particular journal, and the second number refers to the number of articles published and reviewed in this article). This list will guide readers on where to find additional articles on the subject in the future.

- *Computer-Aided Civil and Infrastructure Engineering* (formerly *Microcomputers in Civil Engineering*, 1986–1997) (1989, 52)
- *Journal of Computing in Civil Engineering*, ASCE (1992, 36)
- *Computers and Structures* (1991, 24)
- *Journal of Engineering Mechanics*, ASCE (1991, 13)
- *Journal of Construction Engineering and Management*, ASCE (1991, 10)
- *Journal of Structural Engineering*, ASCE (1995, 9)
- *Canadian Journal of Civil Engineering* (1994, 8)
- *Computer Methods in Applied Mechanics and Engineering* (1993, 7)

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