NASA Conference Publication 3323

Computational Intelligence and Its Impact on Future High-Performance Engineering Systems

Compiled by
Ahmed K. Noor

Proceedings of a workshop sponsored by the
National Aeronautics and Space Administration,
Washington, D.C., and the University of Virginia
Center for Computational Structures Technology,
Hampton, Virginia, and held at Virginia Consortium of
Engineering and Science Universities, Hampton, Virginia
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PREFACE

This document contains the proceedings of the Workshop on Computational Intelligence and Their Impact on Future High Performance Engineering Systems held in Hampton, Virginia, June 27-28, 1995. The workshop was jointly sponsored by the University of Virginia Center for Computational Structures Technology and NASA. Workshop attendees came from government agencies, energy laboratories, industry and universities. The objectives of the workshop were to assess the state-of-technology and level of maturity of various disciplines constituting "Computational Intelligence," and to provide guidelines for focused future research leading to effective use of these facilities in the design/fabrication and operation of future high-performance engineering systems. The presentations addressed activities in the three building blocks of computational intelligence; namely: fuzzy logic, neural networks, and evolutionary computations.

Certain materials and products are identified in this publication in order to specify adequately the materials and products that were investigated in the research effort. In no case does such identification imply recommendation or endorsement of products by NASA, nor does it imply that the materials and products are the only ones or the best ones available for this purpose. In many cases equivalent materials and products are available and would probably produce equivalent results.

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Highlights of the Workshop

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OUTLINE

Since conventional computational methods are incapable of handling complex problems with system uncertainties, intense effort has been devoted to computational intelligence technology which has high potential for solving these problems, and is the focus of the workshop. The outline for the introductory remarks is given in Fig. 1.

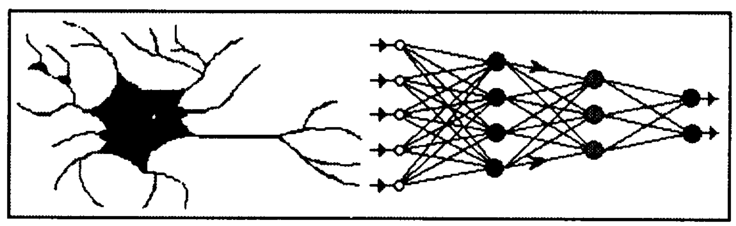
First - definitions of some of the terms are given;

second - the three major components of computational intelligence: namely, fuzzy logic, neural networks, and evolutionary computations, are briefly described;

third - the terms computational intelligence and soft computing are defined; and

fourth - the objectives and format of the workshop are listed along with some of the future directions for research.

- **Definitions**
- **Fuzzy logic and fuzzy sets**
- **Neural networks**
- **Evolutionary computations**



- **Computational intelligence and soft computing**
- **Objectives and format of workshop**
- **Future directions for research**

Figure 1

INTELLIGENCE

The first concept to be briefly discussed in that of intelligence. The definition of this term caused much debate among experts in a number of fields: philosophy, psychology, biology, computer science and engineering.

A functional engineering definition of intelligence is: the capability of a system to adapt its behavior to meet its goals in a range of environments. According to this definition, intelligence is not a unique human quality; machines can be equipped with intelligent facilities. Also, the term artificial intelligence (AI) would not be appropriate.

Most of the AI activities to-date focus on symptoms or consequences of intelligence (e.g., efficient theorem proving, pattern recognition and tree searching).

- **Capability of a system to *adapt* its *behavior* to meet its *goals* in a *range* of environments**
- **Is it a unique human quality?**
- **How about machine intelligence?**
- **Is the term *artificial intelligence* appropriate?**

Figure 2

TYPES OF UNCERTAINTY

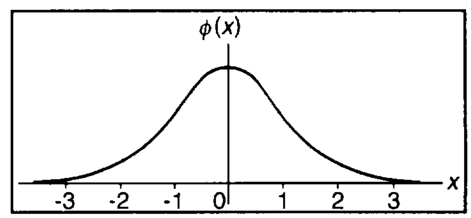
Although it is difficult to list all the sources and kinds of uncertainties, the following three can be identified (Fig. 3):

Probabilistic uncertainty - which arises due to chance or randomness;

Resolutional uncertainty - which is attributed to limitation of resolution (e.g., sensor resolution); and

Fuzzy uncertainty - due to linguistic imprecision (e.g., set boundaries are not sharply defined such as a set of real numbers close to 7).

Sources and kinds of uncertainties include:



- **Probabilistic (randomness)**
- **Resolutional (e.g., sensor resolution)**
- **Fuzzy (set boundaries are vague – not sharply defined, e.g., set of real numbers close to 7)**
  -
  -
  -

Figure 3

FUZZY LOGIC AND FUZZY SETS

The first major component of computational intelligence is fuzzy logic (Fig. 4). Fuzzy logic is a computational paradigm introduced in 1965 by Lotfi Zadeh, to provide a mathematical tool for dealing with uncertainty and imprecision. It is an attempt to emulate human cognition in a simplistic manner.

Fuzzy logic aims at finding acceptable (but not necessarily accurate) solutions in a short time, and permits quantification of information in linguistic form. It is based on a number of mathematical concepts, such as fuzzy sets, membership function, and possibility. Fuzzy sets are imprecisely defined sets (not having a crisp boundary). In contradistinction to ordinary sets, fuzzy sets provide a gradual transition from "belonging" to "not belonging" to a set. This is described by the membership function which takes on values in the interval [0,1].

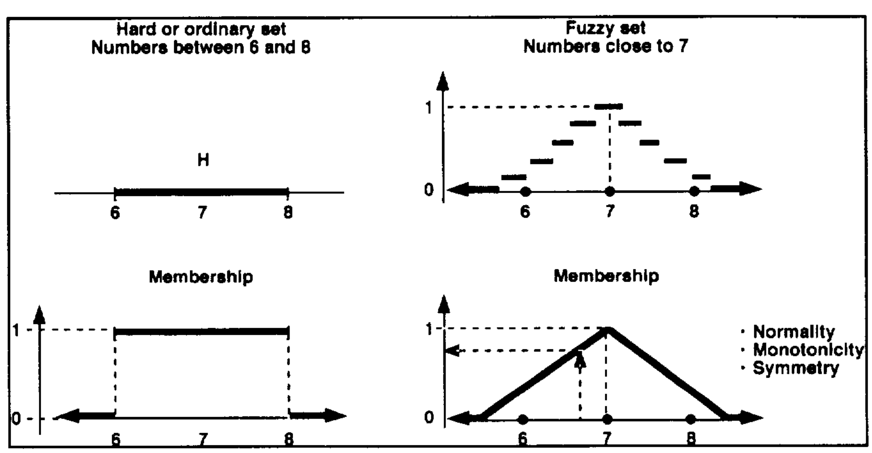
The concept of possibility provides a mechanism for interpreting factual statements involving fuzzy sets.

Fuzzy Logic (Lotfi Zadeh)

- **Computational paradigm that provides a mathematical tool to deal with *uncertainty and imprecision* (typical of human reasoning - emulating human cognition in a simplistic manner).**
- **Aims at finding *acceptable (not necessarily accurate)* solutions in short time.**
- **Permits quantification of information in linguistic form.**

Fuzzy Sets

- **Imprecisely defined sets (not having a crisp boundary).**
- **Transition from "belonging to a set" to "not belonging to a set" is gradual.**



Membership Function

- **Takes on values in the interval [0,1].**

Possibility vs. Probability

- **Mechanism for interpreting factual statements involving fuzzy sets.**

Figure 4

SOLUTION OF PROBLEMS USING FUZZY MODELS

The solution of practical problems using fuzzy models can be conveniently divided into three phases (Fig. 5): In the first phase the real system parameters are converted into linguistic parameters (e.g., small, medium, large), which is referred to as fuzzification.

The second phase is that of analysis with fuzzy models, which involves using:

- if then rules to relate the inputs to the outputs;
- membership functions for inputs and outputs; and,
- a procedure to combine fuzzy sets and rules to produce results.

The third phase consists of converting the output system characteristics from linguistic to real parameters (defuzzification).

The aforementioned methodology can be described as follows: given an insolvable problem in real space, enlarge the space and look for solution in the superset. Finally, specialize the solution to the original real constraints. The same methodology was used for solving some mathematical problems, e.g.,

To understand why the Taylor series $1/(1+x^2)$ of the real variable x diverges at $x = \pm 1$, one can enlarge the space by going to the complex domain and examining the series $1/(1+z^2)$. The series has poles at $z = \pm i$.

- **<u>Fuzzification</u> – Conversion of real system parameters into linguistic parameters**
- **<u>Analysis with fuzzy models</u>**
  - **If then rules relating inputs to outputs**
  - **Membership functions for inputs and outputs**
  - **Procedure to combine fuzzy sets and rules to produce results**
- **<u>Defuzzification</u> of output system characteristics**

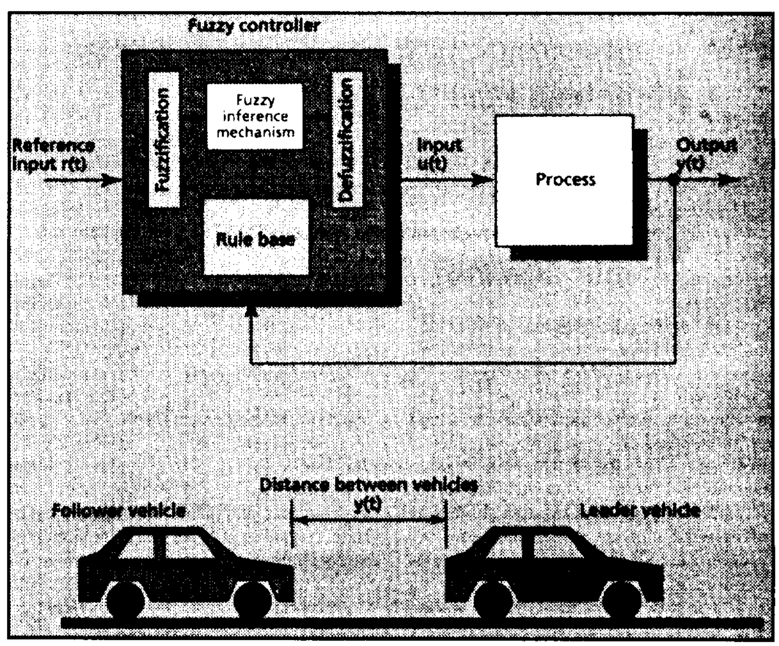


Figure 5

FUZZY LOGIC APPLICATIONS

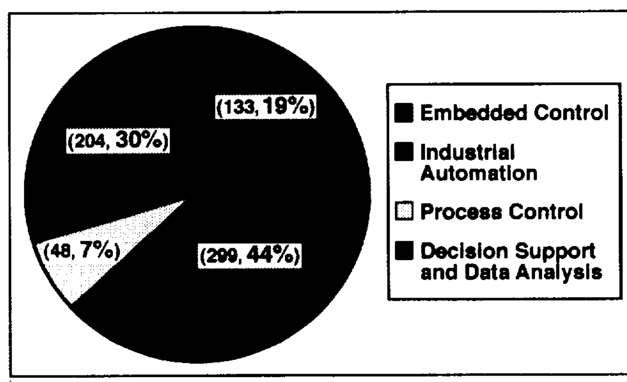
Although the Japanese consumer product industry has shown interest in fuzzy logic since the early 1970's, the first reported application was that of automated control of a steam generator by Assilian and Mamdani in England in 1974. Since then, several Japanese, U.S. and European industries have applied fuzzy logic. A survey was conducted by INFORM in May 1994 of 684 fuzzy logic applications in Europe. Four categories were identified, namely:

- Embedded control - using microcontrollers and microprocessors. Examples of such applications are home appliances.
- Industrial automation - using PCs, workstations, or programmable logic controllers. Examples are machinery control and water treatment plant control.
- Process control - using networks of distributed processors, such as in petrochemical plant control.
- Decision, support and data analysis - using decision support systems consisting of PCs linked to databases. Examples of these applications are preventive maintenance, design evaluation, and concurrent engineering.

The percentage of each category of applications in Europe is shown in the pie chart. The majority of the applications are in industrial automation. By contrast, the majority of applications in Japan are in embedded control, and in the U.S. they are in decision, support and data analysis.

Four general categories

- **Embedded control**
  - **using microcontrollers and micro-processors (e.g., home appliances)**
- **Industrial automation**
  - **using PCs, workstations or pro-grammable logic controllers (e.g., machinery control, water treatment plant control)**
- **Process control**
  - **using networks of distributed processors (e.g., petrochemical plant control)**
- **Decision, support and data analysis**
  - **using decision support systems - PCs linked to databases (e.g., preventive maintenance, design evaluation and concurrent engineering)**



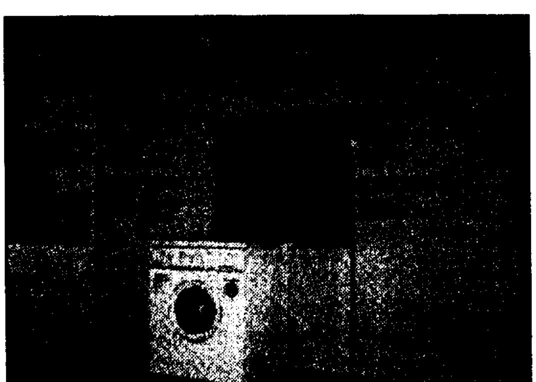
Fuzzy logic control of a hydrogeneration plant

Figure 6

FUZZY LOGIC APPLICATIONS

Figure 7 lists some of the fuzzy logic applications in the U.S., Japan and Europe. The sketches shown are for: a) a washing machine for which the application of fuzzy logic saves 30% in energy and water, and b) an antiskid steering system with fuzzy logic control.

U.S.	Japan	Europe
• Hierarchical control for a turboshaft engine	• Image processing equipment	• Fuzzy boom (Germany)
• Mobile robot navigation	• Consumer products (Sanyo)	• Antiskid steering system
• Sensor processing for manufacturing systems	• Automotive and power generation (Honda, Mazda, Nissan)	• Industrial process control (Denmark)
• Controller for air conditioning system	• Robotics and manufacturing (Mitsubishi)	• Consumer products
• Autonomous vehicle motion planning		



Washing machine AEG

Antiskid steering system

Figure 7

NEURAL NETWORKS

The second major component of computational intelligence is neural networks (Fig. 8). Neural networks are information processing devices (either algorithms or actual hardware). They use simplified mathematical functions to approximate the behavior of neuron collections in the brain. The three principal elements of neural networks are:

- Topology - describing the organization of neural networks into layers and the connections between layers;
- Learning, showing how the information is stored in the network; and
- Recall - describing the method of retrieving the stored information from the network.

Two of the major characteristics of neural networks are:

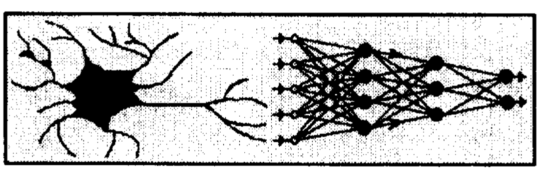
- Each processing element (PE) relies on local information and acts independently of all others.
- Large number of connections in the form of unidirectional communication channels, between PEs, provides a large amount of redundancy and facilitates a distributed representation.

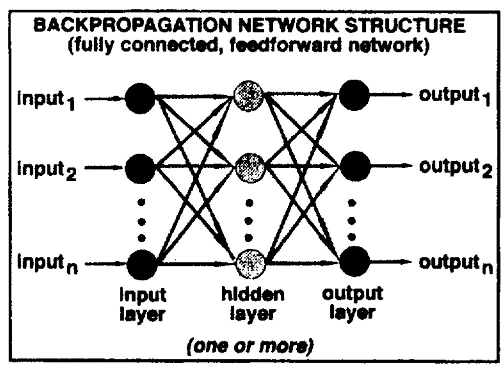
The operations performed by neural networks include: classification, pattern matching, optimization, control and noise removal.

Definition and Principal Elements

BNN	Biological	Neural Networks
ANN	Artificial	
CNN	Computational	

- **Processing devices (either an algorithm or actual hardware)**
- **Simplified mathematical approximations of the behavior of neuron collections in the brain**
- **Information processing systems, having three principal elements**
  - **Topology**
  - **Learning**
  - **Recall**





Characteristics

- **Each processing element (PE) relies on local information and acts independently of all others**
- **Large number of connections (unidirectional communication channels) provides a large amount of redundancy and facilitates a distributed representation**

Operations performed include:

classification, pattern matching, optimization, control, noise removal ....

Figure 8

EVOLUTIONARY COMPUTATIONS

The third major component of computational intelligence is evolutionary computations (Fig. 9). This umbrella term is used to describe methods of simulating evolution on a computer. Based on arbitrary population of trial solutions, evolutionary computations use randomized processes of selection, mutation and (sometimes) recombinations to evolve towards successively better regions in the search space.

There are three main lines of investigation of evolutionary algorithms:

- Evolutionary programming (EP), proposed by Fogel, et al. in 1962. These are crude simplifications of biological reality based on stochastic optimization strategies;
- Genetic algorithms (GAs), first introduced by J. Holland in 1969, which are search and optimization techniques particularly suited for large, complex and poorly understood search spaces; and
- Evolution strategies (ESs), proposed by I. Rechenberg and H. P. Schwefel in 1965.

Each of the aforementioned evolutionary algorithms maintains a population of trial solutions, imposes random changes to these solutions, and incorporates selection to determine which solution to maintain in future generations and which to remove from the pool of trials.

Other classes of evolutionary algorithms have been proposed which can be considered as subclasses of the aforementioned three. For example, classifier systems and genetic programming algorithms can be considered as offsprings of genetic algorithms.

- **Methods of simulating evolution on a computer**
- **Based on arbitrary population of trial solutions**

Use randomized processes of selection, mutation and (sometimes) recombinations	→	**To evolve towards successively better regions in the search space**

<u>Three Main Lines of Evolutionary Algorithms</u>

- **Evolutionary programming EP (L. J. Fogel, et al.)**
  - **Crude simplifications of biological reality**
  - **Stochastic optimization strategy**
- **Genetic algorithms GAs (J. Holland)**

  Search and optimization techniques particularly suited for large, complex and poorly understood search spaces
- **Evolution strategies ESs (I. Rechenberg and H. P. Schwefel)**

Figure 9

COMPUTATIONAL INTELLIGENCE (CI)

The term computational intelligence (CI) was introduced in the early 1990s by James Bezdek. The three building blocks of CI are (Fig. 10):

- Fuzzy logic
- Neural networks
- Evolutionary programming and genetic algorithms.

Jim Bezdek's definition of CI characterizes the notions of computational, artificial and biological intelligence in terms of the relationship between neural networks (NN), pattern recognition (PR), and intelligence (I) (see the sketch in Fig. 10). CI is a low level cognition in the style of the mind.

The following characteristics of CI systems can be identified:

- deal only with numerical data; by contrast, AI systems incorporate knowledge in a non-numerical way;
- have pattern recognition component;
- do not use knowledge in AI sense; and,
- exhibit adaptivity, fault tolerance, speed and error rates approaching human performance.

Building Blocks of CI (James C. Bezdek)

- **Fuzzy logic**
- **Neural networks**
- **Evolutionary programming and genetic algorithms**

B	Biological
A	Artificial
C	Computational

Characteristics of CI Systems

- **Deal only with numerical data (by contrast AI systems incorporate knowledge in a non-numerical way)**
- **Have pattern recognition component**
- **Do not use knowledge in AI sense**
- **Exhibit adaptivity, fault tolerance, speed and error rates approaching human performance**

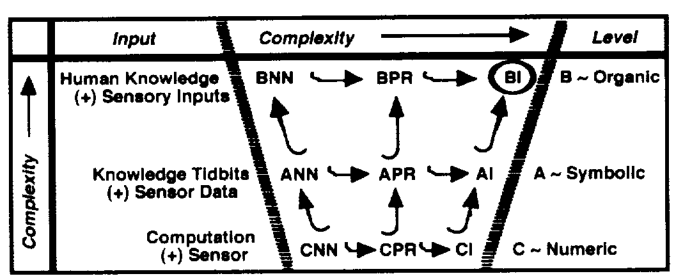


Figure 10

SOFT COMPUTING (SC)

Another important term which was introduced by Lotfi Zadeh is soft computing (SC). It is a collection of methodologies which exploit tolerance for imprecision and uncertainty to achieve tractability, robustness and low solution costs (Fig. 11). The two basic premises of SC are: the real world is pervasively imprecise and uncertain; and precision and certainty carry a cost.

The driver for SC is the principle of complexity which can be described as follows:

- As the complexity of the system increases, the ability to make precise and yet significant statements about its behavior diminishes.
- Threshold is reached beyond which precision and significance (relevance) become almost mutually exclusive characteristics. The shaded area in the sketch represent that of Correct But Irrelevant Computations (CBIC), i.e., forcing precision where it is not possible.

The principal constituents of SC are:

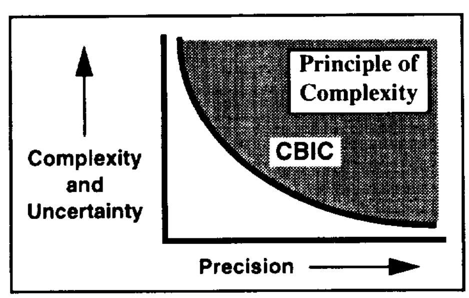
- Fuzzy logic - which is mainly concerned with imprecision and approximate reasoning;
- Neuro computing - which deals with learning and curve fitting; and
- Probabilistic reasoning - for handling uncertain belief propagation.

Definition (Lotfi Zadeh)

Collection of methodologies

which exploit

Tolerance for imprecision and uncertainty —— **to achieve** ——→ **• Tractability • Robustness • Low solution costs**



Basic Premises of SC

- **Real world is pervasively imprecise and uncertain**
- **Precision and certainty carry a cost**

Principal Constituents

- **Fuzzy logic – Imprecision and approximate reasoning**
- **Neuro computing – learning and curve fitting**
- **Probabilistic reasoning – uncertainty and belief propagation**

Figure 11

INFORMATION RESOURCES ON COMPUTATIONAL INTELLIGENCE

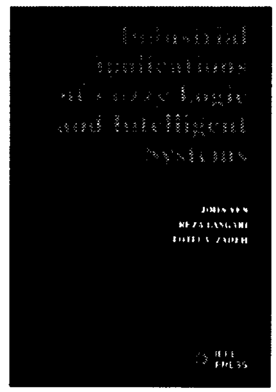
Voluminous literature now exists on different aspects of computational intelligence. Hundreds of monographs, conference proceedings, surveys, and special issues of journals have been published on the subject. In addition, a number of journals, newsletters, and short courses have been devoted to the subject. Tutorial videotapes have been produced by IEEE. Information on computational intelligence software and descriptions of research activities are also available on the Internet (see Figs. 12 and 13).

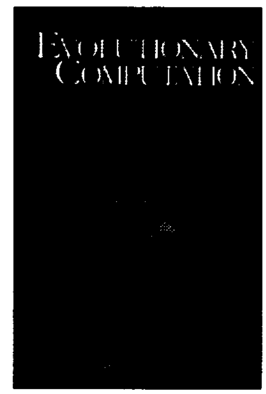
Books

- **Hundreds of books**

  Industrial Applications of Fuzzy Logic and Intelligent Systems, **IEEE Press, 1995**

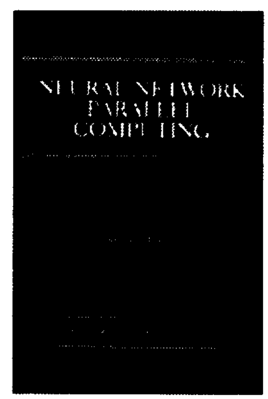
  Evolutionary Computation, Toward a New Philosophy of Machine Intelligence, **IEEE Press, 1995**





Specialized Journals

- **IEEE Transactions on Fuzzy Systems**
- **International Journal of Approximate Reasoning, Elsevier**
- **Fuzzy Sets and Systems, North Holland**
- **SOFT Journal (Japan)**
- **IEEE Transactions on Neural Networks**
- **Neural Network Parallel Computing, Kluwer Publishers**
- **Neural Networks in Design and Manufacturing, World Scientific Publishers**
- **Neural Networks for Optimization and Combinations, World Scientific Publishers**
- **Neural Computation, MIT Press**



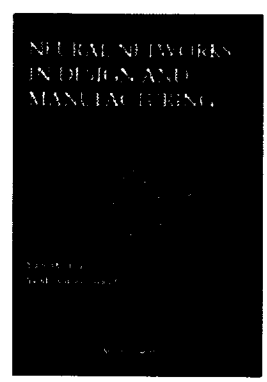


Figure 12

<u>Specialized Journals (Cont'd.)</u>

- International Journal of Neural Systems
- International Journal of Neuroscience
- Neural Processing Letters
- Evolutionary Computation, MIT Press

<u>Special Issues, Proceedings, Journal Articles, Bibliographies and Surveys</u>

- Proceedings of the IEEE, March 1995
- High-Tech Controls for Energy and Environment
- Over 15,000 publications on fuzzy logic

<u>Short Courses</u>

<u>Marketing Information and Catalogs</u>

<u>Online Resources</u>

- Usenet
- WWW/ftp sites
- BBS
- Lists

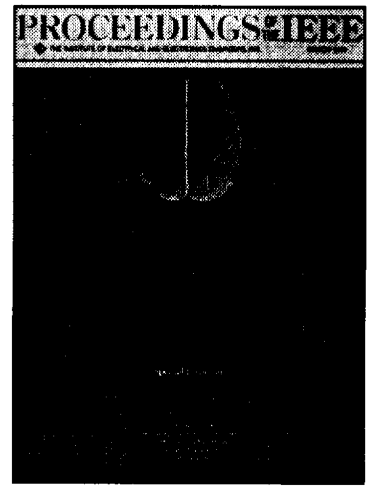


Figure 13

TOOLS FOR CI

Several commercial software systems and some hardware tools are now available for CI. The software tools for neural networks are more mature than others. Figure 14 shows a partial list of the software systems, particularly those dealing with fuzzy logic.

CubiCalc – HyperLogic Corp., Escondido, CA

TILShell – Togai InfraLogic, Houston, TX

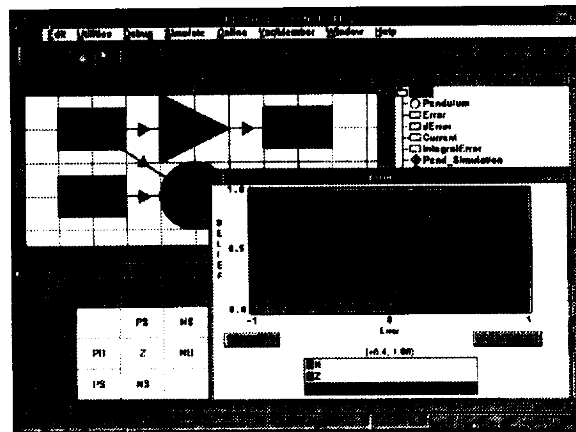
Fuzzy Tech – INFORM, Evanston, IL

FIDE – Aptronix, Santa Clara, CA

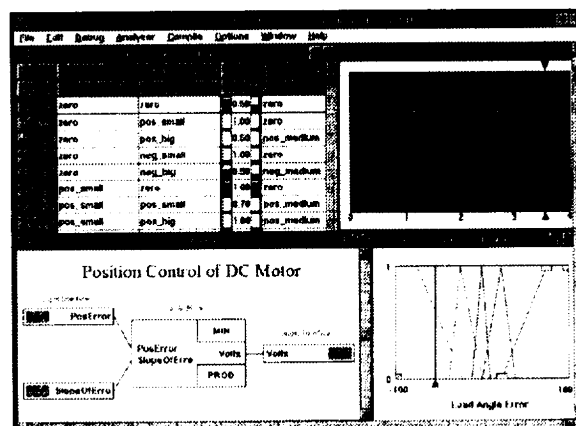
RT/FUZZY – Integrated Systems, Inc.

Fuzzy Decision Maker, Thought Amplifier and Knowledge Builder – Fuzzy Systems Engineering, Poway, CA

Fuzz-C – Byte Craft, Ltd., Ontario, Canada



TILShell



Fuzzy Tech

Figure 14

OBJECTIVES AND FORMAT OF THE WORKSHOP

The objectives of the workshop are to: a) assess the level of maturity of the various computational intelligence tools, and their potential for application to the design/fabrication and operation of future high-performance engineering systems; and b) identify future directions for research and development (see Fig. 15).

The workshop, including thirteen presentations and a panel discussion illuminate some of the diverse issues and provide fresh ideas for future research and development.

Objectives

- **Assess**
  - **Level of maturity of computational intelligence tools**
  - **Potential application to design/fabrication and operation of engineering systems**
- **Identify future directions for research and development**

Format

- **Presentations**
- **Software demonstrations**
- **Panel – open discussion**
- **Proceedings**

Figure 15

FUTURE DIRECTIONS FOR RESEARCH

Two important future research activities are listed in Fig. 16.

1) Development of hybrid CI/AI systems which combine, among other facilities, expert systems, neural networks, fuzzy logic and genetic algorithms.

2) Application of CI/AI systems to highly autonomous engineering systems, which integrate the functions of isolated subsystems to perform complex tasks without human help. Examples of these systems are new millennium spacecraft; future aircraft, which integrate the functions of mission and tactical planning into a single system much as a human co-pilot does; and intelligent vehicle-highway systems which can fully automate the human responsibilities in steering, braking, throttle control, and route selection to reduce congestion and improve safety (see sketch).

For each application, the following needs to be done:

- assessment of the effectiveness of using CI tools and facilities;
- verification of the CI solutions by modeling, simulation and experimentation; and
- cost/benefit evaluation.

- **Development of *hybrid AI/CI* systems**
  - **Expert systems**
  - **Neural networks**
  - **Fuzzy logic**
  - **Genetic algorithms**
- **Application of CI/AI to *highly autonomous* engineering systems (which integrate the functions of isolated subsystems to perform complex tasks without human help).**
  - **New millennium spacecraft**
  - **Future aircraft – integrating the functions of mission and tactical planning**
  - **Intelligent vehicle-highway systems.**

  For each application:
  - **Assessment of *effectiveness***
  - ***Verification* by modeling, simulation and experimentation**
  - ***Cost/benefit* evaluation**

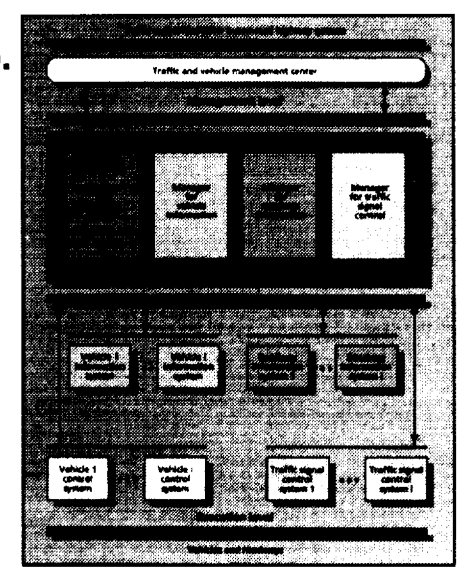


Figure 16

QUESTIONS

In the panel discussion, the following three questions will be addressed:

- What aspects of the design/analysis, prototyping and operations of high-performance engineering systems are particularly suited for application of computational intelligence tools? Can the CI tools out perform the tried-and-true conventional techniques?
- Can the solutions obtained by CI systems be verified by modeling, simulation and experimentation?
- Will the CI applications stand up to objective cost-benefit analyses and the test of time?

- **What *aspects* of the design/analysis, prototyping and operations of high-performance engineering systems are *particularly suited* for application of computational intelligence tools?**

- **Can the solutions obtained by CI be *verified* by modeling, simulation and experimentation?**

- **Can an objective *cost/benefit* assessment be made of the CI application?**

Figure 17

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3. Evolutionary Computation: ftp://rtfm.mit.edu:/pub/usenet/news.answers/ai-faq/genetic