iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 2 **Issue:** X **Month of publication:** October 2014

DOI:

International Journal for Research in Applied Science & Engineering Technology(IJRASET)

Introduction and Security Applications of Computational Intelligence

Nikhil Singla[#1], Sahil Jindal[*2], Vikas Verma[#3], Tushar Mehmi[*4]

[#] CSE Department, Maharishi Dayanand University

***Abstract*—Computational intelligence is the study of the design of intelligent agents. An agent is something that acts in an environment—it does something. Agents include worms, dogs, thermostats, airplanes, humans, organizations, and society. An intelligent agent is a system that acts intelligently: What it does is appropriate for its circumstances and its goal, it is flexible to changing environments and changing goals, it learns from experience, and it makes appropriate choices given perceptual limitations and finite computation.**

The central scientific goal of computational intelligence is to understand the principles that make intelligent behavior possible, in natural or artificial systems. The main hypothesis is that reasoning is computation. The central engineering goal is to specify methods for the design of useful, intelligent artifacts.

It primarily includes artificial neural networks, evolutionary computation and fuzzy logic. In addition, CI also embraces biologically inspired algorithms such as swarm intelligence and artificial immune systems, which can be seen as a part of evolutionary computation, and includes broader fields such as image processing, data mining, and natural language processing. Furthermore other formalisms: Dempster–Shafer theory, chaos theory and many-valued logic are used in the construction of computational models.

***Keywords*—Evolutionary, algoritmizable, cognitive**

I. INTRODUCTION

What exactly is Computational intelligence (CI)? How is it related to other branches of computer science, such as artificial intelligence (AI), classification, cognitive informatics, connectionism, data mining, graphical methods, intelligent agents and intelligent systems, knowledge discovery in data (KDD), machine intelligence, machine learning, natural computing, parallel distributed processing, pattern recognition, probabilistic methods, soft computing, multivariate statistics, optimization and operation research? This is a very confusing issue, hotly debated, but with no consensus in sight. Computational intelligence became a new buzzword that means different things to different people.

Branches of science are not defined, but slowly develop in the process of sharing and clustering of common interests. In CI these interest generally focus on problems that only humans and animals can solve, problems requiring intelligence. Specific interests also focus on methods and tools that are applicable to this type of problems. Starting with seminal papers, special sessions, growing into separate conferences and specialized journals, different branches of CI evolve in many directions, frequently quite far from original roots and inspirations. New communities are formed and need to establish their identity by defining borders distinguishing them from other scientific communities.

Artificial Intelligence (AI) was the first large scientific community, established already in the mid 1950s, working on problems that require intelligence to be solved. Its evolution has been summarized in the 25th anniversary issue of the *AI Magazine* by Mackworth: "In AI's youth, we worked hard to establish our paradigm by vigorously attacking and excluding apparent pretenders to the throne of intelligence, pretenders

such as pattern recognition, behaviorism, neural networks, and even probability theory. Now that we are established, such ideological purity is no longer a concern.We are more catholic, focusing on problems, not on hammers. Given that we do have a comprehensive toolbox, issues of architecture and integration emerge as central."

Many Computational Intelligence Society defines its subjects of interest as neural networks, fuzzy systems and evolutionary computation, including swarm intelligence. The approach taken by the journals and by the book authors is to treat computational intelligence as an umbrella under which more and more methods will be added. A good definition of the field is therefore impossible, because different people include

or exclude different methods under the same CI heading. Chess programs based on heuristic search are already in the superhuman computational intelligence category, but they do not belong to CI defined in such a way. In the early days of CI some experts tried to explicitly exclude such problems. Take for example this definition: "A system is computationally intelligent when it: deals only with numerical (low level) data, has a pattern recognition component, and does not use knowledge in the AI sense".

As in the case of AI the need to create strong identity by emphasizing specific methods defining Computational Intelligence as a field should be replaced by focus on problems to be solved, rather than hammers. Below some remarks on the current state of CI are made, based on analysis of journals and books with “computational intelligence” in their title. Then a new definition of CI is proposed and some remarks on what should computational intelligence really be are made. Finally grand challenges to computational intelligence are discussed.

II. WHAT SHOULD COMPUTATIONAL INTELLIGENCE REALLY BE?

For many CI experts biological inspirations are very important, but even if biology is extended to include all neural, psychological, and evolutionary inspirations this will only cover the main themes (neural, fuzzy and evolutionary) that the CI community works on. The whole Bayesian foundations of learning, probabilistic and possibilistic reasoning, many alternative approaches to handle uncertainty, kernel methods, search algorithms and many others have no biological connections. Why should only genetic algorithms be used if there are many specialized methods to solve specific optimization problems?

Physics studies nature and cannot be defined by its experimental or theoretical tools; the same is true for other branches of science. Computer science studies computable processes and information processing systems. What does computational intelligence study? CI studies problems for which there are no effective algorithms, either because it is not possible to formulate them or because they are NP-hard and thus not effective in real life applications. This is quite broad definition: **computational intelligence is a branch of computer science studying problems for which there are no effective computational algorithms**. Biological organisms solve such problems every day: extracting meaning from perception, understanding language, solving ill-defined computational vision problems thanks to evolutionary adaptation of the brain to the environment, surviving in a hostile environment. However, such problems may be solved in different ways. Defining computational intelligence by the problems that the field studies there is no need to restrict the types of methods used for solution.

A good part of CI research is concerned with low-level cognitive functions: perception, object recognition, signal analysis, discovery of structures in data, simple associations and control. Methods developed for this type of problems include supervised and unsupervised learning by adaptive systems, and they encompass not only neural, fuzzy and evolutionary approaches but also probabilistic and statistical approaches, such as Bayesian networks or kernel methods. These methods are used to solve the same type of problems in various fields such as pattern recognition, signal processing, classification and regression, data mining. Higher level cognitive functions are required to solve non-algorithmizable problems involving systematic thinking, reasoning, complex representation of knowledge, episodic memory, planning, understanding of symbolic knowledge. These problems are at present solved by AI community using methods based on search, symbolic knowledge representation, reasoning with frame-based expert systems, machine learning in symbolic domains, logics and linguistic methods. There is little overlap between problems solved using low and high-level mental functions, although they belong to the same broader category of non-algorithmizable problems.

From this point of view AI is a part of CI focusing on problems that require higher cognition and at present are easier to solve using symbolic knowledge representation. It is possible that other CI methods will also find applications to these problems in future. The main overlap areas between low and high-level cognitive functions are in sequence learning, reinforcement learning, machine learning and distributed multi-agent systems. All tasks that require reasoning based on perceptions, such as robotics, automatic car driving, autonomous systems require methods for solving both low and high-level cognitive problems and thus are a natural meeting ground for AI experts with the rest of CI community.

The idea that all intelligence comes from symbol manipulation has been perhaps misunderstood by AI community. Newell and Simon who originated this idea wrote about physical symbols, not about symbolic variables. Physical symbols are better represented as multi-dimensional patterns representing states of the brain. Symbolic models of brain processes certainly do not offer accurate approximation for vision, control or any other problem that is described by continuous rather then symbolic variables. Approximations to brain processes should be done at a proper level to obtain similar functions. Symbolic dynamics may provide useful information on dynamical systems, and may be useful in modeling transition between low-to high level processes. The division between low and high-level cognitive functions is only a rough approximation to the processes in the brain. Embodied cognition has been intensively studied in the last decade, and developmental ideas showing how higher processes emerge for the lower ones have been embraced by robotics. Even in linguistics it is now commonly acknowledged that real meaning comes from body-based metaphors and the same is true even in mathematics . New CI methods that go beyond pattern recognition and help to solve AI problems may eventually be developed, starting from distributed knowledge representation, graphical methods and spreading activations networks. The dynamics of such models will probably allow for reasonable symbolic approximations.

It is instructive to think about the spectrum of CI problems and various approximations needed to solve them. Neural network models are inspired by brain processes and structures at almost the lowest level, while symbolic AI models by processes at the highest level. The brain has a very specific modular and hierarchical structure, it is not a huge neural network. Perceptron model of a neuron has only one internal parameter, the firing threshold, and a few synaptic weights that determine neuron-neuron interactions. Single neurons probably influence brain information processing in an insignificant way. Perhaps larger neural structures, such as microcircuits or neural cell assemblies, should be used as basic processors for neural modeling. They have more complex internal states and more complex interactions between elements. A network of networks, hiding the complexity of its processors in a hierarchical way, with different emergent properties at each level, will have progressively more internal knowledge and more complex interactions with other such systems. At the highest level models of whole brains with an infinite number of potential internal states and very complex interactions may be obtained. Discussion of such transition from neurons to brains and to societies is presented in.

Computational intelligence is certainly more than just the study of the design of intelligent agents, it includes also study of all non-algoritmizable processes that humans (and sometimes animals) can solve with various degree of competence. CI should not be treated as a bag of tricks without deeper foundations. Competition from good mathematical approaches in various applications should be invited, and knowledge and search-based methods should complement the core CI techniques in problems requiring reasoning. Goldberg and Harik see computational intelligence more as a way of thinking about problems, calling for a “broader view of the scope of the discipline”. They have analysed limitations to progress in computational manufacturing design, finding the models of human behaviours to be most useful. Although this is certainly worthwhile defining clearly the problems that CI wants to solve and welcoming all methods that can be used in such solutions, independent of their inspirations, is even more important.

III. COMPUTATIONAL INTELLIGENCE FOR SMART GRID OPTIMIZATION AND PLANNING

CI can be used throughout a utility to optimize operations and planning. Broadly speaking, it can be used in power generation, transmission, distribution and consumption applications to meet the Smart Grid's safety, security, reliability, resilience and efficiency needs. Many examples are available to illustrate very practical applications.

For example, CI can be used to forecast the amount of renewable energy that might be injected into a grid during a particular time period. We can then use this information to determine how much power production is needed from traditional sources, such as coal.

We can use CI for both short-term and long-term load forecasting. This is particularly important, given that population growth is one of the main factors inspiring the industry to produce more power. Similarly, we can use CI to inform our demand management programs.

CI can be used to help utilities respond to outages caused by natural disasters, such as storms or downed trees, which impact high-voltage transmission lines. When incorporated in a smart grid, CI can detect asymmetric single-phase-to-ground or two-phase-to-ground faults or symmetric three-phase to-ground faults and determine where the faults have occurred in the transmission and distribution system. This is a significant attribute in any power system.

CI can also be applied in conjunction with sensor networks to monitor power quality. If a power quality issue occurs, the system will alert the administrator, who can then take the steps necessary to address the problem.

CI can be used to monitor power losses from the grid. These losses usually average about 7% of a country's power production but in some countries, like South Africa, the losses represent about 17 percent. CI can not only monitor the losses but figure out the cause.

Finally, utilities can use CI to optimize the real-time process of purchasing energy from multiple suppliers based on price, variable rate or other data for recent or forecasted time periods. They can identify the best suppliers through CI as well.

IV. SECURITY APPLICATIONS FOR COMPUTATIONAL INTELLIGENCE

We need to keep the energy supply chain secure. We must protect the grid's IT technologies, for instance, from hackers who might want to stop renewable energy production or access a utility's billing information.

In computer networks, many attacks are known to us. For example, denial-of-service (DoS) attacks are known attacks. We understand these attacks and can apply technologies and systems to help protect our networks against them. But how can we stop unknown attacks?

CI is an algorithmic approach that responds to the unknown in the way human beings respond to problems they haven't encountered before: the system uses the knowledge it has already acquired from previous experiences to develop a new mechanism to help stop the new attack. This is the beauty of CI and explains why CI has value in smart grid networks. It also explains how CI can create robust and dynamic security systems.

Moreover, because CI acquires and learns from traditional attack information, it will study a new attack and compare it to previous attacks. It will alert the network manager or administrator that the attack has occurred and that the system has stopped it. Even if a very strong unknown attack occurs in the smart grid and CI fails to stop it, the system will instantly alert the network manager that further action is required. So CI can determine how to address unknown attacks and it also automatically provides warnings when needed.

V. REFERENCES

[1] A.K. Mackworth, The Coevolution of AI and AAAI, AI Magazine 26(4): 51-52, 2005.
[2] J. C. Bezdek, What is computational intelligence? In: Computational Intelligence Imitating Life, pp. 1–12, IEEE Press, New York, 1994.
[3] D. Poole, A. Mackworth and R. Goebel. *Computational Intelligence – A Logical Approach*. Oxford University Press, New York, 1998.
[4] Z. Chen, Computational Intelligence for Decision Support. CRC Press, Boca Raton, 2000.
[5] A.P. Engelbrecht, Computational Intelligence: An Introduction. Wiley, 2003.
[6] A. Konar, Computational Intelligence: Principles, Techniques and Applications. Springer 2005.
[7] A. Kusiak, Computational Intelligence in Design and Manufacturing. Wiley-Interscience, 2000.
[8] S. Dick and A. Kandel, Computational intelligence in software quality assurance. Series in Machine Perception and Artificial Intelligence, Vol. 63, World Scientific 2005.
[9] R.E. King, Computational intelligence in control engineering, Marcel Dekker Inc., NY, 1999.
[10] S.H. Chen, P. Wang, and P.P. Wang Computational Intelligence in Economics and Finance. Advanced Information Processing Series, Springer 2006.
[11] A. Newell and H.A. Simon, Computer science as empirical enquiry: Symbols and search. Communications of the ACM 19(3), 113–126, 1976.
[12] A. Newell, Unified Theories of Cognition. Cambridge, MA: Harvard University Press 1990.
[13] D. Lind, B. Marcus, Symbolic Dynamics and Coding, Cambridge University Press, 1995.
[14] G. Lakoff, M. Johnson. Metaphors We Live By. University of Chicago Press, 2nd ed, 2003.
[15] G. Lakoff, R. N´unez, Where Mathematics Comes From: How the Embodied Mind Brings Mathematics into Being. Basic Books 2000.
[16] W. Duch and J. Mandziuk, Quo Vadis Computational Intelligence? In: Machine Intelligence: Quo Vadis? Advances in Fuzzy Systems – Applications and Theory (eds. P. Sincak, J. Vascak, K. Hirota), World Scientific 2004.
[17] D.E. Goldberg and G. Harik, A Case Study in Abnormal CI: The Design of Manufacturing and Other Anthropocentric Systems. International J. Computational Intelligence and Organizations,1, 78-93, 1996.
[18] D. Lenat and R. V. Guha, Building Large Knowledge-Based Systems: Representation and Inference in the Cyc Project. Addison-Wesley 1990.
[19] J. Szymanski, T. Sarnatowicz and W. Duch, Towards Avatars with Artificial Minds: Role of Semantic Memory. Journal of Ubiquitous Computing and Intelligence (in print)
[20] E.A. Feigenbaum, Some Challenges and Grand Challenges for Computational Intelligence. Journal of the ACM 50(1), 32–40, 2003. Mandziuk J, Eds, Challenges for Computational Intelligence. Springer 2007