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A CRITICAL OVERVIEW OF DESICION MAKING SUPPORT SYSTEMS FOR COMPLEX DYNAMIC SYSTEMS

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Abstract. This paper analyses briefly the nature and state in modelling and controlling Complex dynamic systems (CDS) and of Intelligent Systems (IS) been related to Decision Support Systems (DSS) theories, research and applications. A brief historical review of DSS and how Artificial Intelligence (AI) has been embedded into the DSS and how this generated the interesting scientific area of Intelligent Decision Support Systems (IDSS). The challenge and absolute need for "Making Decisions" is briefly outlined. The challenge now is to make sense of DSS in ''Decision Making'' by planning it in understanding context and by searching new ways to utilize other advanced methodologies to the challenging issues of CDS in the future. The possibility of using, Fuzzy Cognitive Maps (FCM) and Intelligent Systems (IS) in DSS is reviewed and analyzed. Some drawbacks and deficiencies of FCM are briefly presented and discussed. Open issues for future research of DSS and FCMs are outlined and briefly discussed.

Keywords: web application; database; dynamic model; NoSQL; XML; DOM; PHP.

INTRODUCTION

Throughout the natural and artificial world one observes phenomena of great complexity. Yet research in physics and to some extent biology and other fields has shown that the basic components of many systems are quite simple. It is now a crucial problem for many areas of science to elucidate the mathematical mechanisms by which large numbers of such simple components, acting together, can produce behavior of the great complexity observed. Therefore today's systems have become more and more complex and dynamic. The concept of complex dynamic systems (CDS) arises in many scientific fields and technological areas.

Modelling and controlling complex dynamic systems is a very difficult and challenging task. As a result "complex systems theory" cuts across the boundaries between conventional scientific disciplines. It makes use of ideas, methods and examples from many different fields.

Today, one of the most critical scientific challenges of accepting the "operation" of any complex dynamic system (CDS) is the ability to make Decisions, so the system runs efficiently, and cost effectively. However making Decisions within CDS operations often strains our cognitive capabilities. Uncertainty, risk and ambiguity are prominent in the research and accompanied literature on Decision-Making. The CDS are no longer static but most of its subsystems are dynamic and highly nonlinear. Uncertainty and fuzziness are common terms been used in subtly different ways in a number of scientific fields, including: energy generation and distribution, ecosystems, statistics, economics, finance, physics, psychology, engineering, health delivery, environment, biology, safety and security systems, sociology, philosophy, insurance, geology, military systems and Information and Communication Technologies (ICT).

Therefore in the modern science and technology there are some Research Directions and challenges which are at the forefront of worldwide research activities because of their relevance. This relevance may be related to different aspects. First, from a point of view of researchers it can be implied by just an analytic or algorithmic difficulty in the solution of problems within an area. From a broader perspective, this relevance can be related to how important problems and challenges in a particular area are to society, corporate or national competitiveness. One of such "meta-challenges" in the present world is that of intelligent systems (IS). Another "meta-challenge" and "meta-knowledge" is that of Fuzzy Cognitive Maps (FCMs). For a long time it has been obvious that the complexity of our world and the speed of changes we face in virtually all activities that have impact on our everyday life imply a need to reinvestigate and study extensively many tasks and processes. However they have (IS and FCMs) been so far, very limited to human beings and to our everyday life, because they require some sort of "intelligence". Both theories are new with theoretic approaches, been based on fuzzy logic and Neural Networks. FCM integrates the accumulated experience and knowledge on the operation of the system, as a result of the methods by which it is constructed. On the other hand "Intelligence" and thus IS play a very important role in modeling and controlling dynamic complex systems. Both theories appear in many engineering fields, such as, power systems, manufacturing, aerospace, civil and construction engineering, energy, medical, environment, transportation, agriculture as well on other non- engineering fields such as finances, business and economics, psychology, sociology, physiology, political and social studies and education. Modeling of these systems often result in very high-order models imposing great challenges to the analysis, design and control problems.

All these challenges call for advanced system models and theories, which using FCMs will exhibit some intelligence and will therefore be useful to their human users.

A BRIEF HISTORICAL OVERVIEW OF DESION SUPPORT SYSTEMS (DSS)

Today it is easy to reconstruct the history of computerized Decision Support Systems (DSS) from first-hand accounts and unpublished materials as well as published articles. History is both a guide to future activity in this field and a record of the ideas and actions of those who have helped advance our thinking and practice. History can guide our future if it is analyzed and studied wisely. In a technology field as diverse as DSS, history is not neat and linear. Information Systems, Business researchers, scientists and technologists have built and investigated Decision Support Systems (DSS) immediately after the Second World War. Some researchers trace the scientific origins of DSS to 1951 and the Lyons Tea Shops Business use of the LEO (Lyons Electronic Office I) digital computer.

Now the first computerized DSS based on Distributed computer systems evolved in the early 1950s. However the term Decision Support Systems (DSS) was not used till the early 1970s. According to Keen et all [1], the concept of DSS has evolved from two main areas of research: the theoretical studies of organizational Decision Making (DM) done at the Carnegie Institute of Technology during the late 1950s and the technical work on interactive distributed systems mainly carried out at the Massachusetts Institute of Technology in the early 1960s. It is considered that the field of DSS became a scientific area of research and systemic studies in the early 1970s before gaining in intensity during the 1980s. Executive Information Systems (EIS), Group Decision Support Systems (GDSS) and Organizational Decision Support Systems (ODSS) evolved from the single user and Model-Oriented DSS.

In the late 1960s, a new type of information system became practical – model-oriented DSS or Management Decision Systems (MDS). Two DSS pioneers, Peter Keen and Charles Stabell, claim the concept of decision support evolved from "the theoretical studies of organizational decision making done at the Carnegie Institute of Technology during the late 1950s and early '60s and the technical work on interactive computer systems, mainly carried out at the Massachusetts Institute of Technology in the 1960s. Prior to 1965, it was very expensive to build large-scale information systems. At about this time, the development of the IBM System 360 and other more powerful mainframe systems made it more practical and cost-effective to develop Management Information Systems (MIS) in large companies. MIS focused on providing managers with structured, periodic reports. The goal of the first management information systems (MIS) was to make information in transaction processing systems available to management for decision- making purposes. Unfortunately, few MIS were successful [2]. Perhaps the major factor in their failure was that the IT professionals of the time misunderstood the nature of managerial work. The systems they developed tended to be large and inflexible and while the reports generated from managers' MIS were typically several dozen pages thick, unfortunately, they held little useful management information [2].

The term "Decision Support Systems" first appeared in [3], although Andrew McCosh attributes the birth date of the field to 1965, when Michael Scott Morton's PhD topic, "Using a computer to support the decision-making of a manager" was accepted by the Harvard Business School [4]. Gorry and Scott Morton [3] constructed a framework for improving management information systems using Anthony's categories of managerial activity [3] and Simon's taxonomy of decision types [5]. Gorry and Scott Morton conceived DSS as systems that support any managerial activity in decisions that are semi- structured or unstructured. Keen and Scott Morton [1] later narrowed the definition, or scope of practice, to semi-structured managerial decisions; a scope that survives to this day. The managerial nature of DSS was axiomatic in Gorry and Scott Morton [3], and this was reinforced in the field's four seminal books: Scott Morton [6], McCosh and Scott Morton [4], Arnott [7], and Sprague and Carlson [8].

Much of the early work on DSS was highly experimental. The aim of early DSS developers was to create an environment in which the human decision maker and the IT-based system worked together in an interactive fashion to solve problems; the human dealing with the complex unstructured parts of the problem, the information system providing assistance by automating the structured elements of the decision situation.

According to Sprague and Watson [9], around 1970 business journals started to publish articles on management decision systems, strategic planning systems and decision support systems. For example, Scott Morton and colleagues published a number of decision support articles in 1968. In 1969, Ferguson and Jones discussed a computer aided decision system in the journal Management Science. In 1971, Michael S. Scott Morton's ground breaking book **Management Decision Systems: Computer-Based Support for Decision Making** was published. In 1966-67 Scott Morton had studied how computers and analytical models could help managers make a key decision. He conducted an experiment in which managers actually used a Management Decision System (MDS). T.P. Gerrity, Jr. focused on DSS design issues in [10]. His system was designed to support investment managers in their daily administration of a clients' stock portfolio. DSS for portfolio management have become very sophisticated since Gerrity began his research. In 1974, Gordon Davis, a Professor at the University of Minnesota, published his influential text on Management Information Systems. He defined a Management Information System as "an integrated, man/machine system for providing information to support the operations, management, and decision-making functions in an organization".

PERSONAL DECISION SUPPORT SYSTEMS

Personal DSS (PDSS) are small-scale systems that are normally developed for one manager, or a small number of independent managers, for one decision task. PDSS are the oldest form of decision support system and for around a decade they were the only form of DSS in practice. They effectively replaced MIS as the management support approach of choice. The world of MIS was that of the Cold War and the rise of the Multi-National Corporation. The focus of management in this environment was total integration, efficiency, and central control, and the large, inflexible MIS mirrored this organizational environment.

ARTIFICIAL INTELLIGENCE (AI) AND INTELLIGENT DECISION SUPPORT SYSTEMS (IDSS)

Artificial intelligence (AI) techniques have been applied to decision support and these systems are normally called intelligent DSS or IDSS [11], although the term knowledge-based DSS has also been used. Intelligent DSS can be classed into two generations: the first involvesthe use of rule-based expert systems and the second generation uses neural networks, genetic algorithms and fuzzy logic. A fundamental tension exists between the aims of AI and DSS. AI has long had the objective of replacing human decision makers in important decisions, whereas DSS has the aim of supporting rather than replacing humans in the decision task. As a result the greatest impact of AI techniques in

DSS has been embedded in the PDSS, GSS or EIS, and largely unknown to managerial users. This is particularly the case in data mining and customer relationship management.

EXECUTIVE INFORMATION SYSTEMS AND BUSINESS INTELLIGENCE

Executive information systems are data-oriented DSS that provide reporting about the nature of an organization to management [12]. Despite the 'executive' title, they are used by all levels of management. EIS were enabled by technology improvements in the mid to late 1980s,especially client server architectures, stable and affordable networks, graphicuser interfaces, and multidimensional data modeling. This coincided with economic downturn in many OECD countries that resulted in the downsizing phenomenon that decimated middle management. EIS were deployed to help try to manage the leaner reporting structures. The seminal EIS book, Rockart and DeLong was titled ''Executive Support Systems'', reflecting the decision support heritage. Rockart [13] had earlier contributed what became EIS's major theoretical contribution to general information systems theory, the notion of Critical Success Factors or CSF. By the mid 1990s EIS had become main stream and was an integral component of the IT portfolio of any reasonably sized organization. The Business Intelligence (BI) movement of the late 1990s changed the direction or emphasis of EIS by focusing on enterprise- wide reporting systems although this organizational focus has yet to be widely realized in successful systems.

INTELLIGENCE AND INTELLIGENT SYSTEMS

It is appropriate at this point to briefly comment on the meaning of the word intelligence as generic term. The precise definition of "intelligence" has been eluding mankind for thousands of years. However the true nature of intelligence has been debated more intensely than ever over the last century. As the science of psychology has developed one of the biggest questions it had to answer concerned the nature of Intelligence. Some of the definitions that have been given for intelligence have been the ability to adjust to one's environment. Of course by such a definition even a person who is generally considered to be dull can be regarded as being intelligent if he can take care of himself. Other definition is such as having the tendency to analyze things around you. However it can be argued that such behavior can lead to over-analyzing things and not reacting to one's environment and dealing with it in an "intelligent manner".

All these have lead scientists and engineers to develop a challenging scientific area that of Intelligent Systems (IS). The area of broadly perceived as IS has emerged, in its present form, just after World War II, and was initially limited to some theoretical attempts to emulate human reasoning, notably by using tool from formal logic. The advent of digital computers has clearly played a decisive role by making it possible to solve difficult problems. In the mid-1950 the term artificial intelligence was coined. The early research efforts in this area, heavily based on symbolic computations alone, though have had some successes, have not been able to solve many problems in which numerical calculations have been needed, and new, more constructive approaches have emerged, notably computational intelligence which have been based on various tools and techniques, both related to symbolic and numerical calculations. This modern direction has produced many relevant theoretical results and practical applications in what may be termed intelligent systems.

More recently, this issue has been addressed by disciplines such as psychology, philosophy, biology and of by artificial intelligence (AI); note that AI is defined to be the study of mental faculties through the use of computational models. Again no consensus has emerged as yet of what constitutes intelligence. Intelligence is also considered as a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test- taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings— "catching on," "making sense" of things, or "figuring out" what to do. Fuzzy Logic and Fuzzy Cognitive Maps have emerged as serious scientific developments the last 20-25 years in modeling and controlling dynamic complex. The question is how FCM can be used intelligently to address challenging problems and issues for Decision Support Systems (DSS).

A CRITICAL OVERVIEW OF FUZZY COGNITIVE MAPS

Fuzzy Cognitive Maps (FCMs) consist of concept nodes and weighted arcs, which are graphically illustrated as a signed weighted graph with feedback. Signed weighed arcs, connecting the concept nodes, represent the causal relationship that exists among concepts. In general, concepts of an FCM, represent key-factors and characteristics of the modeled complex system and stand for: events, goals, inputs, outputs, states, variables and trends of the complex system been modeled. This graphic display shows clearly which concepts influences with other concepts and what this degree of influence is. When addressing strategic issues FCMs are used as action- oriented representations of the context the managers are discussing. They are built to show and simulate the interaction and interdependences of multiple belief systems these are described by the participants - by necessity, these belief systems are qualitative and will change with the context and the organizations in which they are developed. They represent a way to make sure, that the intuitive belief that strategic issues should have consequences and implications, that every strategy is either constrained or enhanced by a network of other strategies, can be adequately described and supported.

A SHORT HISTORICAL REVIEW OF FCMS

As said FCMs are directed graphs, or digraphs, and thus they have their historical origins in graph theory. Graph theory is the study of graphs, mathematical structures used to model pair wise relations objects from a certain collec-tion. A graph is thus context refers to a collec-tion of vertices or “nodes” and a collection of edges that connect pairs of vertices. Till today, they have been used to model many types of re-lations and process dynamics in physical, net-works, engineering, biological, health, energy and social systems. Surprisingly, graphs have not been used, almost at all, on economic systems. Political scientist Robert Axelrod [14] was the first to use digraphs to show causal relationship among variables as defined and described by people, rather than by the researcher. Axelrod called these diagraphs Cognitive Maps (CM). Many studies have used CM to look at decision-making as well as to examine people’s perceptions of complex social systems. Kosko, modified Axelrod’s CM’s, which were binary, by applying fuzzy causal functions with real numbers in [-1,1] to the connections, thus the term Fuzzy Cognitive Maps (FCM) [15]. Kosko was also the first to model FCMs and to compute the outcome of a FCM, or the FCM inference, as well as to model the effect of different policy options using a neural network computational method [16], [17].

TODAY’S FUZZY COGNITIVE MAPS THEORIES

FCMs are directed graphs capable of modeling interrelationships or causalities existing among concepts. A simple example is given in figure 1. Concept variables and causal relations constitute the fundamental elements of an FCM. Concept variables are represented by nodes, such as C_1, C_2,.and C_N. Causal variables always depict concept variables at the origin of arrows; effect variables, on the other hand, represent concepts-variables at the terminal points of arrows. For example, at $C_1 \rightarrow C_2$, C_1 is said to impact C_2 because C_1 is the causal variable, whereas C_2 is the effect variable. Each concept is characterized by a number Ai that represents its value and it results from the transformation of the real value of the system’s variable, for which this concept stands, in the interval [0,1]. Causality between concepts allows degrees of causality and not the usual binary logic, so the weights of the interconnections can range in the interval [-1,1]. Fuzzy Cognitive Map models a system as an one-layer network where nodes can be assigned concept meanings and the interconnection weights represent causal relationships among concepts. Thus a FCM is a graph showing the degree of causal relationship - among concepts of the map knowledge expressions and the causal relationships are expressed by and fuzzy weights. Existing knowledge on the behavior of the system is stored in the structure of nodes and interconnections of the map. Relationships between concepts have three possible types; a) either express positive causality between two concepts ($W_{ij}>0$) b) negative causality ($W_{ij}<0$) and c) no relationship ($W_{ij}=0$). The value of W_{ij} indicates how strongly concept C_i influences concept C_j. The sign of W_{ij} indicates whether the relationship between concepts C_i and C_j is direct or inverse. The direction of causality indicates whether concept C_i causes concept C_j, or vice versa. These parameters have to be considered when a value is assigned to weight W_{ij}.

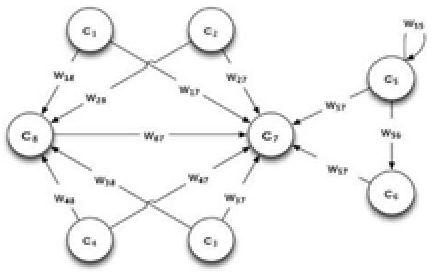

Fig. 1. A simple Illustrative Fuzzy Cognitive Map (FCM)

The sign of each weight represents the type of influence between concepts. There are three types of interconnections between two concepts C_i and C_j:

- • $w_{ij}>0$, an increase or decrease in C_i causes the same result in concept C_j.
- • $w_{ij}<0$, an increase or decrease in C_i causes the opposite result in C_j.
- • $w_{ij}=0$, there is no interaction between concepts C_i and C_j.

The degree of influence between the two concepts is indicated by the absolute value of w_{ij}. The value of each concept at every simulation step is calculated, computing the influence of the interconnected concepts to the specific concept, by applying the following calculation rule:

$$A_i(k+1)=f(k_1 A_i(k)+k_2) \qquad (1)$$

where k represents time, N is the number of concepts and

- $A_i(k+1)$: the value of the concept C_i at the iteration step k+1
- $A_i(k)$: the value of the concept C_j at the iteration step k
- W_{ij} : the weight of interconnection from concept C_i to concept C_j
- k_1: the proportion of the contribution of the previous value of the concept in the computation of the new value
- k_2: the influence of the interconnected concepts in the configuration of the new value of the concept Ai
- f: the sigmoid function

$$f = \frac{1}{1+e^{-\lambda x}} \qquad (2)$$

where $\lambda>0$ determines the steepness of function f. The FCM's concepts are given some initial values which are then changed depending on the weights; the way the concepts affect each other. The calculations stop when a steady state is achieved, the concepts' values become stable. In most applications k_1 and k_2 are set equal to one (1). FCMs have been used in many challenging problem and has shown that are extremely useful (see [18-20]). The book of [18] provides a number of chapters describing theories and applications on different applications, Ref. [19] gives an extensive survey on FCM research results with 115 references, while Ref. [20] provides an excellent survey on learning algorithms for Fuzzy Cognitive Maps.

However despite all these useful and interesting results of FCMs theories and algorithms, there are still many drawbacks and deficiencies of FCMs [21-23].

SOME DEFICIENCIES OF TODAY'S FUZZY COGNITIVE MAPS THEORIES

It is interesting to mention here some of these deficiencies which are analyzed and certain solutions are provided in Ref. [21-23]. An FCM is a qualitative mathematical tool rather than a quantitative tool. It provides a simple, flexible and straightforward approach to model the dynamic behavior of a complex system, which is composed of various components or subsystems. An FCM can always describe any complex dynamic system (CDS) using a mathematical model with the following six (6) characteristics or attributes:

1. Defined causality indicating positive or negative relationship between all components
2. The strength of the causal relationships always take fuzzy values
3. The causal links are always dynamic and never static
4. Past knowledge of the CDS dynamic behavior is available and reliable
5. Human-like reasoning and
6. Always availability of experts knowing the dynamic behavior of the CDS.

Given that the above hold and the FCM methodologies, so far been developed, we can always model any given CDS using FCMs.

One major drawback of the early FCM approach has been the convergence problem of the algorithms. Given the values of the initial values of the weights at least two problems have been observed: 1) always the final values of the weights converge to the same value regardless the original conditions of the system and 2) in some cases the algorithms do not converge at a final steady state value. In order to overcome these two convergence problems learning algorithms are used. The main ideas stem from neural networks. Unsupervised methods such as Hebbian techniques are the most common used. More specifically Nonlinear Hebbian Learning (NHL) has been used to overcome partially this drawback [24].

Another major drawback is that concepts of an FCM include everything: states, inputs, outputs, constraints and all other parameters which are going to be examined regardless their nature. However this is not mathematically correct and logical in any scientific approach. Even the calculation method of the values of the concepts, (Eq.1) has a serious problem-drawback. The calculation equation takes into consideration the change that each concept cause separately instead of the total change which is caused to the concept Ci. This results in a large increase to the value of the concept Ci that goes far beyond the interval [0,1]. This is the reason why the sigmoid function (Eq.2) is needed; to suppress the result to the interval [0,1]. However due to the shape of the sigmoid curve any concept value beyond 3 leads the sigmoid function to correspond it to the value 1 which is greatly problematic as the final output is corresponded to the linguistic variable "high" even if this is not always the expected or correct result. In order to provide a solution to this problem the N concepts of a Fuzzy Cognitive Map are separated into the following three categories:

A. Fuzzy State Concepts: The concepts describing the dynamic operation of the system, x

B. Fuzzy Input Concepts: The inputs of the system, u

C. Fuzzy Output Concepts: The concepts describing the outputs of the system, y

In this way a better knowledge of the dynamic behavior of the CDS is gained. The proposed separation facilitates not only the understanding of the system's operation but also the calculation of the concepts' values in their physical nature as the states, inputs and outputs of the real system. Then as in the classical state space approach the two equations extracted from the classic FCM are the followings:

$$x(k+1) = f[Ax(k) + Bu(k)] \tag{3}$$

$$y(k) = f[Cx(k) + Du(k)] \tag{4}$$

where x(k) Rn is a state vector, u(k) Rr is an exogenous known input vector, y(k) Rm is the output vector and f is an activation function, to be defined by the experts [23]. Another approach has been proposed in [21] which the two state equations are given as follow:

$$x_{k+1} = Ax_k + Bu_k \tag{5}$$

$$y_k = Cx_k + Du_k \tag{6}$$

They were used to calculate the variation caused by the change in the input and state concepts to the state and output concepts at each time step (k).

In both representations eq. 3 and 4 as well as in eq. 5 and

6 the matrices A, B, C and D are individual weight matrices derived from the initial weights defined by the experts. Each weight matrix have the appropriate dimensions depending on the A)-C) categories of the total number N of concepts [21].

The elements of matrix A depend on the states weights and the elements of matrix B show how each input concept affects the state concepts of the system. Matrix C shows how the output concepts are related to the state concepts and matrix D shows how the input concepts directly affect the output concepts. In the same paper a new sigmoid function f is proposed [21] and is given as

$$R(x) = \begin{cases} 0, & x < 0.5 \\ \frac{x-0.5}{0.5}, & x > 0.5 \end{cases} \quad (7)$$

Another interesting problem and in some way a deficiency of today's FCM theories is the causality notion. The values of the weights Wij for the interconnection between the concepts express the kind and degree of causality. Now is this related to the statistical correlation coefficient? And if yes how? Not an easy question to be answered. It would require a whole new paper. The research team of LAR is investigating this difficult problem as well as the other deficiencies. My own scientific feeling says that correlation does not necessary implies causality while the reverse is true. Thus causality always implies correlation.

CLOSING REMARKS AND FUTURE RESEARCH

In this paper the interesting overview of the general notion of Decisions Support Systems (DSS) is provided. The important scientific areas of Intelligence and Intelligent Systems (IS) and their relation and contribution to Decision Support Systems (DSS) is emphasized. A new Intelligent Decision Making Support Systems (IDMSS) based on Fuzzy Cognitive Maps (FCMs) is needed as a useful theoretical concept when studying and developing the future decision support systems. The brief presentation of basic theories of FCMs along with their drawbacks and deficiencies was outlined.

If most of these limitations of FCMs are resolved in a well defined mathematical formulation then FCMs will be a first class model for modelling, studying and analyzing CDS.

There are so many unanswered questions in the fields of CDS, DSS, AI and FCMs that make the future research directions to be a very large number , difficult in nature and very challenging. Starting with the FCMs since I considered them to be the future fundamental Building blocks for all the other scientific fields here are some: formulate mathematically better the proposed separation of the concepts into states, inputs and outputs; based on this separation investigate the learning algorithms; generate new models of FCMs for CDS using learning methods; develop new DSS using the new models of FCMs; develop new DMSS using intelligent systems and advanced neural network theories; develop mathematical models using new advance FCMs for different applications and using a number of experts; How is causality is related to the statistical correlation coefficient; develop new software tools for various CDS and perform extensive simulations using real data from a large number of applications. Another interesting future research direction is to study and investigate control issues of complex dynamic systems using the new state FCM models. There is very little been done on this control issues. Today's FCMs are more for modelling and making decisions for complex dynamic systems. FCM theories do not know the term and role of feedback control for complex dynamic systems.

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Abstract: This paper analyses briefly the nature and state in modelling and controlling Complex dy-namic systems (CDS) and of Intelligent Systems (IS) been related to Decision Support Sys-tems (DSS) theories, research and applications. A brief historical review of DSS and how Ar-tificial Intelligence (AI) has been embedded into the DSS and how this generated the inter-esting scientific area of Intelligent Decision Support Systems (IDSS). The challenge and ab-solute need for “Making Decisions” is briefly outlined. The challenge now is to make sense of DSS in ‘’Decision Making’’ by planning it in understanding context and by searching new ways to utilize other advanced methodologies to the challenging issues of CDS in the fu-ture. The possibility of using, Fuzzy Cognitive Maps (FCM) and Intelligent Systems (IS) in DSS is reviewed and analyzed. Some drawbacks and deficiencies of FCM are briefly pre-sented and discussed. Open issues for future research of DSS and FCMs are outlined and briefly discussed.

Key words: web application; database; dynamic model; NoSQL; XML; DOM; PHP.

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