15 SOFT COMPUTING IN CONSTRUCTION INFORMATION TECHNOLOGY

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Abstract

The last decade, civil engineering has exercised a rapidly growing interest in the application of neurally inspired computing techniques. The motive for this interest was the promises of certain information processing characteristics, which are similar to some extend, to those of human brain. The immediate examples of these include an ability to learn and generalize. In parallel to this and further developments in the information systems technology, established the essential motivation that the construction industry should benefit from these developments for enhanced and effective executions. Today such information processing methods are collectively referred to as soft computing (SC). Explicitly, soft computing is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of certainty and imprecision. SC consists of several computing paradigms, including neural networks, fuzzy set theory, approximate reasoning and combinatorial optimization methods such as genetic algorithms. SC finds important applications in diverse disciplines. As a branch of artificial intelligence, soft computing is closely related to computational intelligence where in essence SC methods are implemented by machine learning techniques. Paper deals with SC in the context of construction information technology (CIT) pointing out the important role it can play. It exemplifies the SC applications in CIT supported by pilot implementations, which are carried out as a part of ongoing departmental research program.

Keywords: *Soft computing, neural networks, fuzzy logic, genetic algorithms, IT*

INTRODUCTION

In the last decade, there has been a rapidly growing interest in the application of neurally inspired computing techniques. The essential thrust for this development was the anticipation of more effective use of brain-like information processing methods alongside with their rapid developments. The most commonly cited examples of brain-like information processing activities are ability to learn and generalise from experience, ability to process information, which may be incomplete or even partly erroneous, ability to process information rapidly and ability to adapt solutions over time to compensate for changing circumstances. Such information processing capabilities are commonly referred to soft computing activities and today they are in various contexts focal points in construction information technology (CIT). Also, the related actual implementations are the commonplace in the construction technology. The purpose of this work is in the context of CIT, to describe these neurally inspired computing methodologies in a unified form as soft computing methodologies and to exemplify these by means of ongoing departmental researches. This will provide further insight into understanding the important role of SC in CIT that it can play. The organization of the material is as follows. The following section describes soft computing methods subject to CIT implementations. Section three reports some actual implementations carried out as part of the departmental research program and this is followed by conclusions.

SOFT COMPUTING, INFORMATION TECHNOLOGY AND CIT

Soft computing (SC) is an innovative approach to constructing computationally intelligent systems. Zadeh (1994) introduced the term. SC is not a single methodology, rather, it is a partnership (Zadeh, 1998*)*. Explicitly, *soft computing is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of certainty and imprecision*. Next to SC, information technology (IT) has been identified as the essential means of data and process integration in industry leading to effectiveness (mostly in terms of cost) and efficiency increase. The role of IT in building and construction has a rapid growth in the last decade. The main motive behind is apparently due to the multidisciplinary nature of construction technology and ensuing demand for effective information processing of exponentially growing information. In this respect and referring to soft computing, highly parallel brain-like processing is very appealing in IT environment, since this implies fast computation producing meaningful results even when the input data set contains errors or it is incomplete.

In general terms, SC includes a new form of logic known as fuzzy logic (FL) with approximate reasoning, neural networks (NN), and combinatorial optimization paradigms which include major evolutionary algorithms such as genetic algorithms (GAs). These are briefly mentioned below.

Fuzzy Logic

Fuzzy logic is based on the concept of fuzzy sets (Zadeh, 1973). A fuzzy set is a generalization of a classical set in the sense that memberships are graded between 0 and 1. In this case, if x is a variable over a domain of discourse U, and X is a fuzzy set over U, then $\mu_X(x)$ is defined as the degree of membership of x in X. A system of fuzzy sets over a domain can form a fuzzy partition of the domain. A brief introduction related to soft computing in CIT is given in another presentation (Durmisevic et al., 2001).

Artificial Neural Networks

Artificial neural networks (ANN), or connectionist systems, are finding applications in almost all branches of science and engineering. An ANN consists of highly interconnected simple processing units called neurons. A major concern in the development of a neural network is determining an appropriate set of weights that make it perform the desired function. This is accomplished by means of special algorithms, which are called training algorithms. Applications in construction technology only go back slightly more than a decade, but already cover a range of topics as diverse as process optimisation (Flood 1990), determining the loads on the axles of fast moving trucks (Gagarine et al. 1992,1994), seismic hazard prediction (Wong et al., 1992). There are a number of ANN paradigms. From the CIT viewpoint, the important ones are feed-forward multilayer perceptron (MLP) network, Hopfield network, Khonen network. These are used in civil engineering for the identification and modelling representing the dynamic behaviour of structures and to the active control for protecting these structures from the damaging effects of destructive environmental loadings. Referring to construction engineering and management, evaluating CT with ANN is given by Chao and Skibniewski (1998).

Evolutionary algorithms

Evolutionary algorithms are heuristic search algorithms which are extremely useful in CIT for optimization problems which are in particular ill-posed, that is, they are not feasible to tackle because of some practical reasons or they cannot be treated by known analytical methods at all. In this respect, an important heuristic search methodology of concern is genetic algorithm(GA)s. As algorithm, they are different from traditional optimisation methods in the following respects.
- they work with a coding of the variables set and not with the variables themselves
- they search from a population of points rather than by improving a single point
- they use objective function information without any gradient information
- their transition scheme is probabilistic
- they can deal with a multi-objective optimisation tasks

Main steps in the algorithm are as follows:

Coding - An essential characteristic of a genetic algorithm is the coding of the variables that describe the problem where the variables are transformed to a binary string of specific length called chromosome.

Reproduction – Production of the next generation of population as result of a selection process based on a problem specific criterion known as *fitness function*.
Crossover-mutation – By crossover, two members of the population are selected randomly and exchange part of their chromosomal information with a specified probability. By mutation, certain digits of the chromosome are altered with a specified probability.

Decoding – By decoding, the solution for each specific instance is determined and the value of the objective function that corresponds to the individuals is evaluated. As result of this evaluation, if necessary, the same steps are repeated from the reproduction phase onwards until the desired convergence is reached. The basic parameters of a simple genetic algorithm are the population size of the generation, the probability of crossover and the probability of mutation. By varying these parameters, the convergence of the problem is controlled.

Information Technology and CIT

During the last decade there have been a tremendous growth in interest in information systems technology (Zwass 1998; Turban & Aronson, 2001) and the application of soft computing techniques to engineering systems and related technologies including civil engineering and construction technology. At the same period, it became clear that, ANN and fuzzy logic systems are, in essence, equivalent (Jang and Sun, 1993). In particular, fuzzy system structures are identified to be equivalent to feed-forward type ANN structures where the sigmoidal or gaussian type of nonlinearities correspond to membership functions in the fuzzy system. By means of this equivalence, the classical knowledge based systems with symbolic logic could be represented by fuzzy logic where classical logic If-Then rules are expressed by fuzzy If-Then rules. Thereby, in a complex construction information environment, the rules can be established by machine learning, rather then coding expert knowledge in a suitable programming language and embedding in the data base. Since the number of rules necessary to form a satisfactory knowledge base increases exponentially with the increase of information volume, today in a complex information environment like CIT, it is formidable task to establish an expert system with satisfactory performance beyond a mere decision support system (DDS). Therefore, knowledge management is a focal point of investigation in such systems (Carrillo et al. 2000). In this respect, the fuzzy logic systems with machine learning techniques are apparently most prospective computational means in CIT for data mining knowledge management and decision-makings (Hirota, Pedrycz, 1999).

Although feed-forward ANN systems are equivalent to fuzzy logic systems under lenient conditions, since fuzzy logic systems considers local representations in a system modeling, the feed-forward type of networks with the same property are most suitable. Classical MLP type neural networks are suitable for global representation of the system that they are modeling or considering for diverse purposes like fault diagnosis, performance evaluation and so on. For local models, an appropriate type of network is known as radial basis functions network which has a basic structure for multivariable functional approximation with a rich mathematical background (Powel 1992; Schilling et al., 2001). Such a network also has the advantage of exercising powerful clustering algorithms with appropriate machine learning methodologies for the exhaustive exploitation of the information at hand. Clustering is one of the powerful machine learning method can be grouped in two main categories:

- *Unsupervised learning of the centre locations*. In this category, the original data set is analysed to identify the common features. Traditional clustering based methods (Bezdek, 1981) and fuzzy clustering based methods (Pedrycz, 1998) are of particular interest in this case.
- *Supervised learning of the centre locations*. In this category, the selection of centres is performed according to given data sets belonging to input and output spaces of the network.

Although RBF network is a kind ANN, due to its clustering-related features it is of outstanding interest to CIT whereas conventional feed-forward ANN structures with standard back-propagation (BP) algorithms are of main interest to CT rather than CIT. In the following section, some departmental ongoing researches will exemplify applications of SC to CIT where from the CIT viewpoint some relevant details will be presented as well.

SOFT COMPUTING APPLICATIONS TO CIT

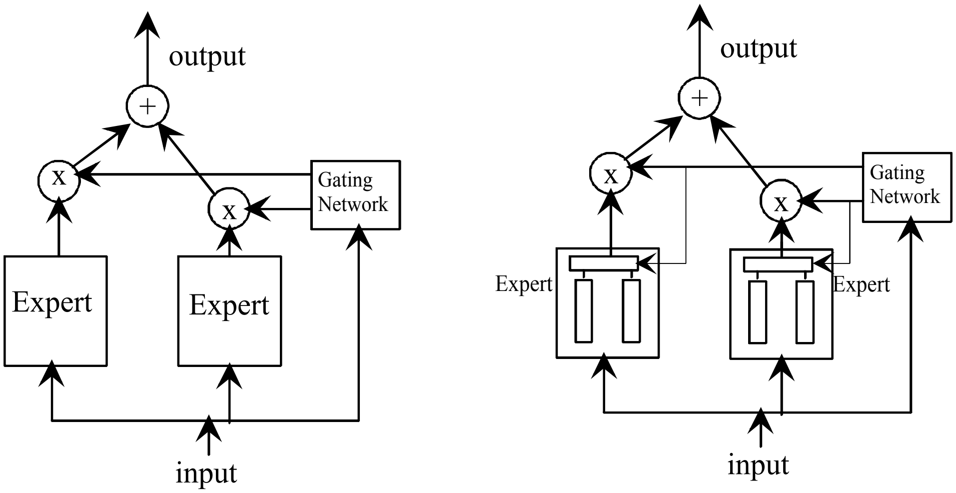
Expert Systems by Machine Learning

Referring to the important role of machine learning in SC applied to CIT, several departmental researches have been carried out. In this section we highlight these researches to emphasise the eminent role of SC in CIT. Due to the complexity of information, fuzzy techniques should be associated with machine learning. An architectural design example by soft computing deals with the architectural design data, which are 'soft' requiring SC techniques next to SC requirement due to complexity. Basically, the design variables constitute a 43-dimensional input space and two-dimensional output space where knowledge model of the input and output variables are aimed. As machine learning method used in this application, a powerful supervised clustering method, known as, orthogonal least squares (OLS) algorithm (Chen et al., 1989, 1990, 1991) is used. Additionally, the clusters (receptive fields) are selected among a series of input 43-dimesional input sets so that the information used for modeling is preserved as intact as possible without any mathematical manipulations apparently suitable for the convenience of machine learning, like back-propagation algorithm. The design information made available to RBF network at input is basically linguistic and qualitative. In basic mathematical terms, if we assume that the input vector x(t) represents a n-dimensional vector of real-valued fuzzy membership grades: $x(t) \in [0,1]^n$, then, the output y(t) of the model represents an m-dimensional vector of corresponding real-valued membership grades, $y(t) \in [0,1]^m$. This structure actually performs a non-linear mapping from an n-dimensional hyper-cube $I^n=[0,1]^n$ to an m-dimensional hyper-cube $I^m=[0,1]^m$:
$x(t) \in [0,1]^n \rightarrow y(t) \in [0,1]^m$

In the actual implementation, $x_i(t)$ (i=1,2,…,n) in x(t) represents the degree to which a qualitative input fuzzy variable $x_i'(t)$ belongs to a fuzzy set, while $y_j(t)$ (j=1,2,…,m) in y(t) represents a degree to which a qualitative output fuzzy variable $y_j'(t)$ belongs to a fuzzy set. It is interesting to note that, complex, unknown relationships between input and output variables are accurately identified and embedded in the network structure as a knowledge base in terms of fuzzy If-Then rules, where these rules are established by machine learning. Such a network with its inherent fuzzy logic based inference system, knowledge base and input-output, forms an intelligent expert system where the inference as a response to some unknown input set is not restricted to a repertoire of rules whereas this is the case for conventional expert systems. The network gives answers according to its own internal criteria formed during the machine learning and not restricted to a human expert's knowledge domain. This is presumably the key advantage of machine-learning based expert systems whereby any complexity of information in the CIT domain can be coped with. This process categorically belongs to a new technology termed as *computational intelligence* which is a branch of artificial intelligence using soft computing techniques. The description of the data set, some implementation details and results are given in another presentation (Durmisevic et. al, 2001).

Mixture of Experts and Neuro-Fuzzy Systems

In a complex CIT environment, depending on the level of complexity, the machine-learned expert systems can be used in parallel in a hierarchical form as shown in *figure 1a* where each expert



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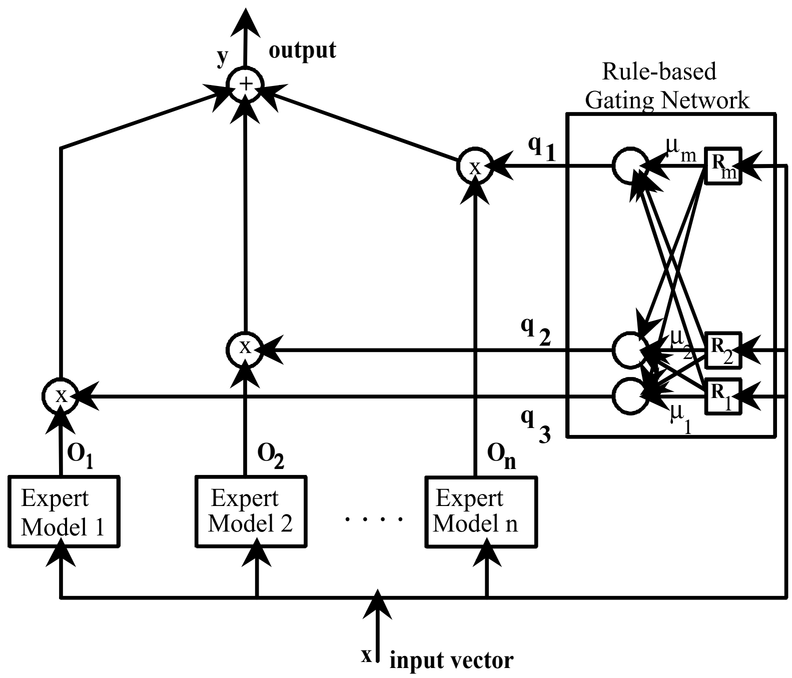
❑ *Figure 1 : Mixture of experts network (a) and its multi-level form (b)*

network is a machine-learned system having different speciality in CT domain. They play the role of human experts in decision-making. A gating network for a final decision-making can weight each expert decision. Such a system is termed as *hierarchical mixture of experts*. The combination of mixture of experts can be devised in any complexity as shown in *figure 1b.*

Although, in general terms neural and fuzzy systems are equivalent, that is, a neural network approach for a task can alternatively be devised as fuzzy logic approach, the performance of the case may apparently be application dependent. Both systems may have their own merits for the particular application. However, in some cases, it may be more convenient to use both approaches explicitly without referring to their equivalence. Such systems are called neuro-fuzzy systems. As an example, the gating network in *figure 1*, can be formed by a fuzzy system as shown in *figure 2*.



❑ *Figure 2 : A neuro-fuzzy mixture of experts network*

Realization of a neuro-fuzzy mixture of experts network for building design information management is reported earlier (Ciftcioglu et al. 2000a).

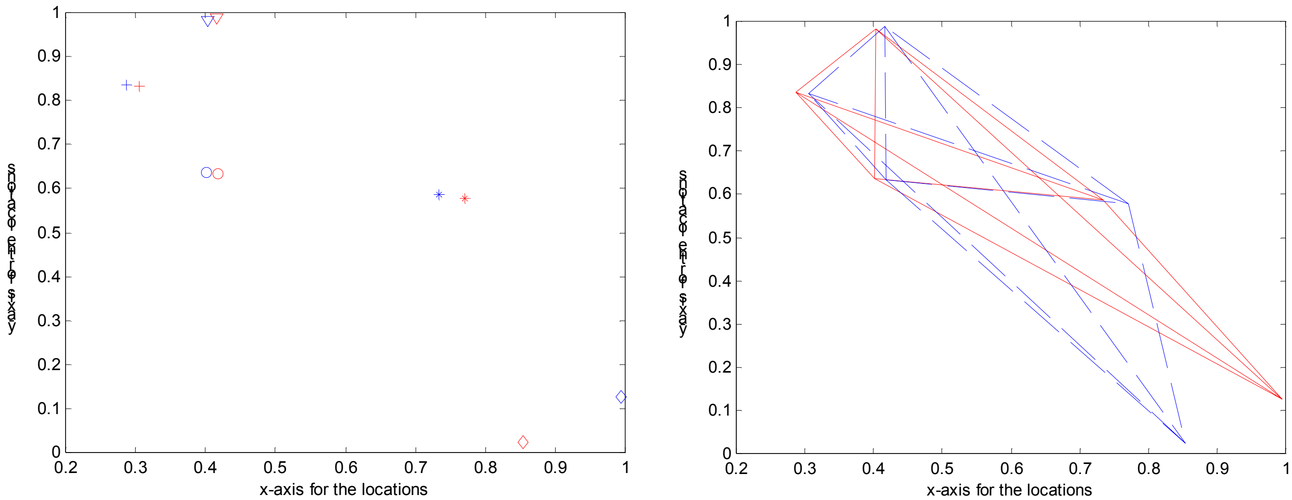
Genetic Algorithms

Many information processing tasks can eventually be cast to a minimization or maximization problem where the subject quantity is termed as cost function or cost functional in a multi-objective situations. Mathematical programming methods suit the continuous problems better. For discrete problems, searching for optimal solution is relatively difficult task. This is due to the ill-defined nature of the problem. As the CIT is multidisciplinary, the information subject to treatment may be partially soft i.e., qualitative and lingustic and partially exact whereby it may pose ill-defined optimization problem. Therefore, in many cases CIT tasks require special attention. To deal with such problems method of GAs can be extremely effective. They belong to the class of random search algorithms. In the canonical genetic algorithm (Goldberg 1989) an individual chromosome is represented by a binary string. Although GAs are randomized, they are not a simple random walk in the space of solutions. They efficiently incorporate information from previous stages to create new search points in the solution space with improved performance. They are related to simulated annealing optimization method (Aarts & Lentra 1997; Aarts & Korst, 1989), which searches for minimal cost function termed as *energy state*. Referring to a CT environment, there are many engineering issues suitable for solution by GAs(Koumousis and Georgion, 1994). From the CIT viewpoint, GAs are especially suitable due to their ability to deal with ill-posed CIT problems on one side, and on the other side the ability to combine with the other SC methods on the other (Billing and Zheng 1995; Thrift 1992).
One of the important design information in Architecture is related to space layout. These are a variety of approaches dealing with the topic, which in most cases fall into category of design

optimisation. These extend from dimensionless form of rectangular units on a plan to area, width and length of each space and the optimal dimensions according to some pre-defined criterion. However in most cases, the criterion used is not satisfactory enough for a design since the optimization (unconstrained or constraint) is based on a scalar quantity as uni-objective, which is generally referred to as "cost function". In contrast to this, in most applications the case needs multi-objective considerations for effective designs. Because of this multi objectivity requirement, such designs mostly boil down to some trivial solutions with a number of simplifying assumptions and approximations. In essence, the problem stems from its ill-conditioned nature, that is, it is not convenient to be dealt with conventional analytical computation and design methods. One reason one can think of that some of the requirements may be qualitative next to qualitative design requirements. Such a design task is tackled by GAs. The problem statement is based on graph representation of the layout and adjacencies between the nodes are considered. The desired relations (multi objective attributes and constraints) on the graph are considered to be privacy. It is related to the Euclidean distance between the point of locations through a function designed for this purpose. In a design optimisation problem, in general, the adjacencies can be assigned through elaboration of the following design aspects (Ciftcioglu et al, 2000b):

1. Connectivity pattern defined by type of the nodes: Depending on the functionality of the spaces (e.g., offices), different adjacency values can be attached to the spaces that are directly connected with each other and to those that are indirectly connected for example via a corridor. This can be shown through adequate adjacency value
2. Optimal distance in relation with the requirements: This is connected to various factors like functional and structural factors. For example, for a certain level of sound attenuation, less soundproof walls are used, as the distance between two spaces (represented as nodes) can be larger, and vice-versa.
3. Cost function derived from the above-mentioned aspects, etc.

In this GA exercise, on a 2-dimensional space layout, n=5 point-of-locations with special privacy (adjaceny) requirements among themselves, are considered. Accordingly, in a grapgh representations there are n(n-1)/2=10 privacy (adjaceny) relationships are involved. Initially, with known five locations, the corresponding 10 privacy (adjaceny) values are computed through a complex relationship where Eudlidean distance was the independent parameter. Afterwards, as a design optimization task, given the computed privacy (adjaceny) values, the corresponding point-of-locations fulfilling these adjacency requirements are asked. The GA results together with the actual points initially used for privacy computations are shown in figure 3. In figure 3(b) the relevant points given in figure 3(a) are connected for easy recognition of these points. Since the adjacency values are relative, the deviations of the localities determined by GA from those initially taken ones do not mean that they are real deviations from what is required. To check the real deviations, ten adjaceny values given as reqirement specifications are indicated in figure 4 together with the counterparts determined by GA. For seemingly simple, however such a rather complex optimization problem, the results of GA is found to be demonstrative enough and satisfactory for the present purpose. Accuracy of convergence could be increased with the increase of population size and number of maximum number of iterations initially given. The GA parameters used in this study are as follows. Population size=600, maximim iterations=450, crossover probabiliy=0.8, mutation probability=0.02, binary length for each variable is twelve.



(a) *(b)*

Figure 3: GA results for given design optimisation problem where the locations are determinedaccording to given adjacency requirements . In figure (b), the relevant points are connected

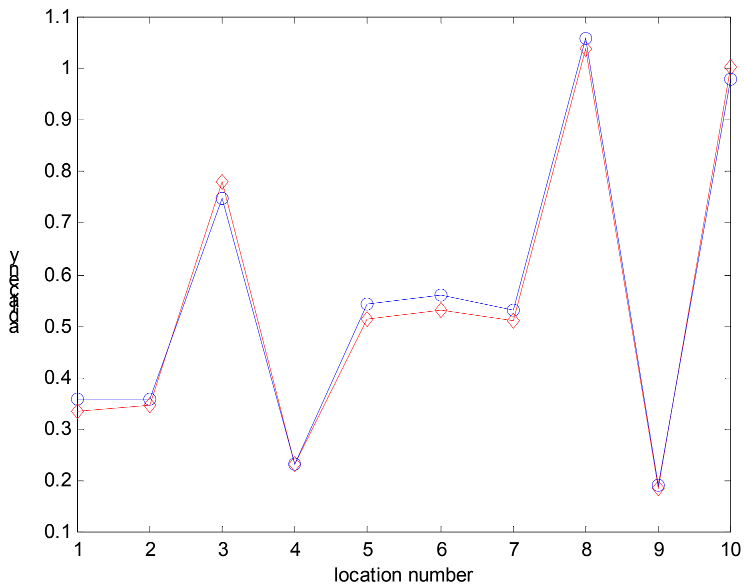


Figure 4: Relative adjacencies obtained from the GA together with the required ones. The design requirements are shown by lines with circles

CONCLUSIONS

The concept of soft computing in the context of CIT is considered and its potential important role that it can play in CI industry and CIT is described and highlighted by examples. This is performed by means of several studies carried out within the framework of our departmental research program. One example is from building design case using actual building design data for design evaluation where the knowledge base contains all the local and global information and their inherent relationships among themselves. The knowledge representation is performed by means of a series of fuzzy systems having their both fuzzy input space and output space in the form of mixture of experts emulation human experts. The associations between the spaces are established by machine learning techniques of artificial intelligence. Such an 'intelligent' knowledge base can make inference resulting in 'intelligent' due outcomes, which need not necessarily to be coded in advance. In other words, this is an inductive and computational inference for decision-making compared to conventional knowledge base systems where inference is deductive thus prescribed by rules designed in advance. Another example described an application of genetic algorithm to a seemingly simple, however rather complex design optimization problem, as a demonstrative example. It pointed out the potential role of evolutionary computation in the areas, which are of interest to CIT. Finally, it is emphasized that soft computing, as a special branch of artificial intelligence, undoubtedly is of particular interest to CIT.

REFERENCES

Aarts E. and Lenstra J.K., (1997), *Local Search in Combinatorial Optimization*, John Wiley & Sons, New York

Aarts E. and Kordt J., (1989), *Simulated Annealing and Boltzmann Machines*, John Wiley & Sons, New York

Bezdek, J.C., (1981), *Pattern recognition with fuzzy objective function algorithms*, Plenum, New York

Billings S.A. and Zheng G.L., (1995), "Radial basis function network configuration using genetic algorithms", *Neural Networks*, Vol.8, No.6, pp.877-890

Chen S, C.F.N. Cowan and Grant, P.M. (1991) “Orthogonal least squares slgorithm for radial basis functions network”, *IEEE Trans. on Neural Networks*, Vol.2, No.2, March

Chen S., Billings S.A., Cowan C.F.N. and Grant P.M., (1990), “Practical identification of NARMAX models using radial basis functions”, Int. J. Control, 1990, Vol.52, No.6, pp.1327-1350

Chen S., Billings S.A. and Luo W, (1989) “Othogonal least squares methods and their application to non-linear system identification”, *Int. J. Control*, Vol.50, No.5, pp.1873-1896

Carrillo M,C., Anumba C.J., Kamara M., (2000), "Knowledge management strategy for construction: Key I.I. and contextual issues" in Proc. *CIT2000:Construction Information*

Technology 2000, G. Gudnason (Ed.), Icelandic Building Research Institute Chao L. and Skibniewski J., (1998), "Neural networks for construction technology" in *Artificial Neural networks for Civil Engineers: Advanced Features and Applications*, ASCE (American Society of Civil Engineers), Reston, VA

Ciftcioglu O., Durmisevic S. and Sariyildiz S., (2000a), " Building design support by hierarchical expert networks" in *Proc. CIT2000:Construction Information Technology 2000*, G. Gudnason (Ed.), Icelandic Building Research Institute

Ciftcioglu O., Durmisevic S. and Sariyildiz S., (2000b), "Design for space layout topology by neural network" in *Proc.5th International Conference on Design and Decision Support Systems in Architecture and Urban Planning*, H. Timmerman (Ed.) University of Eindhoven, August 22-25, 2000, Ampt van Nijkerk, The Netherlands

Flood I., (1990),"Solving construction operational problems usin artificial neural networks and simulated evolution", Proc. *CIB W-55 and W-65 Joint Symp. On Build. Economics and Constr. Mgmt.*, Vol. 6, University of technology, Sydney, Australia, pp-197-208

Durmisevic S., Ciftcioglu O and Sariyildiz S.(2001), " Knowledge Modeling of 'Soft' Data in Architectural Design", Proc. Construction Information Technology (CIB W78), Paper W78.018, South Africa

Gagarine N., Flood I., and Albrect P., (1992), " Weighing trucks in motion using gaussian-based neural networks", *Proc. Int. Conf. On Neural Networks, Vol.II*, IEEE, Newyork, N.Y.,

Gagarine N, Flood I., and Albrect P., (1994), "Computing truck attributes with artificial neural networks", *J. Comp. In Civ. Engrg*., ASCE, 8(2), pp.179-200

Goldberg, D.E. (1989), *Genetic Algorithms in Search, Optimization, and Machine Learning*, Reading, MA:Addison Wesley

Hirota K. and Pedrycz W., (1999), "Fuzzy computing for data mining", *Proc. IEEE , special issue on Computational Intelligence*, September

Jang J.S.R and Sun C.T., 1993, “Functional Equivalence Between Radial Basis Function Networks and Fuzzy Inference Systems”, *IEEE Trans. Neural Networks*, Vol.4, No.1,

Koumousis V.S. and Georgiou P. G., (1994) "Genetic algorithms in discrete optimization of steel truss roofs', *Journal of Computing in Civil Engineering*, Vol.8, No.3, July 1994

Pedrycz W., (1998), "Conditional Fuzzy Clustering in the Design of Radial basis Function Neural Networks", *IEEE Trans. Neural* Networks, Vol.9, No.4, pp.601-612, July

Powell, M.J.D. (1992), "Radial basis functions in 1990"*, Advanced Numerical Analysis, Vol.2. p.105-210*

Schilling R.J., Carroll J.J. and Ajlouni A.F., (2001), "Approximation of nonlinear systems with radial basis function networks", *IEEE Trans. Neural Networks*, Vol.12, number 1, JanuaryThrift P., (1992), "Fuzzy logic synthesis with genetic algorithms" in Proc. 4th Int. Conf. On *Genetic Algorithms*, Belew R.K. and Booker L.B. (Eds.), Morgan Kaufmann Publishers, San Mateo, California, pp.509-513

Turban E and Aronson J.E., (2001), Decision Support Systems and Intelligent Systems, Prentice-Hall International Inc, , New Jersey

Wong F., Tung A. and Dong W., (1992), "Seismic hazard prediction using neural nets", Proc., 10th World Conference on Earthquake Enginering, pp.339-343

Zadeh, L.A., (1973), “Outline of a new approach to the analysis of complex systems and decision processes”, *IEEE Trans. Systems, Man, and Cybernetics*, Vol. SMC-3, No.1, January

Zadeh L.A.., (1994), “Fuzzy logic, neural network, and soft computing”, *Commu. ACM*, Vol.37

Zadeh, L.A., (1998), “Roles of soft computing and fuzzy logic in the conception, design and development of information/intelligent systems" in "Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications", O. Kaynak, L.A. Zadeh, B. Turksen and I.J. Rudas (Eds.), NATO ASI Series F: Computer and Systems Sciences, Vol. 162

Zwass V., (1998), *Information Systems*, McGraw-Hill, Boston, Massachusetts