Next Generation Artificial Neural Networks for Civil Engineering

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At first glance, artificial neural networks appear to be one of the great success stories in the history of computing in civil engineering. In the Journal of Computing in Civil Engineering, for example, 54 out of 445 papers published since 1995 (12%) have used the term “neural” in their title (ASCE 2006), while the distribution of these publications by year indicates that there has been no decline in interest over the last decade (see Fig. 1). Moreover, according to the ISI Web of Knowledge (Thompson Corporation, 2006) and summarized in Table 1, the two most frequently cited articles from all issues of the ASCE Journal of Computing in Civil Engineering are on artificial neural networks. The enthusiasm with which the research community has adopted this technology over the last 15 years, reporting successful applications within every branch of civil engineering, makes it difficult to ignore.

Yet, a more in-depth analysis concludes that progress in applied artificial neural networks largely stagnated following the initial applications of the early 1990s. These first applications were mostly simple function models and pattern classifiers that mapped directly from an input vector to an output vector, the types of problem that have otherwise been solved using methods such as multi-variate regression analysis. Although many new applications have been found in the ensuing years (along with several refinements to the technique), these have still been predominantly simple vector mapping problems. This is a far cry from the potential of artificial neural networks anticipated by many, to provide a computational device that can emulate higher-level cognitive processes. Such a capability would allow a wealth of new problems to be tackled in civil engineering that have so far eluded solution, including, for example: determining legal compliance of designs from drawings and specifications; identifying constructability problems from the design of a building; and measuring construction progress from site images.

This lack of progress in the development of artificial neural networks is also apparent when a comparison is made with the most popular computational model, the general purpose electronic digital computer. This is significant given that the initial development of artificial neural networks dates back to the mid 1950s (Rosenblatt 1958) making the technology just a decade or so younger than that of electronic digital computing. Since its inception, the electronic digital computer has evolved steadily from a device comprising just a few hundred primary processing units (transistors) into one comprising billions organized into a sophisticated structure of higher-order functional subsystems. Artificial neural networks on the other hand, have failed to advance beyond simple applications that require rarely more than a few hundred primary processing units (neurons in this case) arranged with almost no higher-order structuring.

If we measure complexity in these simple terms (as the number of primary processing units that can be employed usefully in an application) then we can compare today’s general purpose digital computer to the brain of a rabbit (comprising in the order of $10^9$ neurons), while artificial neural networks have progressed no further than the brain of the humble nematode (comprising just $302$ neurons). Obviously the number of primary processing units that can be employed usefully in a given application provides a very simplified means of comparing complexity—an artificial neuron is usually a much more complicated processing device than a transistor and, moreover, it is likely that significant aspects of the computational mechanisms underlying biological neural networks are yet to be discovered and could be dependent on processes that operate at a lower level than individual neurons (see Bullock 2005 for example). Nevertheless, the comparison clearly demonstrates that a plateau has been reached in the development of this technology and that this plateau is at a low elevation.

This begs the question: ‘Why has there been such a high and sustained level of interest in applying artificial neural networks to civil engineering, if progress in their development has been so limited?’ The answer is that artificial neural networks, despite their presently rudimentary form, are very good at solving direct mapping problems that are non-linear and comprise several independent variables, a common class of problems in engineering. In this context, they often provide more accurate solutions than the alternative modeling techniques, and place little demand on the modeler in terms of understanding the basic form of the function being represented. However, solving direct vector mapping problems can only be considered a primitive first step in the application of artificial neural networks, if we dare aspire to the computational capabilities of biological neural systems.

Perhaps unsurprisingly, the biological model suggests that an increase in cognitive skills can be achieved by moving towards

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**Fig. 1.** Distribution of articles published in the Journal of Computing in Civil Engineering using the term “neural” in their title (ASCE 2006)
networks of greater complexity. More precisely, there is an apparent correlation between the cognitive skills of a species and its encephalization quotient (EQ) (the ratio of actual brain size to expected brain size needed for the basic control and monitoring of the body) (Jerison 2000). It also seems that an increase in the number of neurons alone is not sufficient to provide higher levels of cognitive skills, but that these must also be formed into a structured system of higher-order functional units such as is found in the visual system (Sirosh and Miikkulainen 1997). The sticking point in the development of applied artificial neural networks has not been an inability to construct systems comprising many millions of neurons (this is perfectly feasible with today’s technology); rather, it has been, at least in part, a lack of knowledge about how to organize neurons into appropriate higher-order network structures. Note that the term “higher-order structures” is used in this editorial to refer to the connection structure of a network and should not be confused with the term “higher-order neural networks,” which is commonly used in the literature to refer to neural networks composed of Sigma-Pi neurons.

The contention of this editorial is that, there is much that can be done to advance the scope of application and utility of artificial neural networks by shifting research towards the development of higher-order structures. Three basic forms of connection structuring can be identified, namely, concurrent, serial, and hierarchic organizations of higher-order units (the latter being an integration of the output of several units to provide a summary or abstraction of their results). The boundaries of these higher-order units may be very distinct with relatively few connections between the constituent neurons and those in other units, or they may be indistinct with many cross-connections. Moreover, any unit may feedback recursively to other units in the structure including itself. For versatility in application, the structuring of a network will often have to allow for a variable format in the configuration of input data—this is to allow the network to function in an environment where there is spatial variance in the definition of a problem (resulting from scaling, rotation, translation and/or shearing of the data format, for example), temporal variance (resulting from the use of arbitrary starting points in input data streams, changes in the rate of data flow, and/or gradual shifts in the nature of a problem over time) and stochastic variance (resulting from noise and/or missing data values). Complementary to the structure of a network is the mode of operation of the neurons and their connections. Here, no restrictions are proposed: studies might consider anything from neurons that act as simple logic gates (effectively making the network operate as a digital circuit) through to pulse frequency coded units (see Kartam et al. 1997) for a classification of the alternative modes of neuron operation.

To an extent, inspiration for the design of these higher-order network structures can be gained by studying neural subsystems in the central nervous system. For example, the self-organizing subsystems that solve certain early processing tasks in the visual system (such as, line detection) are understood well enough to be replicated using artificial neural networks (Sirosh and Miikkulainen 1997). However, the organization of structures that perform higher-order operations than this, later in the visual system (such as face recognition) are not well understood. Moreover, most engineering problems do not have analogs in nature with readily available solutions provided by biological neural systems. Given this, and the fact that suitable higher-order structures cannot normally be derived by design, it seems that we must turn to techniques such as genetic algorithms for their development. Interestingly, of the top five most frequently cited articles in the Journal of Computing in Civil Engineering (Table 1), three were on neural networks and two were concerned with genetic algorithms.

While genetic algorithms and related optimization techniques have been used to develop artificial neural network applications for many years (over 15 years in the case of civil engineering), this has been restricted to developing single network units rather than the higher-order structures proposed here. Such an approach will require a sophisticated genetic coding system and corresponding set of objective functions to facilitate development of appropriate neural systems at the macro-level (the connectivity between the higher level neural units), the meso-level (the connectivity between the neurons within a given unit), and the micro-level (the mode of operation of the individual neurons). In addition, the method of development might be designed to evolve automatic learning responses in a network when subjected to input data, including learning of connection weights and self-organization of the connection structure. In the longer term, other processing mechanisms operating at levels below and above that of the neuron may be considered, particularly as we come to understand these processes from biological studies.

In summary, over the last decade, artificial neural networks have been a primary focus of interest for research in computer-based civil engineering. As far as they have been applied, they have provided convenient and often highly accurate solutions to problems from all branches of civil engineering. However, the extent of this application has rarely ventured beyond rudimentary problems such as simple function modeling and pattern classification. In order to achieve the full potential of this technology, as promised by biological neural systems, researchers must take on the challenge of developing networks that are vastly more complex than have been developed to date. Complexity, in this sense, requires not just an increase in the number of neurons, but also a rich higher-order structuring of the network, such as is found in biological neural systems. Promising approaches to the development of these structures are genetic algorithms and related methods. While these will require the design of sophisticated genetic coding mechanisms, the potential payoff is considerable in terms of broadening the scope of application of computing to civil engineering. We are, of course, a very long way from being able to replicate or even go beyond human cognitive skills using artificial neural networks, but it is time at least to take the next tentative step towards this ambition.

<table>
<thead>
<tr>
<th>Title</th>
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<tr>
<td>Neural networks in civil engineering, Parts I and II (Flood and Kartam 1994)</td>
<td>131</td>
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<tr>
<td>Neural networks for river flow prediction (Karunanithi et al. 1994)</td>
<td>97</td>
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<td>Genetic algorithms in pipeline optimization (Goldberg and Kuo 1987)</td>
<td>74</td>
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<td>Genetic algorithms in discrete optimization of steel truss roofs (Koumousis and Georgiou 1994)</td>
<td>37</td>
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<td>Damage detection in structures based on feature-sensitive neural networks (Szewczyk and Hajela 1994)</td>
<td>35</td>
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Table 1. Five most frequently cited articles in the Journal of Computing in Civil Engineering (Thomson Corporation 2006)
References


