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Fully Automated Design of Super–High-Rise Building Structures by a Hybrid AI Model on a Massively Parallel Machine

Hojjat Adeli and H. S. Park

■ This article presents an innovative research project (sponsored by the National Science Foundation, the American Iron and Steel Institute, and the American Institute of Steel Construction) where computationally elegant algorithms based on the integration of a novel connectionist computing model, mathematical optimization, and a massively parallel computer architecture are used to automate the complex process of engineering design.

Design automation of one-of-a-kind engineering systems is considered a particularly challenging problem (Adeli 1994). Adeli and his associates have been working on creating novel design theories and computational models with two broad objectives: (1) automation and (2) optimization (Adeli and Hung 1995; Adeli and Kamal 1993; Adeli and Zhang 1993; Adeli and Yeh 1989; Adeli and Balasubramanyam 1988a, 1998b; Paek and Adeli 1988; Adeli and Alrijleh 1987). Civil-engineering structures are typically one of a kind as opposed to manufacturing designs that are often mass produced. To create computational models for structural design automation, we have been exploring new computing paradigms. Two such paradigms are neurocomputing and parallel processing.

We first created a neural dynamics model for optimal design of structures by integrating penalty function method, Lyapunov stability theorem, Kuhn-Tucker conditions, and the neural dynamics concept (Adeli and Park 1995a). Neural dynamics is defined by a system of first-order differential equations governing time-evolution changes in node (neuron) activations. A pseudoobjective 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. In other words, the new neural dynamics model for structural optimization problems guarantees global convergence and robustness. However, the model does not guarantee that the equilibrium point is a local minimum. We use the Kuhn-Tucker condition to verify that the equilibrium point satisfies the necessary conditions for a local minimum. In other words, a learning rule is developed by integrating the Kuhn-Tucker necessary condition for a local minimum with the formulated Lyapunov function.

The neural dynamics model was first applied to a linear optimization problem, the minimum-weight plastic design of low-rise planar steel frames (Park and Adeli 1995). In this application, nonlinear code-specified constraints were not used. It was shown that the neural dynamics model yields stable results no matter how the starting point is selected.

Next, encouraged by the robustness and global convergence of the model, we developed a nonlinear neural dynamics model for optimization of large space structures (Adeli and Park 1995b). The model consists of two information flow-control components and two information server components. The schematic functional interaction of various components is shown in figure 1.

The first information flow control component is a neural dynamics system of differential equations that corresponds to a learning rule governing time-evolution changes in node activations. The second component is the network topology with one variable layer and as many constraint layers as the number of loading conditions. The first information server component performs finite-element analysis and finds the magnitudes of constraint violations. The other information server finds the design sensitivity coefficients. The nonlinear neural dynamics model was applied to minimum weight design of four example structures, the largest being a 1310-member 37-story space truss structure. It was concluded that the new approach results in a highly robust algorithm for optimization of large structures (Adeli and Park 1995c).

To achieve automated optimum design of realistic structures subjected to actual design 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 1994, 1989), we developed a hybrid counterpropagation neural (CPN) network–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 topology of the hybrid neural network model is shown in figure 2 (Adeli and Park 1996). The number of nodes in the variable layer corresponds to the number of independent design variables *(K)* in the structural optimization problem. Nodes in the constraint layer receive the discrete cross-sectional properties from the CPN as input, evaluate the prescribed constraints, and generate the magnitudes of constraint violations as output. The functional activations at the nodes in the variable layer receive information about the search direction (encoded as the weights of the links connecting the constraint layer to the variable layer) and magnitudes of constraint violations as input and generate the improved design solutions as output.

The number of nodes in the constraint layer is equal to the total number of constraints imposed on the structure. There are as many constraint layers as there are loading combinations acting on the structure. The number of stress constraints is in the thousands for a large structure with thousands of members. As such, the number of violated stress constraints requiring computation of sensitivity coefficients tends to be very large. To accelerate the optimization process and reduce the required central processing unit time for computation of sensitivity coefficients, only the most violated constraint in each group of members linked together as one design variable is allowed to represent the status of the constraints for the group. Therefore, a competition is introduced into the constraint layer to select the most critical node among the nodes belonging to one linked design variable.

Both excitatory and inhibitory connection types are used to adjust the states of the nodes. Gradient information of the objective function is assigned to the inhibitory recurrent connections in the variable layer. Gradient information of the constraint functions is assigned to the inhibitory connections from the constraint layer to the variable layer.

The counterpropagation network is a combination of supervised and unsupervised mapping neural networks (Hecht-Nielsen 1987a, 1987b). The counterpropagation part of the model consists of two layers: (1) competition and (2) interpolation. Nodes in the competition layer receive the values of improved design solutions from the nodes in the variable layer, calculate the Euclidean distances between the input and the connection weights, and select the winning node. Nodes in the interpolation layer recall the corresponding cross-sectional properties encoded in the connection weights associated with the winning node.

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 can be done only on multiprocessor supercomputers (Adeli 1992a, 1992b). A high degree of parallelism can be exploited in a neural computing model (Adeli and Hung 1995). Consequently, we created a data-parallel neural dynamics model for discrete optimization of large steel structures and imple-

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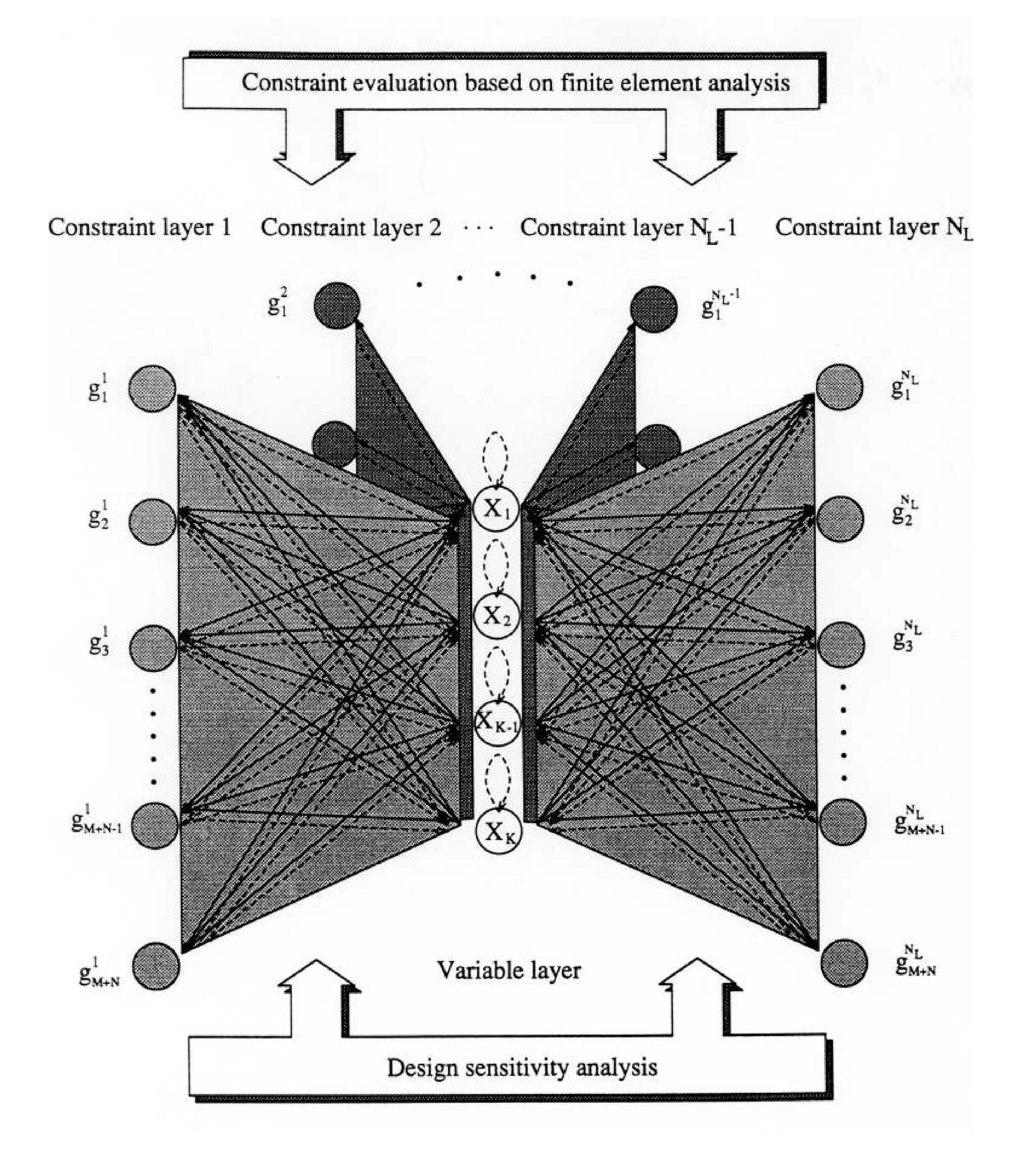

Figure 1. Functional Interactions of Various Components of the Neural Dynamics Model for Optimization of Structures.

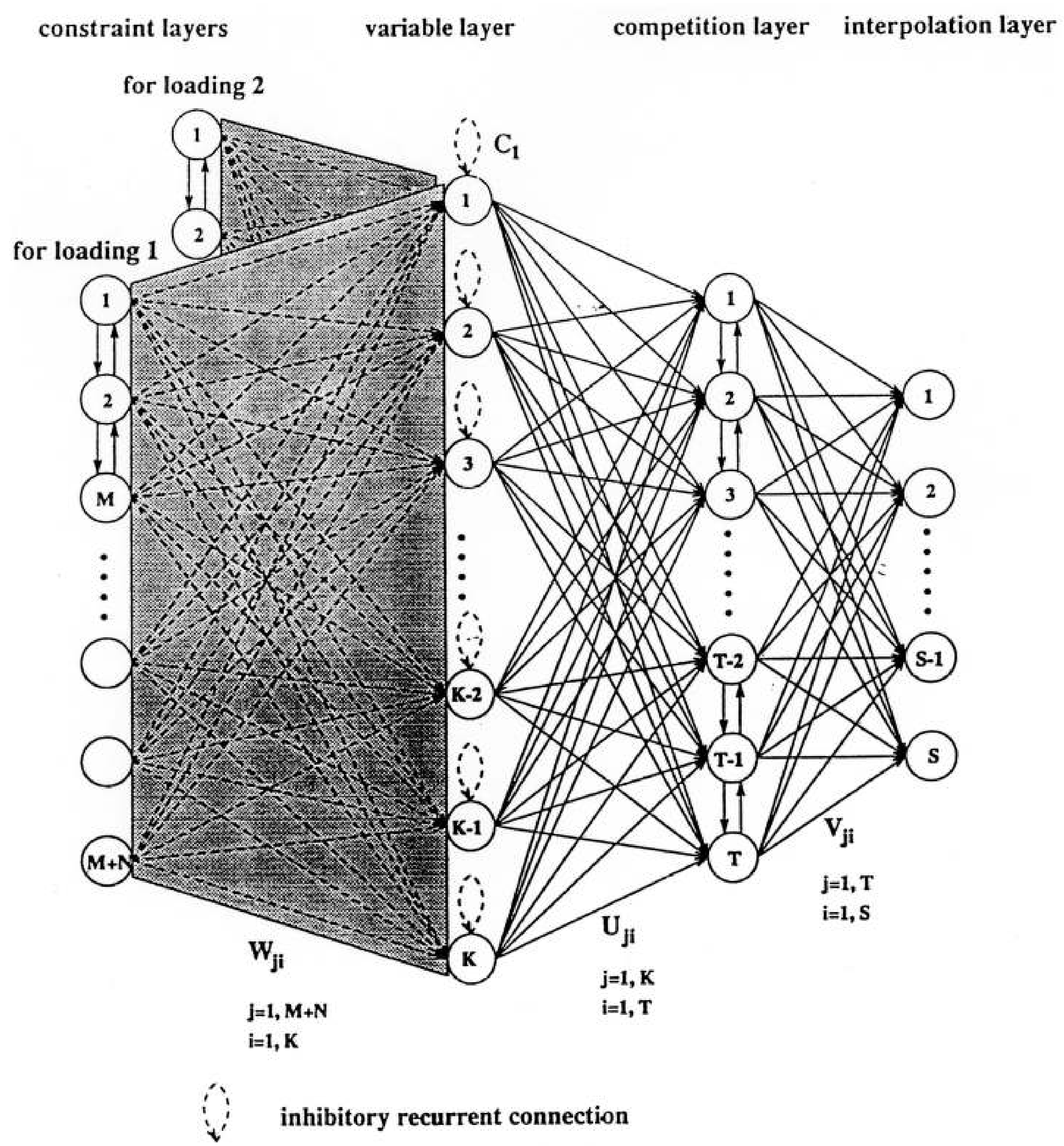

Figure 2. The Topology of the Hybrid Neural Network Model.

mented the algorithm on a distributed memory multiprocessor, the massively parallel Connection Machine CM-5 system (Park and Adeli 1996).

There are four stages in the hybrid neural dynamics model: (1) mapping the continuous design variables to commercially available discrete sections using a trained CPN network; (2) generating the element stiffness matrixes in the local coordinates, transforming them to the global coordinates, and solving the resulting simultaneous linear equations using the preconditioned conjugate gradient (PCG) method; (3) evaluating the constraints based on the AISC ASD or LRFD specifications; and (4) computing the improved design variables from the nonlinear neural dynamics model.

The design variables are the cross-sectional areas of the members. For integrated design of steel structures, a database of cross-section properties is needed for computation of element stiffness matrixes and evaluation of the AISC ASD and LRFD constraints. A counterpropagation network consisting of competition and interpolation layers is used to learn the relationship between the cross-sectional area of a standard wide-flange (*W*) shape and other properties such as its radii of gyration (Adeli and Park 1995b).

The recalling process in the CPN network is done in two steps: In the first step, for each design variable, a competition is created among the nodes in the competition layer for selection of the winning node. The weights of the links between the variable and competition layers represent the set of cross-sectional areas of the available standard shapes. In the second step, discrete cross-sectional properties encoded in the form of weights of links between the competition and the interpolation layers are recalled. The weights of the links connecting the winning nodes to the nodes in the interpolation layer are the cross-sectional properties corresponding to an improved design variable.

In the second stage of the neural dynamics model for optimal design of structures, sets of linear simultaneous equations need to be solved to find the nodal displacements. Iterative methods are deemed more appropriate for distributed memory computers where the size of the memory is limited, for example, to 8 megabytes (MB) in the case of the CM-5 system used in this research. As a result, a data-parallel PCG method is developed in this research (Adeli and Kumar 1995).

The third stage consists of constraint evaluation using the nodal displacements and member stresses obtained in the previous stage. Three types of constraint are considered: (1) fabrication, (2) displacement, and (3) stress (including buckling). For the LRFD code, the primary stress constraint for a general beam-column member is a highly nonlinear and implicit function of design variables.

In the final stage, the nonlinear neural dynamics model acts as an optimizer to produce improved design variables from initial design variables. It consists of a variable layer and a number of constraint layers equal to the number of different loading conditions.

In our data-parallel neural dynamics model (Park and Adeli 1996), we exploit parallelism

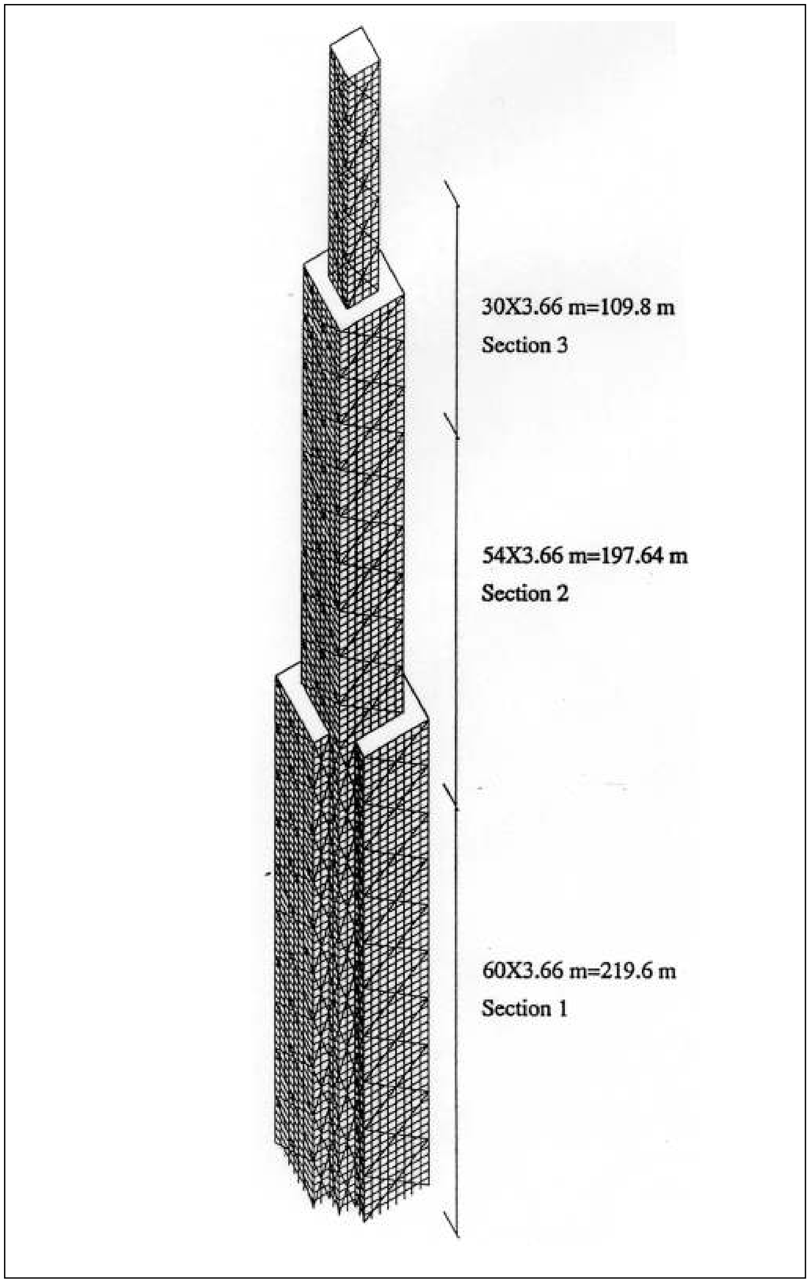

Figure 3. A Very Large Structure Designed Automatically by the Neural Dynamics Algorithm.

in the four stages of the neural dynamics model. The model has been implemented on a CM-5 system. The main components of the CM-5 system are a number of processing nodes (PNs); partition managers (PMs); and two high-speed, high-bandwidth communication networks called *data* and *control networks*. A PN has four vector units (VUs) with 8 MB of memory to a unit and can perform high-speed vector arithmetic computations with a theoretical peak performance of 128

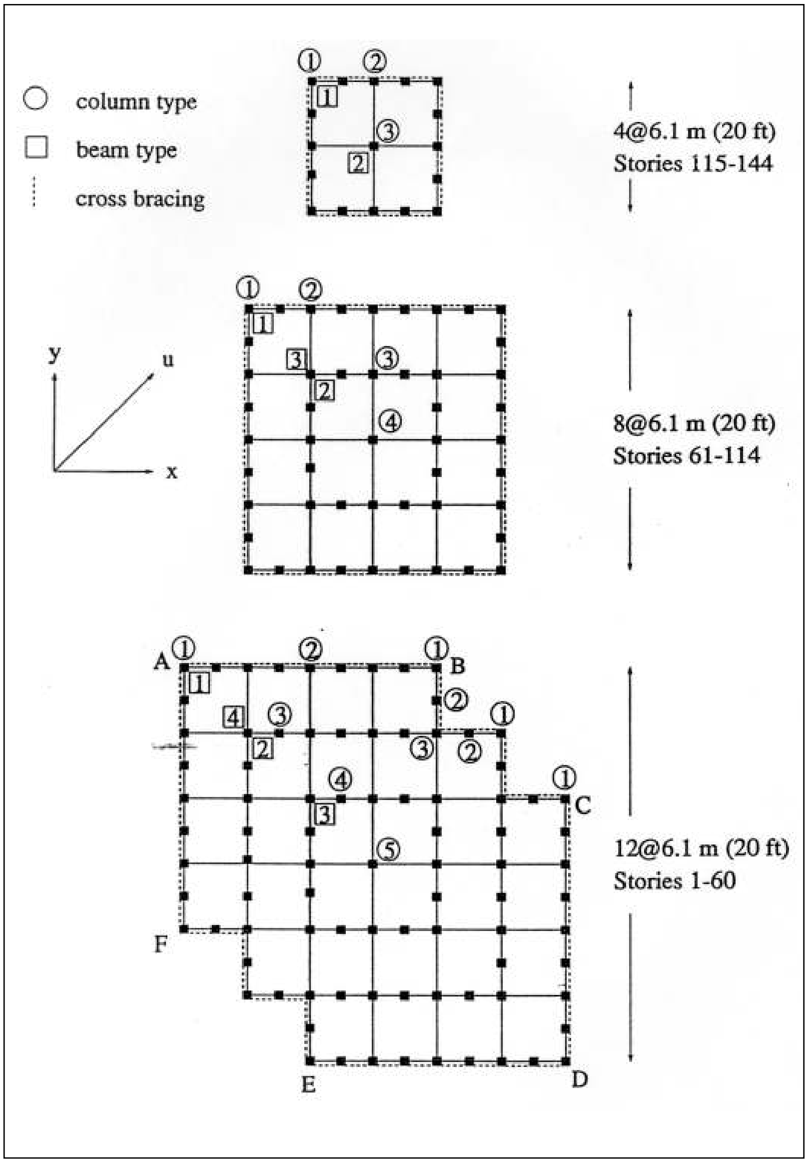

Figure 4. Plan of the Building in Figure 3.

million floating-point operations per second (MFLOPS).

The neural dynamics algorithm developed in this research can be applied to steel structures of arbitrary size and configuration. Figure 3 presents an example of a very large structure designed automatically by the neural dynamics algorithm on a CM-5 system. This example is a 144-story steel super–high-rise building structure with a height of 526.7 meters (1728 feet). This structure is a modified tube-in-tube system consisting of a space moment-resisting frame with cross-bracings on the exterior of the structure. The structure has 8,463 joints; 20,096 members; and an aspect ratio of 7.2. Based on symmetry and practical considerations, the members of the structure are divided into 568 groups (figure 4). Complete details of the structure can be found in a forthcoming article (Park and Adeli 1996).

The neural dynamics model yields minimum weights of 682.2 megaNewtons (MN) (153381.4 kilopounds [kips]) and 669.3 MN (150467.2 kips) after 20 iterations using the ASD and LRFD codes, respectively. These weights translate into 1.57 kiloPascals (kPa) (34.43 pounds per square foot [psf]) and 1.54 kPa (33.78 psf) for ASD and LRFD codes, respectively. It can be noted that the amount of steel used in what is currently the tallest building structure in the world—the 109-story, 445-meter-high Sears building in Chicago—is about 33 psf (Adeli 1988).

An attractive characteristic of the neural dynamics model is its robustness and stability. We have studied the convergence histories using various starting points. We noted that the model is insensitive to the selection of the initial design. This insensitivity is specially noteworthy because we applied the model to optimization of large space-frame structures subjected to actual design constraints of the AISC ASD and LRFD codes. In particular, the constraints of the LRFD code are complicated and highly nonlinear and implicit functions of design variables. Further, the LRFD code requires the consideration of the second-order Pd and PD effects.

The largest structural optimization problem ever solved and reported in the literature is a 100-story high-rise structure with 6136 members and variables (no design linking strategy was used) (Soegiarso and Adeli 1994). The structure was a space-truss structure and not subjected to any code-specified constraints. The example presented in this article is a space-frame structure with complicated code-specified design constraints and is by far the largest structure optimized according to the AISC ASD and LRFD codes ever reported in the literature. This research demonstrates how a new level is achieved in design automation of one-of-a-kind engineering systems through the ingenious use and integration of a novel computational paradigm, mathematical optimization, and new high-performance computer architecture.

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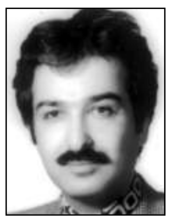

Hojjat Adeli received his Ph.D. from Stanford University in 1976. He is currently a professor of civil engineering and a member of the Center for Cognitive Science at The Ohio State University. A contributor to 44 different research journals, he has authored over 270 research and scientific publications in various fields of computer science and engineering. His most recent book is entitled *Machine Learning—Neural Networks, Genetic Algorithms, and Fuzzy Systems* (Wiley 1995). Adeli is also the founder and editor in chief of the *Integrated Computer-Aided Engineering.* He has been an organizer or a member of the advisory board of more than 80 national and international conferences and a contributor to more than 90 conferences.

H. S. Park received his Ph.D. from The Ohio State University in 1994. He is currently a senior researcher and software developer at Daewoo Institute of Construction Technology, a research and development firm in Korea. Park is the co-author of seven research articles in the area of neural network computing.