Mathematical Modelling of Decision Making Support Systems Using Fuzzy Cognitive Maps

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Abstract. This chapter critically analyses the nature and state of Decision Support Systems (DSS) theories, research and applications. A thorough and extensive historical review of DSS is provided which focuses on the evolution of a number of sub-groupings of research and practice: personal decision support systems, group support systems, negotiation support systems, intelligent decision support systems, knowledge management- based DSS, executive information systems/ business intelligence, and data warehousing. The need for new DSS methodologies and tools is investigated. The DSS area has remained vital as technology has evolved and our understanding of Decision-Making process has deepened. DSS over the last twenty years has contributed both breadth and depth to DSS research. The challenge now is to make sense of it in ''Decision Making'' by planning it in understanding context and by searching new ways to utilize other advanced methodologies. The possibility of using Fuzzy Logic, Fuzzy Cognitive Maps and Intelligent Control in DSS is reviewed and analyzed. A new generic method for DSS is proposed, the Decision Making Support System (DMSS). Basic components of the new generic method are provided and fully analyzed. Case studies are given showing the usefulness of the proposed method.

Keywords: Decision Support Systems, Intelligent Control, Fuzzy Systems, Decision Making Support Systems, Fuzzy Cognitive Maps.

1 Introduction

One of the challenges of accepting the "operation" of any complex system is the ability to make Decisions so the system runs efficiently and cost effectively. However making Decisions concerning complex systems often strains our cognitive capabilities. Uncertainty and related concepts such as risk and ambiguity are prominent in the research and accompanied literature on Decision-Making. Uncertainty is a term used in subtly different ways in a number of scientific fields, including statistics, economics, finance, physics, psychology, engineering, medicine, energy, environment, biology, sociology, philosophy, insurance, geology, military

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systems and Information and Communication Technologies (ICT). It applies to making decisions = predictions of future events, to physical measurements already made and/or computer generated data based on manmade "systems". This prominence is well deserved. Ubiquitous in realistic settings, uncertainty constitutes a major obstacle to effective Decision Making Process (DMP).

Currently, the prevalent view within many of the engineering, medical and human sciences, bestows the status of "scientific data" (physical and human produced data), mainly on those facts and propositions that stem directly from empirical and/or experimental work. In practice, experiment subjugates theory, leaving to theory the modest function of data interpretation. Nevertheless, "scientific data" are only isolated elements that must be interpreted and synthesized by holistic theory. In the absence of theory, the myriad arrays of "scientific data" turn into a heap of disparate material that is difficult to generalize, let alone correctly interpret.

Therefore in a complex system, there are a large number of "scientific data" been processed and a substantial amount of evidence that Decision Making (DM) and Human Intuitive Judgment (HIJ) can be far from "optimal" solutions. In almost all situations Decision Making (DM) has been a major focus of science throughout the human history. All these decisions prior to the development of the computer were made by people using various theories and methods and were recorded by hand.

These methods were originated from artificial intelligence, statistics, probability, cognitive psychology and information science. After the 1950, when the computer appeared for first time all these techniques were integrated in computing environments and thus enhancing the DM and the HIJ. Thus the concept of Decision Support systems (DSS) emerged after the 1950s as it will be seen in section 2. The concept of DSS since the 1980s is extremely broad and its definitions vary, depending on the scientist's or the researcher's point of view. Today the whole issue of defining DSS is still open. In this chapter a new systemic approach to the concept of "DSS" is undertaken.

Decision Support Systems (DSS) are defined as any interactive computer – based support system for making decisions in any complex system, when individuals and/or a team of people are trying to solve unstructured problems on an uncertain environment.

DSS have gained an increased popularity in various domains the last 10 years. There is no scientific field that, in one way or another, decisions are taken everyday using extensively advanced techniques of integrating digital computer systems. All scientific fields been mentioned earlier that encounter uncertainty are candidate for using one or another type of DSS.

DSS are especially valuable in situations in which, the amount of ''scientific data'' is prohibitive for the ''human decision maker'' without any aid to proceed in solving difficult problems faced by any complex system. Advanced DSS can aid human cognitive deficiencies by integrating various methodologies and tools utilizing a number of different information sources in order to reach ''acceptable decisions''. The benefits in using DSS are: increases efficiency, productivity, competiveness, cost effectiveness and high reliability. This gives business and other ''systems'' a comparative advantage over other competitors.

In this chapter the overall concept of Decision Support Systems is critically reviewed and analyzed. In section 2, a historical review starting from the ancient times till today is provided. In section 3 many but not all definitions and theories of DSS are analyzed. In section 4 the scientific areas of Fuzzy Logic and Intelligent Control are briefly reviewed as also their role in analyzing and modeling complex systems while basic theories of FCM are provided in section 5. The new generic DSS embedding ''Decision Making'' in the loop is presented and justified in section 6 while section 7 provides two illustrative case studies using the new proposed generic methodology. In section 8 a new Five Steps Approach to Success (5-SAS) which is further enabling to formulate more effective, flexible and cost effective DMSS. Future research topics are presented and certain specific directions are analyzed in section 9. Finally, section 10 provides a summary and closing remarks of the challenging issues been raised throughout the whole chapter.

2 A Historical Overview of Decision Support Systems (DSS)

Today it is still possible 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. In a technology field as diverse as DSS, history is not neat and linear. Different people and from different scientific fields have perceived the field of computerized DSS, from various points and so they report different accounts of what happened and what was important. Some of this can be sorted out, but more data gathering is necessary. For example in the field of Medicine, Clinical Decision Support Systems (CDSS) have been developed since the late 1960s and have played a very important role in providing health care for the patients.

Information Systems and Business researchers and technologists have built and investigated Decision Support Systems (DSS) for the last 60 years. Some researchers trace the origins of DSS to 1951 and the Lyons Tea Shops Business use of the LEO (Lyons Electronic Office I) *digital computer*. Now this is true but for computerized DSS ONLY. Decisions were made from the classical world and the time of Greek Civilization till today. From a strict historical point of view the Delphic Oracle could be considered as the first formal DSS. Ancient Delphi was a small City located in the Central Greece and was the focal point for intellectual enquiry, as well as an occasional meeting place for kings, leaders and intellectuals of the known ancient world. The Delphic Oracle extended considerable influence throughout the Ancient Greek world and it was consulted by everybody (from Kings to single citizens) before all major undertakings: wars, the founding colonies, legislating laws and so forth. It also was respected by the semi-Hellenic countries around the world such a Lydia, Caria, Egypt and even Persia. The

Delphic Oracle was using an extensive distributed system of “informal data points” throughout the cities of the Classical world. It had developed, on the Temple of Apollo, (ancient God) an extensive data base library for all events of that period. These information was used by the priests and Pythia before giving an answer-prophesy to the question been put in front of them. 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.

In this chapter a starting point in collecting more firsthand accounts and in building a more complete mosaic of what was occurring in Universities, Research Institutes, software companies and in organizations to build and use computerized DSS in the last 60 years.

According to Keen [42]-[43], 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. in 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 [44]. 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 [45]. 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 [45]-[46]. The title of Dearden’s (1972) Harvard Business Review article, “MIS is a Mirage”, summarized the feelings of the time.

The term “Decision Support Systems” first appeared in [47], 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 (McCosh, 2004). Gorry and Scott Morton (1971) constructed a framework for improving management information systems using Anthony's categories of managerial activity [47] and Simon's taxonomy of decision types (Simon, 1960/1977). 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 [44] 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 [47], and this was reinforced in the field's four seminal books: Scott Morton [52], McCosh and Scott Morton [51], Keen and Scott Morton [44], and Sprague and Carlson [50].

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. The emphasis of this process was not to provide the user with a polished application program that efficiently solved the target problem. In fact, the problems addressed are by definition impossible, or inappropriate, for an IT-based system to solve completely. Rather, the purpose of the development of a DSS is an attempt to improve the effectiveness of the decision maker. In a real sense, DSS is a philosophy of information systems development and use and not a technology.

According to Sprague and Watson [48], 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 [49]. 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." Davis's Chapter 12 titled "Information System Support for Decision Making" and Chapter 13 titled "Information System Support for Planning and Control" created the setting for the development of a broad foundation for DSS research and practice.

By 1975, J. D. C. Little was expanding the frontiers of computer-supported modeling. Little's DSS called BRANDAID and was designed to support product, promotion, pricing and advertising decisions. Also, Little (1970) in an earlier article identified criteria for designing models and systems to support management decision--making. His four criteria included: robustness, ease of control, simplicity, and completeness of relevant detail. All four criteria remain relevant in evaluating modern Decision Support Systems. Klein and Methlie (1995) note "A study of the origin of DSS has still to be written. It seems that the first DSS papers were published by PhD students or professors in business schools, who had access to the first time-sharing computer system: Project MAC at the Sloan School, the Dartmouth Time Sharing Systems at the Tuck School. In France, HEC was the first French business school to have a time-sharing system (installed in 1967), and the first DSS papers were published by professors of the School in 1970. The term SIAD ('Systèmes Interactif d'Aide à la Décision' the French term DSS) and the concept of DSS were developed independently in France, in several articles by professors of the HEC working on the SCARABEE project which started in 1969 and ended in 1974."

3 Decision Support Systems (DSS)

3.1 Definitions

The concept of a decision support system (DSS) is extremely broad and its definitions vary depending on the author's point of view. It can take many different forms and can be used in many different ways [53]. On the one hand, Finlay [54] and others define a DSS broadly as "a computer-based system that aids the process of decision making". In a more precise way, Turban [55] defines it as "an interactive, flexible, and adaptable computer-based information system, especially developed for supporting the solution of a non-structured management problem for improved decision making. It utilizes data, provides an easy-to-use interface, and allows for the decision maker's own insights." Other definitions fill the gap between these two extremes. For Keen and Scott Morton [44], DSS couple the intellectual resources of individuals with the capabilities of the computer to improve the quality of decisions. "DSS are computer-based support for management decision makers who are dealing with semi-structured problems." For Sprague and Carlson [50], DSS are "interactive computer based systems that help decision makers utilize data and models to solve unstructured problems "On the other hand, Schroff [56] quotes Keen [75] ("there can be no definition of DSS, only of Decision Support") to claim that it is impossible to give a precise definition including all the facets of the DSS. Nevertheless, according to Power [57], the term DSS remains a useful and inclusive term for many types of information systems that support decision making.

3.2 Basic Theories of Computerized Decision Support Systems

Typical application areas of DSSs are management and planning in business, health care, the military, and any area in which management will encounter complex decision situations. Decision support systems are typically used for strategic and tactical decisions faced by upper-level management—decisions with a reasonably low frequency and high potential consequences—in which the time taken for thinking through and modeling the problem pays off generously in the long run.

There are three fundamental components of DSSs.

- Database management system (DBMS). A DBMS serves as a data bank for the DSS. It stores large quantities of data that are relevant to the class of problems for which the DSS has been designed and provides logical data structures (as opposed to the physical data structures) with which the users interact. A DBMS separates the users from the physical aspects of the database structure and processing.
- Model-base management system (MBMS). The role of MBMS is analogous to that of a DBMS. Its primary function is providing independence between specific models that are used in a DSS from the applications that use them. The purpose of an MBMS is to transform data from the DBMS into information that is useful in decision making. Since many problems that the user of a DSS will cope with may be unstructured, the MBMS should also be capable of assisting the user in model building.
- Dialog generation and management system (DGMS). The main product of an interaction with a DSS is insight. As their users are often managers who are not computer-trained, DSSs need to be equipped with intuitive and easy-to-use interfaces. These interfaces aid in model building, but also in interaction with the model, such as gaining insight and recommendations from it.

While a variety of DSSs exists, the above three components can be found in many DSS architectures and play a prominent role in their structure.

Past practice and experience often guide computerized decision support development more than theory and general principles. Some developers say each situation is different so no fundamental theory is possible. Others argue that we have conducted insufficient research to develop theories. For these reasons, the theory of decision support and DSS has not been addressed extensively in the literature.

The following set of six propositions from the writings of the late Nobel Laureate Economist Herbert Simon form an initial theory of decision support. From [71] we draw three propositions.

<u>Proposition 1:</u> If information stored in computers is accessible when needed for making a decision, it can increase human rationality.
<u>Proposition 2:</u> Specialization of decision-making functions is largely dependent upon developing adequate channels of communication to and from decision centers.
<u>Proposition 3:</u> When a particular item of knowledge is needed repeatedly in decision making, an organization can anticipate this need and, by providing the individual with this knowledge prior to decision, can extend his or her area of rationality. Providing this knowledge is particularly important when there are time limits on decisions.

Now three additional propositions are identified:

Proposition 4: In the post-industrial society, the central problem is not how to organize to produce efficiently but how to organize to make decisions – that is, to process information. Improving efficiency will always remain an important consideration.
Proposition 5: From the information processing point of view, division of labor means factoring the total system of decisions that need to be made into relatively independent subsystems, each one of which can be designed with only minimal concern for its interactions with the others.
Proposition 6: The key to the successful design of information systems lies in matching the technology to the limits of the attention of users. In general, an additional component, person, or machine for an information-processing system will improve the system's performance when the following three conditions are true:

1. The component's output is small in comparison with its input so that it conserves attention instead of making additional demands on attention.
2. The component incorporates effective indexes of both passive and active kinds. Active indexes automatically select and filter information.
3. The component incorporates analytic and synthetic models that are capable of solving problems, evaluating solutions, and making decisions.

In summary, computerized decision support is potentially desirable and useful when there is a high likelihood of providing relevant, high quality information to decision makers when they need it and want it.

3.3 Theories for Modern Decision Support Systems

The modern era in DSS started in the late 1990s with the specification of HTML 2.0, the expansion of the World Wide Web in companies, and the introduction of handheld computing. Today, the Web 2.0 technologies, mobile-integrated communication and computing devices, and improved software development tools have revolutionized DSS user interfaces. Additionally, the decision support data store back-end is now capable of rapidly processing very large data sets. Modern DSS are more complex and more diverse in functionality than earlier DSS built prior to the widespread use of the World Wide Web. Today, we are seeing more decision automation with business rules and more Knowledge-Driven DSS. Current DSS are changing the mix of decision-making skills needed in organizations. Building better DSS may provide one of the "keys" to competing in a global business environment.

The following attributes are increasingly common in new and updated Decision Support Systems. Some attributes are more closely associated with one category of DSS, but sophisticated DSS often have multiple subsystems. Contemporary DSS include five attributes:

1. Multiple, remote users can collaborate in real-time using rich media.
2. Users can access DSS applications anywhere and anytime.
3. Users have fast access to historical data stored in very large data sets.
4. Users can view data and results visually with excellent graphs and charts.
5. Users can receive real-time data when needed.

3.4 Different Approaches to Decision Support Systems

DSS is not a homogenous field. There are a number of fundamentally different approaches to DSS and each has had a period of popularity in both research and practice. Each of these "DSS types" represents a different philosophy of support, system scale, level of investment, and potential organizational impact. They can use quite different technologies and may support different managerial constituencies. Another dimension to the evolution of DSS is improvement in technology, as the emergence of each of the DSS types has usually been associated with the deployment of new information technologies. The nature and development of four selected DSS types is discussed next.

3.4.1 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 Management Information Systems (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. The emergence of PDSS also mirrored its social and organizational environment. The 1960s and 1970s saw a radicalization of Western society, especially in response to the Vietnam War. The emphasis was on empowering individuals and a democratization of decision-making. PDSS followed this philosophy by supporting individual managers rather than attempting to support the more nebulous concept of "the organization".

The major contribution of PDSS to Information sciences (IS) theory is evolutionary systems development [58]. The notion that a DSS evolves through an iterative process of systems design and use has been central to the theory of decision support systems since the inception of the field. Evolutionary development in decision support was first hinted at [72] and [73] as part of their description of middle-out design. This was a response to the top-down versus bottom-up methodology debate of the time concerning the development of transaction processing systems. Courbon [74] provided the first general statement of DSS evolutionary development. In what they termed an "evolutive approach", development processes are not implemented in a linear or even in a parallel fashion, but in continuous action cycles that involve significant user participation. As each evolutive cycle is completed the system gets closer to its final or stabilised state. Keen [75], building on Courbon's work, developed a framework or model for understanding the dynamics of DSS evolution. The importance of this work was to give the concept a larger audience. Amongst other contributors to PDSS development theory, Sprague and Carlson [50] defined an evolutionary DSS development methodology, and Silver [76] extended Keen's approach by considering how PDSS restrict or limit decision-making processes.

3.4.2 Intelligent Decision Support Systems

Artificial Intelligence (AI) techniques have been applied to decision support and these systems are normally called intelligent DSS or IDSS [59] although the term knowledge-based DSS has also been used [60].Intelligent DSS can be classed into two generations: the first involves the use of rule-based expert systems and the second generation uses neural networks, genetic algorithms and fuzzy logic [61]. 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.

3.4.3 Executive Information Systems and Business Intelligence

Executive Information Systems (EIS) are data-oriented DSS that provide reporting about the nature of an organization to management [62]. 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, graphic user 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 [69] was titled ''Executive Support Systems'', reflecting the decision support heritage. Rockart had earlier contributed what became EIS's major theoretical contribution to general information systems theory, the notion of Critical Success Factors or CSF [63]. CSF are the small number of factors that must go right for an organization, business unit, or individual executive to prosper. If a manager notices from an EIS report that the business is not performing in any critical area, the EIS enables the manager to drill-down through a report hierarchy to discover the possible sources of the variance. The multidimensional view of data, institutionalized as the 'data cube", was the foundation of early EIS vendor offerings like HOLOS and Cognos. This multidimensionality was later codified and described as OnLine Analytical Processing (OLAP) [70].

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. Dashboard-style interfaces and web delivery changed the look and feel of EIS, and the broader measures of balanced score cards [64] displaced some, but not all, of the CSF framework of EIS reporting. Business Intelligence (BI) is a poorly defined term and its industry origin means that different software vendors and consulting organizations have defined it to suit their products; some even use 'BI' for the entire range of decision support approaches. Business Intelligence (BI) as the contemporary term for both model-oriented and data-oriented DSS that focus on management reporting, that is, BI is a contemporary term for EIS.

3.4.4 Data Warehouses

The development of large-scale EIS created the need for continuous high quality data about the operations of an organization. The bull market of the 1990s led to a plethora of mergers and acquisitions and an increasing globalization of the world economy. Large organizations were faced with significant challenges in maintaining an integrated view of their business. This was the environment of the birth of data warehousing. A data warehouse is simply a set of databases created to provide information to decision makers; they provide raw data for user-focused decision support through PDSS and EIS.

There are two fundamental approaches to data warehouses: enterprise level data warehouses [65] and division or department level data marts [66]. This architectural debate has raged since the mid 1990s and shows no signs of abating in practice. The major contribution of data warehousing to IS theory is dimensional modeling [67]. Using dimensional models very large data sets can be organized in ways that are meaningful to managers. They are also relatively easy to query and analyze. In this sense, data warehousing provides the large scale IT infrastructure for contemporary decision support. As a result data warehouse development is dominated by central IT departments that have little experience with decision support. A common theme in industry conferences and professional books is the rediscovery of fundamental DSS principles like evolutionary development [68]. An issue that needs to be addressed very serious and the appropriate attention.

3.5 Different Driven Types of Decision Support Systems

Another classification of DSS is from a structural driven point of view. Here we provide the most common types, without a lot of details. The interested reader can easily find the appropriate material on basic textbooks.

Data Driven

These DSS has file drawer systems, data analysis systems, analysis information systems, data warehousing and emphasizes access to and manipulation of large databases of structured data.

Model Driven

The underlying model that drives the DSS can come from various disciplines or areas of specialty and might include accounting models, financial models, representation models, optimization models, etc. With model drive DSS the emphasize is on access to and manipulation of a model, rather than data, i.e. it uses data and parameters to aid decision makers in analyzing a situation. These systems usually are not data intensive and consequently are not linked to very large databases.

Knowledge Driven

These systems provide recommendation and/or suggestion schemes which aid the user in selecting an appropriate alternative to a problem at hand. Knowledge driven DSS are often referred to as management expert systems or intelligent decision support systems. They focus on knowledge and recommends actions to managers based on an analysis of a certain knowledge base. Moreover, it has special problem solving expertise and are closely related to data mining i.e. sifting through large amounts of data to produce contend relationships.

Communication Driven

This breed of DSS is often called group decision support systems (GDSS). They are a special type of hybrid DSS that emphasizes the use of communications and decision models intended to facilitate the solution of problems by decision makers working together as a group. GDSS supports electronic communication, scheduling, document sharing and other group productivity and decision enhancing activities and involves technologies such as two-way interactive video, bulletin boards, e-mail and others.

Inter- and Intra-organization Driven

These systems are driven by the rapid growth of Internet and other networking technologies such as broadband WAN's, LAN's, WIP and others. Inter-organization DSS are used to serve companies stakeholders (customers, suppliers, etc.), whereas intra-organization DSS are more directed towards individuals inside the company and specific user groups. The latter, because of their stricter control, are often stand-alone units inside the firm.

4 Fuzzy Logic and Intelligent Control

4.1 Fuzzy Logic Basic Theory

Fuzzy logic starts with and builds on a set of user-supplied human language rules. The fuzzy systems convert these rules to their mathematical equivalents. This simplifies the job of the system designer and the computer, and results in much more accurate representations of the way systems behave in the real world [28]-[30].

Additional benefits of fuzzy logic include its simplicity and its flexibility. Fuzzy logic can handle problems with imprecise and incomplete data, and it can model nonlinear functions of arbitrary complexity. "If you don't have a good plant model, or if the system is changing, then fuzzy will produce a better solution than conventional control techniques," says Bob Varley, a Senior Systems Engineer at Harris Corp., an aerospace company in Palm Bay, Florida.

In fuzzy logic, unlike standard conditional logic, the truth of any statement is a matter of degree. (How cold is it? How high should we set the heat?) We are familiar with inference rules of the form p -> q (p implies q). With fuzzy logic, it's possible to say (.5* p) -> (.5 * q). For example, for the rule if (weather is cold) then (heat is on), both variables, cold and on, map to ranges of values. Fuzzy inference systems rely on membership functions to explain to the computer how to calculate the correct value between 0 and 1. The degree to which any fuzzy statement is true is denoted by a value between 0 and 1.

Not only do the rule-based approach and flexible membership function scheme make fuzzy systems straightforward to create, but they also simplify the design of systems and ensure that you can easily update and maintain the system over time.

The Mamdani Fuzzy Inference Systems (FIS) [25]-[26], was the first system proven in a practical way as universal approximator of functions. Later Kosko and Wang formally settled that any relationship among input and output variables can be approximated by means of FIS, built in linguistic terms with a high grade of accuracy [27] (universal approximator).

In Fuzzy Logic theory there are three outstanding definitions:

a) Fuzzy Set is called any set that allows to its members having different degree of membership (Membership function) in universe [0,1].
b) Universe of Discourse is the range of all possible values for an input to a fuzzy system
c) Membership Function (MF) shows the degree that set x belongs to set A according to the following equation (Fig. 1):

$$\mu_A(x): X \rightarrow [0,1] \tag{4.1}$$

Fuzzy sets are usually represented from ordered pairs sets according to the following equation:

$$A = \int\{\mu_A(x)/x\} \text{ or } A = \sum\{\mu_A(x)/x\} \text{ for } x \in X \tag{4.2}$$

Fig. 2 shows the basic architecture of a fuzzy logic controller containing the rule-base, the inference mechanism and the defuzzification method.

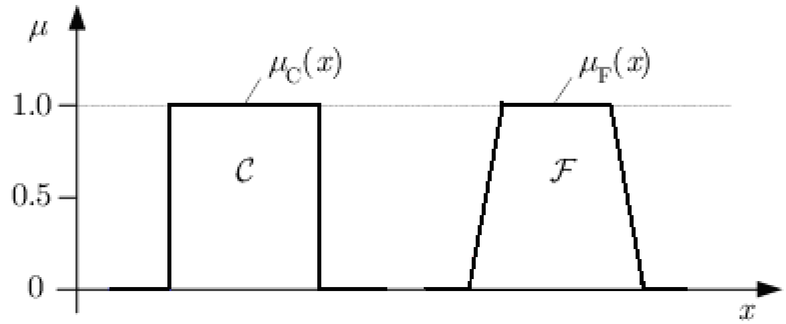

Fig. 1 Membership function characteristics of a conventional/crisp set on the left and of a fuzzy one on the right

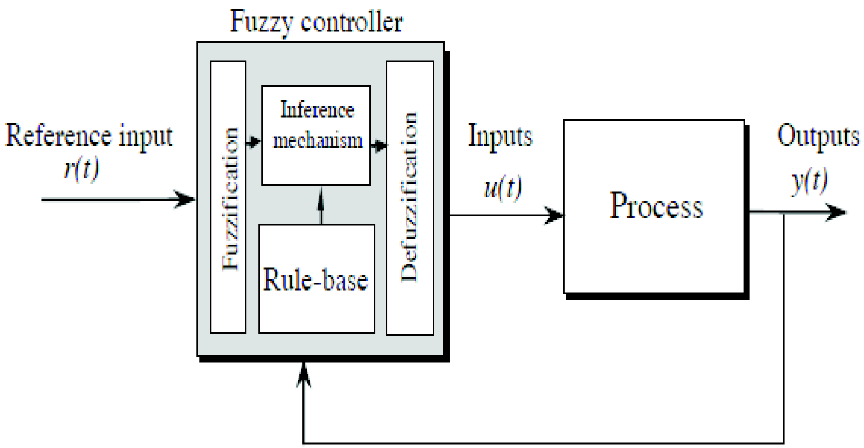

Fig. 2 Fuzzy Controller Architecture

The fuzzy controller has four main components: (1) The rule-base" holds the knowledge, in the form of a set of rules, of how best to control the system. (2) The inference mechanism evaluates which control rules are relevant at the current time and then decides what the input to the plant should be. (3) The fuzzification interface simply modifies the inputs so that they can be interpreted and compared to the rules in the rule-base. And (4) the defuzzification interface converts the conclusions reached by the inference mechanism into the inputs to the plant.

Defuzzification refers to the way a crisp value is extracted from a fuzzy set as a representative value. In general, there are five methods [31]-[36] for defuzzifying a fuzzy set A of a universe of discourse Y. The adopted defuzzyfication strategy for this chapter is the Center of Area (COA):

$$\widehat{y_{COA}} = \frac{\int y_i \mu_A(y_i) y dy}{\int \mu_A(y_i) dy} \tag{4.3}$$

where $\mu_A(y)$ is the aggregated output MF (i.e. Fig. 3) [35]. This is the most widely adopted defuzzyfication strategy, which is reminiscent of the calculation of expected values of probability distributions.

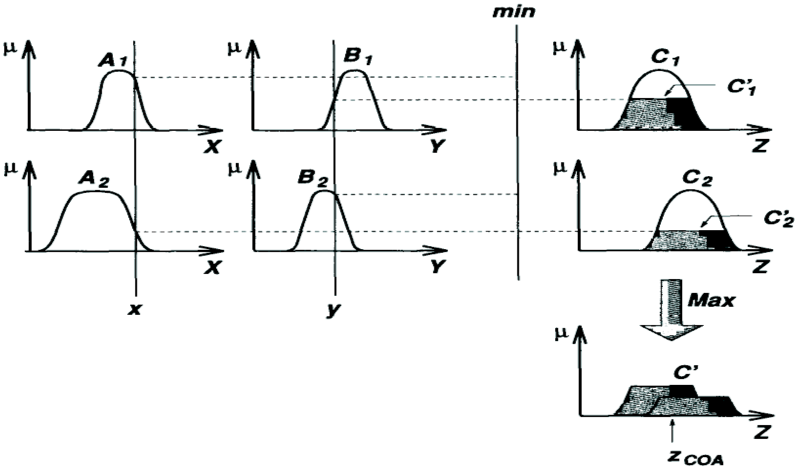

Fig. 3 The Mamdani fuzzy inference system using min and max for T-norm and T-conorm operators, respectively

4.2 Intelligent Control and Intelligence

Intelligent control describes the discipline where control methods are developed that attempt to emulate important characteristics of human intelligence. These characteristics include adaptation and learning, planning under large uncertainty and coping with large amounts of data. Others describe as Intelligent Control, the discipline where control algorithms are developed by emulating certain characteristics of intelligent biological systems, is being fueled by recent advancements in computing technology and is emerging as a technology that may open avenues for significant technological advances. Today, the area of Intelligent Control tends to encompass everything that is not characterized as conventional control. The main difficulty in specifying exactly what is meant by the term Intelligent Control stems from the fact that there is no agreed upon definition of human intelligence and intelligent behavior and the centuries old debate of what constitutes intelligence is still continuing, nowadays among educators, psychologists, computer scientists and engineers.

It is appropriate at this point to briefly comment on the meaning of the word intelligent in "intelligent control". Note that the precise definition of "intelligence" has been eluding mankind for thousands of years. More recently, this issue has been addressed by disciplines such as psychology, philosophy, biology and of course by artificial intelligence (AI); note that AI is defined to be the study of mental faculties through the use of computational models. 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.

Intelligent controllers can be seen as machines which emulate human mental faculties such as adaptation and learning, planning under large uncertainty, coping with large amounts of data etc. in order to effectively control complex processes; and this is the justification for the use of the term intelligent in intelligent control, since these mental faculties are considered to be important attributes of human intelligence. An alternative term is "autonomous (intelligent) control"; it emphasizes the fact that an intelligent controller typically aims to attain higher degrees of autonomy in accomplishing and even setting control goals, rather than stressing the (intelligent) methodology that achieves those goals. We should keep in mind that "intelligent control" is only a name that appears to be useful today. In the same way the "modern control" of the 60's has now become "conventional (or traditional) control", as it has become part of the mainstream, what is called intelligent control today may be called just "control" in the not so distant future. What are more important than the terminology used are the concepts and the methodology, and whether or not the control area and intelligent control will be able to meet the ever increasing control needs of our technological society [37]-[40].

The term "intelligent control" has come to mean, particularly to those outside the control area, some form of control using fuzzy and/or neural network methodologies. Intelligent Control, however does not restrict itself only to those methodologies. In fact, according to some definitions of intelligent control not all neural/fuzzy controllers would be considered intelligent. The fact is that there are problems of control today, that cannot be formulated and studied in the conventional differential/difference equation mathematical framework using "conventional (or traditional) control" methodologies; these methodologies were developed in the past decades to control dynamical systems. To address these problems in a systematic way, a number of methods have been developed in recent years that are collectively known as "intelligent control" methodologies.

There are a number of areas related to the area of Intelligent Control. Intelligent Control is interdisciplinary as it combines and extends theories and methods from areas such as control, computer science and operations research. It uses theories from mathematics and seeks inspiration and ideas from biological systems. Intelligent control methodologies are being applied to robotics and automation, communications, manufacturing, traffic control, to mention but a few application areas. Neural networks, fuzzy control, genetic algorithms, planning systems, expert systems, and hybrid systems are all areas where related work is taking place. The areas of computer science and in particular artificial intelligence provide knowledge representation ideas, methodologies and tools such as semantic networks, frames, reasoning techniques and computer languages such as prolog. Concepts and algorithms developed in the areas of adaptive control and machine learning help intelligent controllers to adapt and learn. Advances in sensors, actuators, computation technology and communication networks help provide the necessary for implementation Intelligent Control hardware.

5 Basic Theories of FCM

5.1 Basic Theories

Fuzzy cognitive map is a soft computing technique that follows an approach similar to human reasoning and the human decision-making process. An FCM looks like a cognitive map, it consists of nodes (concepts) that illustrate the different aspects of the system's behavior. These nodes (concepts) interact with each other showing the dynamics of the model. Concepts may represent variables, states, events, trends, inputs and outputs, which are essential to model a system. The connection edges between concepts are directed and they indicate the direction of causal relationships while each weighted edge includes information on the type and the degree of the relationship between the interconnected concepts. Each connection is represented by a weight which has been inferred through a method based on fuzzy rules that describes the influence of one concept to another. This influence can be positive (a promoting effect) or negative (an inhibitory effect). The FCM development method is based on Fuzzy rules that can be either proposed by human experts and/or derived by knowledge extraction methods [1], in such a way that the accumulated experience and knowledge are integrated in the causal relationships between factors, characteristics and components of the process or system modeled [2].

5.2 Mathematical Representation of Fuzzy Cognitive Maps

The graphical illustration of an FCM is a signed directed graph with feedback, consisting of nodes and weighted arcs [15]. Nodes of the graph stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist between the concepts (Fig. 4).

Each concept is characterized by a number A_i that represents its value and it results from the transformation of the fuzzy real value of the system's variable, for which this concept stands, in the interval [0, 1]. Between concepts, there are three possible types of causal relationships that express the type of influence from a concept to the others. The weights of the arcs between concept C_i and concept C_j could be positive ($W_{ij} > 0$) which means that an increase in the value of concept C_i leads to the increase of the value of concept C_j, and a decrease in the value of concept C_i leads to the decrease of the value of concept C_j. Or there is negative causality ($W_{ij} < 0$) which means that an increase in the value of concept C_i leads to the decrease of the value of concept C_j and vice versa. The sign of W_{ij} indicates whether the relationship between concepts C_i and C_j is direct or inverse.

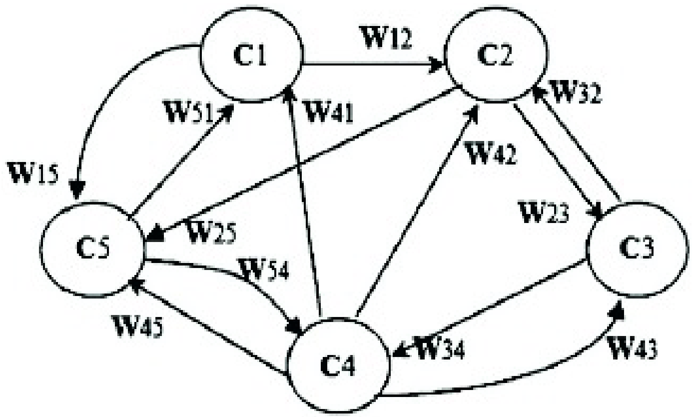

Fig. 4 The fuzzy cognitive map model

The value A_i of concept C_i expresses the degree which corresponds to its physical value. At each simulation step, the value Ai of a concept C_i is calculated by computing the influence of the interconnected concepts C_j's on the specific concept C_i following the calculation rule:

$$A_i^{(k+1)} = f(A_i^{(k)} + \sum_{\substack{j \neq i \\ j=1}}^{N} A_j^{(k)} w_{ji}) \tag{5.1}$$

where $A_i^{(k+1)}$ is the value of concept C_i at simulation step k + 1, $A_i^{(k)}$ is the value of concept C_j at simulation step k, w_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is the sigmoid threshold function:

$$f = \frac{1}{1 + e^{-\lambda x}} \tag{5.2}$$

where $\lambda > 0$ is a parameter determining its steepness. In this approach, the value $\lambda = 1$ has been used. This function is selected since the values A_i of the concepts lie within [0, 1].

We briefly referred to FCMs as further information and details about Fuzzy Cognitive Maps and their theories are outlined analytically in [41].

6 A New DSS Methodology Using Decision Making Analysis and FCMs

6.1 A New Decision Making Support System (DMSS)

So far DSSs research has widened its focus to serve more and more different scientific disciplines. This can be seen from the many papers been published the last10-15 years. Since the 2000s the DSS application in all scientific fields has exploded on a geometric way. The articles analyzed is DSS research published are numerous between 2000 and 2012 in 14 journals: Decision Sciences (DS); Decision Support Systems (DSS); European Journal of Information Systems (EJIS); Information and Management (I&M); Information and Organization (I&O), formerly Accounting, Management and Information Technologies; Information Systems Journal (ISJ); Information Systems Research (ISR); Journal of Information Technology (JIT); Journal of Management Information Systems (JMIS); Journal of Organizational Computing and Electronic Commerce (JOC&EC); Journal of Strategic Information Systems (JSIS); Group Decision and Negotiation (GD&N); Management Science (MS); and MIS Quarterly (MISQ).

It would take many pages to study, investigate and analyze all these papers in a systematic way. We should also mention that there are many other papers that are published in scientific journals of other fields, i.e. in Journals of the Medical field or the Manufacturing area or Fuzzy Systems. All these require a systematic research to analyze and formulate new generic methodologies for the challenging area of DSS.

Till now all different types or formulation of the ''DSS'' has a common denominator; **that decisions are made**. This generates the need to embed the ''Decision Making'' part as a necessary step in the overall integrated effort on taking decisions by humans been contronted by problems in studying and analyzing complex systems. In the present section we justify the need for the new terms of Decision Making Support Systems (DMSS) in which the experts play a major role. In addition on our DMSS approach the Fuzzy Cognitive Maps' theories will be utilized appropriately.

Today more than ever, modeling is rarely a one-shot process and good models, are usually refined and enhanced as their users gather practical experiences with the system recommendations. The generic approach of Decision Making Support System (DMSS) is shown in Fig. 5. Basic prerequisite for the smooth function of the proposed model is that we have a minimum number of experts ($\mathrm{N} \geq 2$).

The new DMSS idea is an innovative approach because we define as a DMSS the relative box shown in Fig. 5 combining for the first time the following (in contrast with the conventional DSS):

a) FCM model
b) Experts ($N \geq 2$)
c) Learning algorithms
d) Decision Making Trees

The significant difference between the proposed generic DMSS and all other DSSs methodologies is that the four components a) to d) are present in any decision process. Please note that existing DSSs methodologies and tools are utilized. It is also very important to note that each one of the four components a) to d) has and plays a different role in the new generic DMSS. It is necessary to fully understand the potential of the FCMs models been combined with appropriate experts and utilizing learning techniques. In order to better understand the Decision Making process some theoretical remarks are provided next.

6.2 Decision Analysis and Fuzzy Cognitive Maps

Decision analysis is based on a number of quantitative methods that aid in choosing amongst alternatives. Traditional decision analysis is used to indicate decisions favoring good outcomes even though there is an uncertainty surrounding the decision itself. Furthermore, the value of each possible outcome of a decision, whether measured in costs and benefits or utility, usually varies [41].

Over the last years, several approaches have been investigated in the field of Decision Analysis, with the most popular one to be used that of Decision Trees (DT). Some methods combine DT with other machine learning techniques, such as Neural Networks [3] or Bayesian Networks [4]. However, very little work has been reported in combining a DT with FCMs. Some research work of this combination has been the literature the last ten years [5]-[8]. In this chapter the technique of combining a DT with an FCM model in Decision Analysis is presented.

The derived FCM model is subsequently trained using an unsupervised learning algorithm to achieve improved decision accuracy. In this chapter, the C4.5 has been chosen as a typical representative of the decision tree approach. Similarly, the Nonlinear Hebbian Learning (NHL) algorithm is chosen as a representative o unsupervised FCM training.

The generic approach of the DT-FCM's function is briefly outlined in Fig. 5. If there is a large number of input data, then the quantitative data are used to induce a Decision Tree and qualitative data (through experts' knowledge) are used to construct the FCM model. The FCM's flexibility is enriched by the fuzzification of the strict decision tests (derived fuzzy IF-THEN rules to assign weights direction and values). Finally, the derived FCM model (new weight setting and structure) is trained by the unsupervised NHL algorithm to achieve a decision [41].

This methodology can be used for three different circumstances, depending on the type of the initial input data: (1) when the initial data are quantitative, the DT generators are used and an inductive learning algorithm produce the fuzzy rules which then are used to update the FCM model construction; (2) when experts' knowledge is available, the FCM model is constructed and through unsupervised NHL algorithm is trained to calculate the target output concept responsible for the decision line; and (3) when both quantitative and qualitative data are available, the initial data are divided and each data type is used to construct the DTs and the FCMs separately. Then the fuzzy rules induced from the inductive learning restructure the FCM model enhancing it. At the enhanced FCM model the training algorithm is applied to help FCM model to reach a proper decision.

The new technique has three major advantages. First, the association rules derived from the decision trees have a simple and direct interpretation and introduced in the initial FCM model to update its operation and structure. For example, a produced rule can be: If the *variable 1* (input variable) has *feature A* Then the *variable 2* (output variable) has *feature B*.

Second, the procedure that introduces the Decision Tree rules into an FCM also specifies the weight assignment through the new cause-effect relationships among the FCM concepts. Third, as will be demonstrated through the experiments, this technique fares better than the best Decision Tree inductive learning technique and the FCM decision tool.

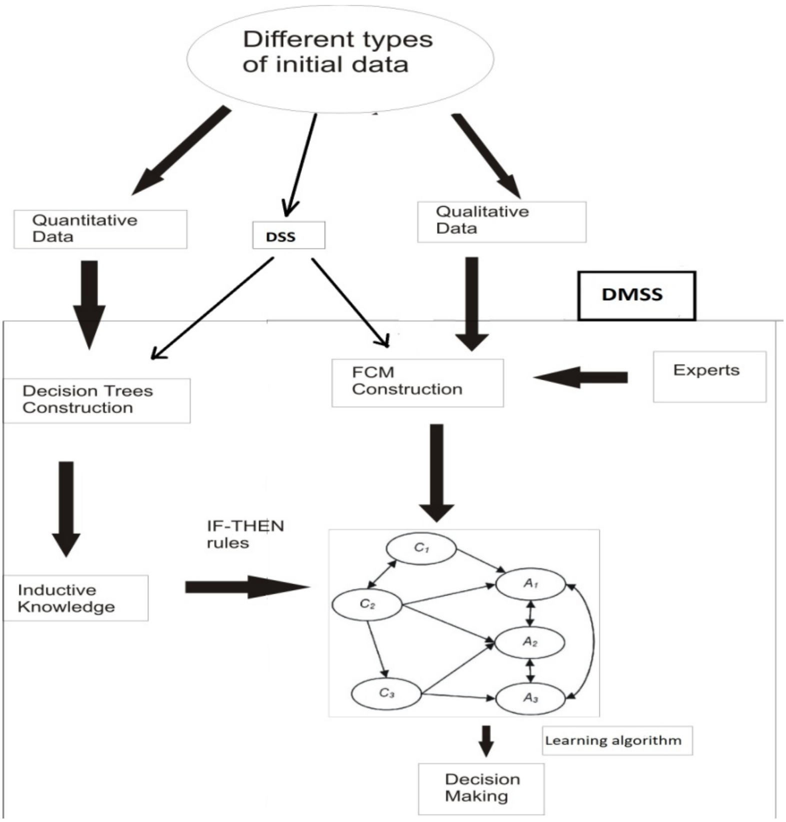

Fig. 5 The proposed generic approach of Decision Making Support System

7 Case Studies

The method used to develop and construct a Decision Making Support System (DMSS) using FCMs has considerable importance in order to represent the policy decision procedure as accurately as possible. The methodology described here extracts the knowledge from the experts and exploits their experience of the process [9].

The appropriate experts, consisting in most cases of interdisciplinary teams, determine the number and kind of concepts that comprise the FCM models of the DMSS. Each expert from his/ her experience knows the main factors that contribute to the decision; each of these factors is represented by one concept of the FCM. The expert also understands potential influences and interactions between factors themselves or between factors and decisions, thus establishing the corresponding fuzzy degrees of causation between concepts. In this way, an expert's knowledge is transformed into a dynamic weighted graph, the DMSS using FCMs. Experts describe the existing relationship between the concepts firstly, as ''negative'' or ''positive'' and secondly, as a degree of influence using a linguistic variable, such as ''low'', ''medium'', ''high'', etc.

More specifically, the causal interrelationships among concepts are declared using the variable *Influence* which is interpreted as a linguistic variable taking values in the universe of discourse U = [-1, 1]. Its term set T(influence) is suggested to be comprised of eight variables. Using eight linguistic variables, an expert can describe in detail the influence of one concept on another and can discern between different degrees of influence. The nine variables used here are: T(influence) = {zero, very very low, very low, low, medium, high, very high, very very high, one}. The corresponding membership functions for these terms are shown in Fig. 6 and they are μ_z, μ_{vvl}, μ_{vl}, μ_l, μ_m, μ_h, μ_{vh}, μ_{vvh} and μ_0. A positive sign in front of the appropriate fuzzy value indicates positive causality while a negative sign indicates negative causality.

Once one expert describes each interconnection as above, then, all the proposed linguistic values for the same interconnection, suggested by experts, are aggregated using the SUM method and an overall linguistic weight is produced, which with the defuzzification method of center of area (COA), is transformed to a numerical weight w_{ji}, belonging to the interval [-1, 1]. A detailed description of the development of FCM model is given in [2].

Generally, the value of each concept at every simulation step is calculated, computing the influence of the interconnected concepts to the specific concept [9]-[10], by applying the following calculation rule:

$$A_i^{(k+1)} = f(k_2 A_i^{(k)} + k_1 \sum_{\substack{j \neq i \\ j=1}}^{N} A_j^{(k)} w_{ji}) \tag{7.1}$$

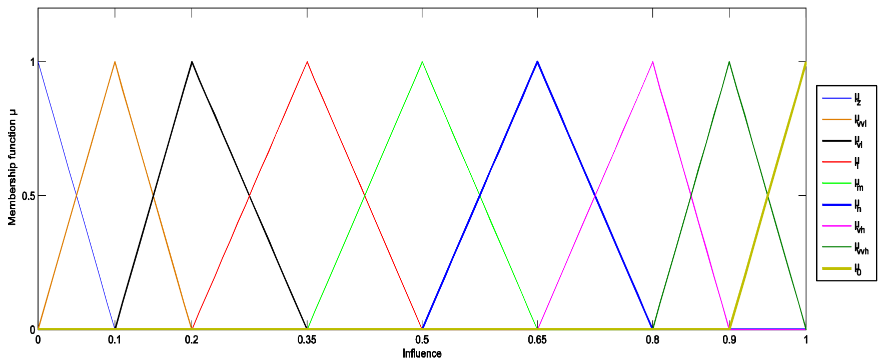

Fig. 6 Membership functions of the linguistic variable *Influence*

where $A_i^{(k+1)}$ is the value of the concept C_i at reputation step k+1, $A_i^{(k)}$ is the value of the concept C_j at iteration step k, w_{ij} is the weight of interconnection from concept C_j to concept C_i and f is the sigmoid function. The k_1 expresses the influence of the interconnected concepts in the configuration of the new value of the concept A_i and k_2 represents the proportion of the contribution of the previous value of the concept in the computation of the new value.

The sigmoid function f belongs to the family of squeezing functions, and usually the following function is used:

$$f = \frac{1}{1+e^{-\lambda x}} \tag{7.2}$$

This is the unipolar sigmoid function, where $\lambda>0$ determines the steepness of the continuous function $f(x)$. The following examples show how the FCMs lead to the proposed decision making approach strictly following the experts' knowledge.

<u>Example_7.1: Decision Making in Hybrid Renewable Energy System using FCMs</u>

In this example it is considered that $k_1=k_2=1$, $\lambda=1$ and an initial matrix $w^{initial}=[w^{ij}]$, i,j=1,…,N, with $w_{ii}=0$, i=1,…,N, is obtained.

In the current Decision Making Analysis model there are two decision concepts (outputs), i.e. the two renewable energy sources are studied: concept 4 PV-System and concept 5 Wind-Turbine-System. The factor concepts are considered as measurements (via special sensors) that determine how each RES will function in this model and they are:

- C_1 : insolation (kW_p/m^2)
- C_2 : temperature
- C_3 : wind
- C_4 : PV-System
- C_5 : Wind-Turbine-System

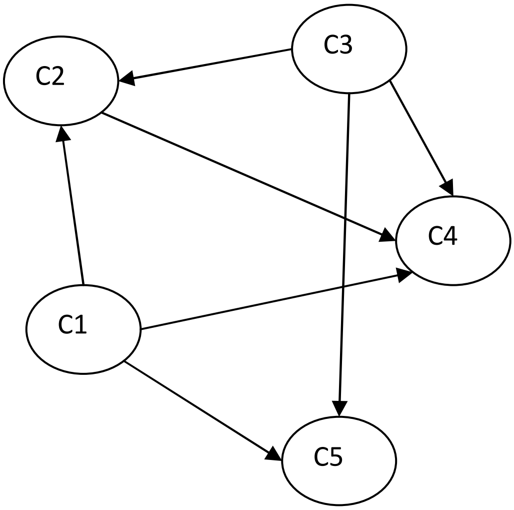

Fig. 7 A conceptual model for Hybrid RES System

Table 1 Weights between concepts for FCM for Hybrid RES System

	C1	C2	C3	C4	C5
C1	0	0.15	0	0.82	0.1
C2	0	0	0	-0.24	0
C3	0	-0.15	0	0.26	0.76
C4	0	0	0	0	0
C5	0	0	0	0	0

In order to show how the crisp values of the weights created in Table_1, we are going to give a specific example for the calculation of the crisp value of a single weight describing the correlation between node C2 (temperature) and node C4 (PV-Systems' performance). Preferences of three experts on how they define this correlation follow:

1st expert:
If a small change happens in node C_2 then a very very low change is caused in node C_4

Infer: Influence from concept C_2 to C_4 is negatively very very low

2nd expert:
If a small change happens in node C_2 then a very low change is caused in node C_4

Infer: Influence from concept C_2 to C_4 is negatively very low

3rd expert:

If a small change happens in node C_2 then a low change is caused in node C_4

<u>Infer:</u> Influence from concept C_2 to C_4 is negatively low

Fig 8 shows the three linguistic variables which are being proposed:

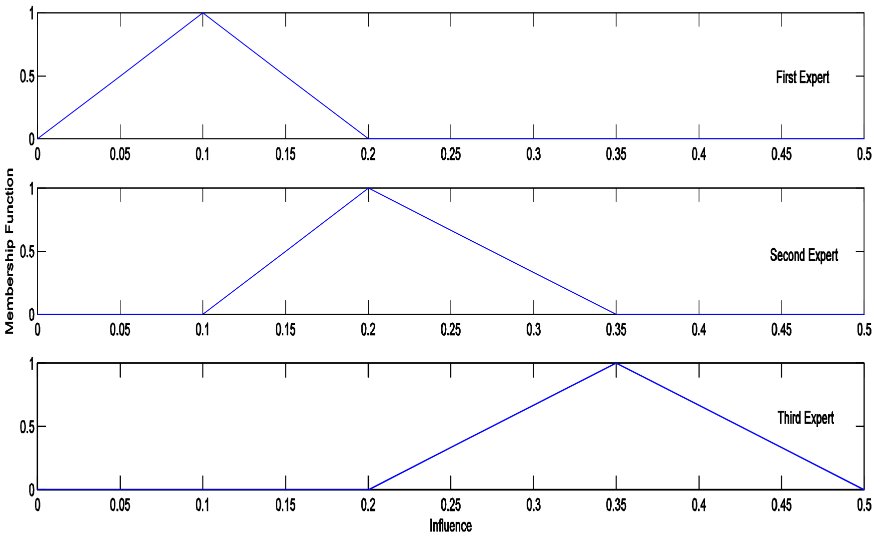

Fig. 8 Example of the three linguistic variables proposed by three experts to describe the correlation among two concepts

These linguistic variables (very very low, very low, low) are aggregated and a total linguistic weight is produced, which is transformed into a crisp value w24=-0.2389 after the CoA defuzzyfication method (Fig. 9).

The same procedure was followed for the determination of the rest weights of the FCM model. A weight matrix $w^{initial}$ which contains the initial proposed weights of all interconnections among the concepts of the FCM model is shown in Table_1.

Detailed information for hybrid renewable energy systems are given in [11]-[14]. One case study from the literature is examined here concerning the decision making approach of hybrid renewable energy source system. In Table 2 the initial factors used by the model are presented. In addition, the degree of occurrence of each factor is denoted with qualitative degrees of very very high, very high, high, medium, low, very low, and 0 for insolation (C1), low, medium, high and very high for temperature (C2) and for wind (C3). Respectively for the output concepts C4, C5 the qualitative degrees are low, medium and high. C4 and C5 are considered a % percentage of the maximum performance at STC conditions.

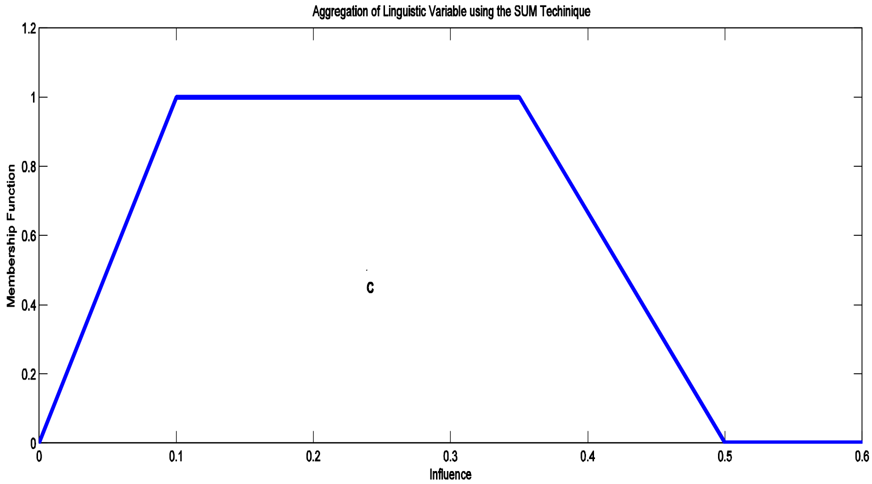

Fig. 9 Aggregation of the three linguistic variables using the SUM method. The C point is the crisp value of the relative weight after the *CoA* defuzzyfication method

Case_1 (without training algorithm)

Table 2 Initial factor-concepts fuzzy value

Factor-concepts	Case 1
C1	VVH
C2	M
C3	M

The initial values of the outputs were set equal to zero.

Table 3 Final decision-concepts

Decision-concepts	Case 1
C4 (PV-System)	**0.7937**
C5 (Wind-Turbine-System)	**0.7963**

The iterative procedure is being terminated when the values of C_i concepts has no difference between the latest two iterations. Considering $\lambda=1$ for the unipolar sigmoid function and after $N=10$ iteration steps the system reaches an equilibrium point.

We considered initial values for the concepts after COA defuzzyfication method [31]-[34]:

$$A^{(0)} = [0.90\ 0.3334\ 0.3334\ 0.839\ 0.459]$$

The fuzzy rule considered for the calculation of the initial conditions of the output concepts C4, C5 follows:

- ***If*** C1 is VVH ***and*** C2 is M ***and*** C3 is M ***Then*** C4 is VVH ***and*** C5 is M;

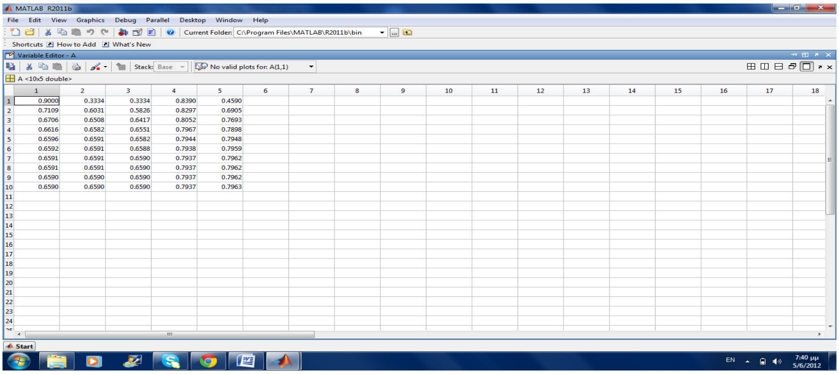

Fig. 10 Value of concepts for each iteration step

It is observed that in the latest three iterations there is no difference between the values of concepts C_i. So after 10 iteration steps, the FCM reaches an equilibrium point where the values do not change any more from their previous ones, that is:

$$A^{(10)} = [0.6590\ 0.6590\ 0.6590\ \mathbf{0.7937}\ \mathbf{0.7963}]$$

Finally it is observed that the PV-System (C_4) and the Wind-Turbine-System (C_5) function under the 79.37% and 79.63% of their optimum performance in STC conditions respectively.

Case_2 (with Nonlinear Hebbian Training algorithm)

Firstly the experts suggested us a desired region where the decision output concepts (DOCs) should move. The desired regions for the output nodes reflect the prospered operation of the modeled system.

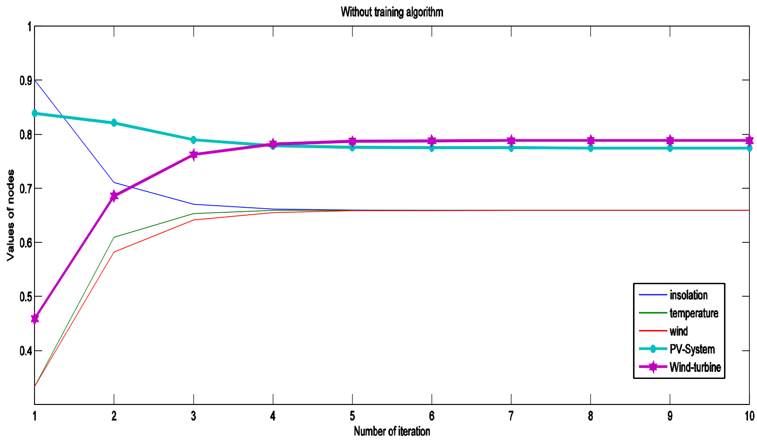

Fig. 11 Subsequent values of concepts till convergence

$$0.72 \leq DOC_4 \leq 0.83$$
$$0.70 \leq DOC_5 \leq 0.85$$

Basic factor of the NHL algorithm is the minimization of two basic criterion functions in order to have a convergence after a finite number of iteration steps [16]-[17]:

$$F1 = J1 = \ \|DOC_i - T_i\|_2^2 < 0.005$$

and

$$F2 = J2 = \ \left|DOC_i^{(k)} - DOC_i^{(k-1)}\right| < 0.005$$

where T_i is the hypothetic desired value of the output and it is usually the average of the defined range by the experts. Basic idea of the NHL algorithm is the adaption of the initial ($w_{ij}^{initial}$) matrix weights defined by the experts in a way that the Decision Output Concepts converge inside the desired region:

$$w_{ij}^{(k)} = \gamma * w_{ij}^{(k-1)} + \eta * A_j^{(k-1)}\left(A_i^{(k-1)} - sgn\left(w_{ij}\right) * w_{ij}^{(k-1)} * A_j^{(k-1)}\right) \quad (7.3)$$

Each non-zero element of the final weight matrix w_{ij}^{final} has been improved and has been converged into an optimal value according to the specific criteria functions of the problem. We could define an acceptable range of change for these weights. If one weight takes a value out of the desired regions then we should consider it better whether experts' suggestion of the initial value of the weight is correct or not, i.e.:

if $\left|w_{ij}^{final} - w_{ij}^{initial}\right| > l$ then that means that concept C_i has a different relationship (than the initial defined from the experts one) with concept C_j and their correlation should be reevaluated.

The learning parameters γ, η of the above equation are very important and they usually take values between $\gamma \ni [0.9, 1]$ and $\ni [0, 0.1]$.

Defining the initial values of the concepts:

$$A^{initial} = [0.90\ 0.3334\ 0.3334\ 0.839\ 0.459]$$

we take the following after 7 iterations:

$$A^{final} = [0.6592\ 0.6761\ 0.6588\ \mathbf{0.8003\ 0.7991}]$$

It is observed that the values of the concepts C_4, C_5 in the final state are inside the suggested desired regions.

Example_7.2: Decision Making for the Stability of an Enterprise in a Crisis Period using FCMs

In this example it is considered that k1=k2=1, λ=1 and an initial matrix winitial=[wij], i,j=1,…,N, with wii=0, i=1,…,N, is obtained

In the current DMA model there is one decision concept (output), i.e. the stability of an enterprise in a crisis period is studied: concept_8. The factor concepts are considered as measurements (via special statistic research) that determine how each measurement-concept will function in this model and they are:

- C_1 : sales
- C_2 : turnover
- C_3 : expenditures
- C_4 : debts & loans
- C_5 : research & innovation
- C_6 : investments
- C_7 : market share
- C_9 : present capital

- **C_8 : stability of enterprise (output of the system)**

At this point it should be noted that in economic systems we can’t talk about causality but only for correlation between the defined factor-concepts of this problem. Experts noted that the acceptable-desired region for the final value of concept C8 is:

$$0.70 \leq C_8^{(final)} \leq 0.95$$

If $C_8^{(final)}$ is inside this region then we can say with great certainty that the enterprise is out of danger and the economic crisis period does not put at risk the stability and the smooth function of the enterprise.

Weights in table_4 are determined after defuzzifying (with COA method) the fuzzy values that were given from the experts (mostly economists) [18]-[24].

Table 4 Weights between concepts for CFCM for Hybrid RES System

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0	0.6	0	-0.4	0.2	0.3	0.6	0.8	0
C2	0	0	0	-0.2	0.2	0.5	0.1	0.3	0
C3	0	0	0	0.4	-0.5	-0.4	0	-0.6	-0.5
C4	0	0	-0.4	0	-0.7	-0.8	0	-0.7	-0.4
C5	0.2	0.3	0	0	0	0.5	0.3	0.2	-0.2
C6	0.3	0.2	0.6	0.5	-0.3	0	0.3	0.3	-0.4
C7	0.4	0.3	0	-0.2	0	0	0	0.4	0.5
C8	0	0	0	0	0	0	0	0	0
C9	0	0	0	-0.3	0.2	0.4	0	0.2	0

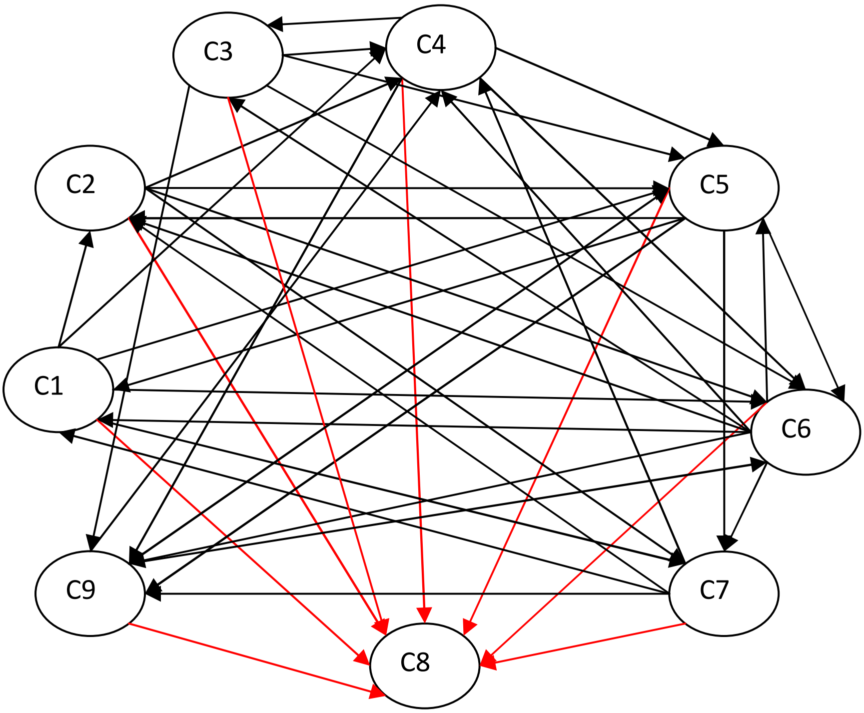

Fig. 12 A conceptual FCM model for Stability of the Enterprise

In addition, the degree of occurrence of each input-concept factor is denoted with qualitative degrees of *high, medium,* and *low*. Respectively for the output concept C8 the qualitative degrees are *very low*, *low, medium, high* and *very high*.

Table 5 Initial factor-concepts fuzzy value

Factor-concepts	Case 1
C1	H
C2	M
C3	L
C4	L
C5	M
C6	L
C7	L
C9	M

The initial values of the outputs were set equal to zero.

Table 6 Final decision-concepts

Decision-concepts	Case 1
C8 (Stability of the Enterprise)	**0.8391**

The iterative procedure is being terminated when the values of C_i concepts has no difference between the latest three iterations. Considering $\lambda=1$ for the unipolar sigmoid function and after 11 iteration steps the FCM reaches an equilibrium point.

We considered initial values for the concepts:

$$A^{(0)} = [0.8867\ 0.4667\ 0.0967\ 0.0967\ 0.4667\ 0.0967\ 0.0967\ 0.65\ 0.4667]$$

The fuzzy rule considered for the calculation of the initial condition of the output concept C8 follows:

- ***If*** C1 is H ***and*** C2 is M ***and*** C3 is L ***and*** C4 is L ***and*** C5 is M ***and*** C6 is ***and*** C7 is L ***and*** C9 is M ***Then*** C8 is VVH;

It is observed that in the latest three iterations there is no difference between the values of concepts C_i . So after 11 iteration steps, the FCM reaches an equilibrium point where the values do not change any more from their previous ones, that is:

$$A^{(11)} = [0.8140\ 0.8708\ 0.7145\ 0.6121\ 0.4743\ 0.7462\ 0.8581\ \mathbf{0.8391}\ 0.4779]$$

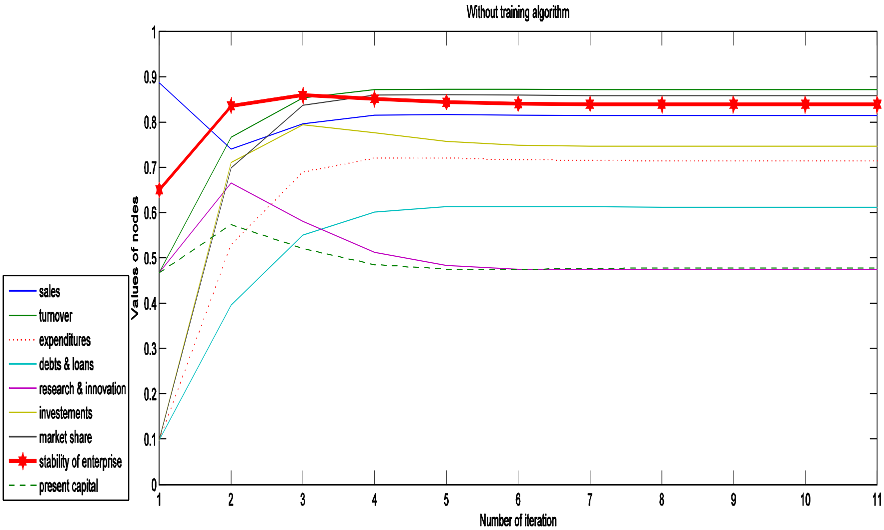

Fig. 13 Subsequent values of concepts till convergence

Since the final value of $C_8^{(final)}$ is inside the acceptable region, defined by the experts, then we could assume with great certainty that the enterprise can survive the crisis period.

8 The Five Steps Approach to Success (5-SAS)

In order to achieve an optimal Decision Making Support System (DMSS) a new five steps approach is proposed:

1) Determine the final objective. The final objective should be realistic. Be optimistic and self-confident. You can reach no goal if you don't believe it. ''**Think Different**'' was an advertising slogan for Apple Computer in 1997. We borrowed the last words of this slogan and advise everyone with the following: '' *…while some see them as the crazy ones, we see genius. Because the people who are crazy enough to think they can change the world, are the ones who do*.''
2) Justify the reasons you want to reach your goal. If you want your reasons to meet the objective you have to choose realistic and reasonable ones. So ***if*** your reasons are reasonable ***then*** continue the procedure ***else*** redefine the final objective.
3) Define the initial conditions of the system. Specify analytically the present state of the system and possible reasons for justifying it. ***If*** the process is stochastic ***then*** continue the procedure ***else*** follow conventional methods.

4) Perform a systematic mathematical approach to solve the well defined problem. Then identify all possible/available methods and solutions. ***If*** there is at least one available solution ***then*** continue the procedure ***else*** try to investigate other solutions. ***If*** there is no method-solution ***then*** stop for the moment and start a research effort to generate a new method-solution. This might need alliance and/or close collaboration with other scientists.
5) Decide the optimal solution regarding specific criteria (cost-functions) according to the problem, i.e.: a) Realistic , b) Cost-effective, c) Executable, d) Reasonable and e)Time-effective.

Now applying the Five-Steps Approach to Success (5-SAS) into the DMSS, exploiting experts' knowledge and FCMs, will help to decide an acceptable solution.

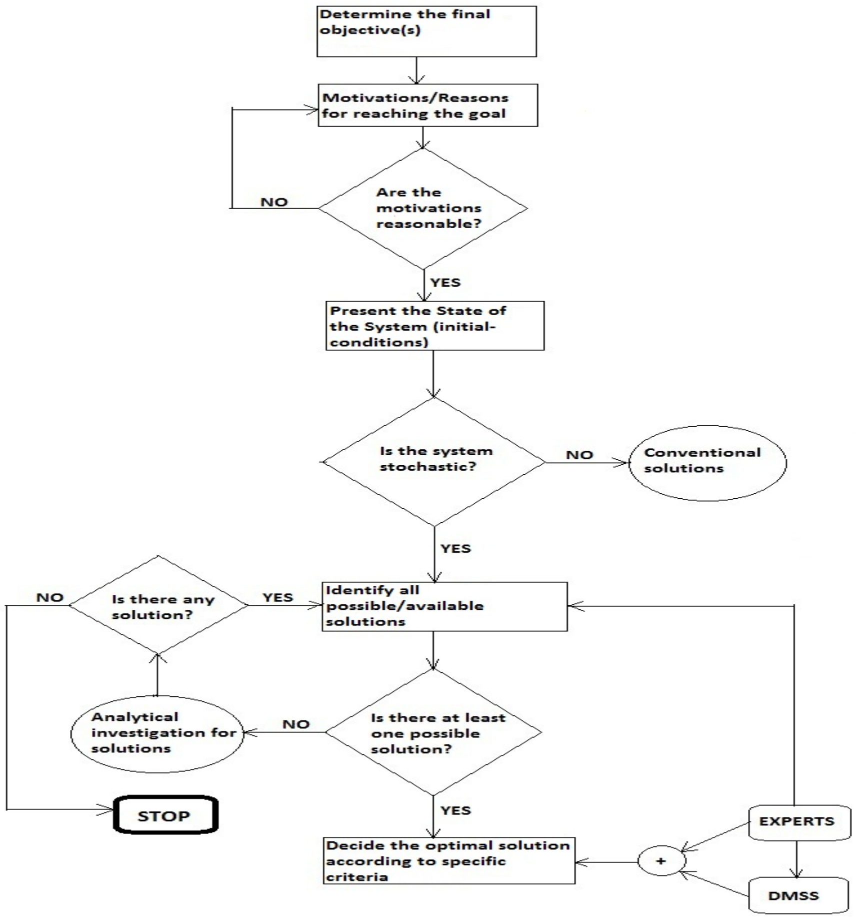

Fig. 14 Flowchart of the Five Step Approach

This Five Step Approach (5-SAS) can and should be used when implementing DMSS methodologies. Especially this 5-SAS will be very useful when specific problems of complex systems (health, energy, agriculture, finance, environment, etc.) are considered, analyzed and investigated.

9 Future Research

By studying and analyzing most of DSS's research papers over the last 10 years as well as after studying the previous sections of this chapter a number of very interesting and challenging topics can be identified for further research.

There are a number of excellent theoretical and applied scholarly "results" on the broad concept of DSS. However there is no integral and unified theory behind all these techniques. Moreover, there is a sincere skepticism of even the possibility of developing such a theory. Many practitioners of human DMSSs note the significant gap between theoretical research and application. The proposed new DMSS in this chapter could be used as a starting point searching for such a unified theory. It is very interesting and promising the fact that in the proposed DMSS using experts, learning techniques and FCM's theory a new mathematical formulation is obtained and further research could enhance the capabilities of human decision makers.

It is known that, using the AHL algorithm, the FCM model is improved and the weights W are determined using a number of experts, so that the a new weight matrix can be used for the same initial values of concepts, but arriving on different final values. This gives new perspectives in searching for a more efficient and active DMSSs. The link of the AHL algorithms and their positive contributions to further, explore the potential of DMSS in solving problems of complex systems. This direction can be pursued in searching for new Evolutionary Computation Learning Algorithms for specific applications. It should be emphasized that the AHL is problem- dependent and although it starts using the initial weight matrix, but throughout the process of DM is independent from the initial conditions of the system. This needs further investigation

The new proposed DMSS algorithm needs to be fully developed on a more generic software platform. Then with appropriate changes it should be available for daily use when real-time data from a given application are provided. Special attention must be paid as to how the experts are selected and used on a real DMSS application.

The Five Steps Approach to Success (S-SAS) needs further mathematical development so it can be used on many real-life applications. Again the importance of using N-experts in the proposed methodology should not be underestimated. The most significant weakness of the new DMSS is their dependence on the experts beliefs been used to construct the FCMs and their potential convergence to undesired or unrealistic states of the complex system. This however can be further investigated by introduction new unsupervised learning methods for FCM training which then in return improves further the credibility and reliability of the new proposed DMSS methodology including the 5-SAS.

Another area for future research is to explore the current trends in mobile computing. Mobile computing is a facilitator that provides the means for the user to interact with existing systems, regardless of the location of either the user or the system. Mobile devices provide a new platform for DMSSs that challenges traditional approaches to DSSs. The size, speed, and reach of “scientific data” combined with continuously available support introduce a substantial technological advantage to Decision Making (DM). Mobile devices capture “scientific data” and allow for real-time monitoring or updating of data from the field, which, in turn, can be fed back into the decision loop. Mobile computing has complexities that will require some theoretical foundational work, however although the technology exists, connect users to resources can be difficult. Thus the need to explore both the technology and the use of the technology in real DMSSs. A new system is needed to coordinate collaborative intelligent systems using FCMs designed specifically for mobile applications.

10 Summary and Closing Remarks

Decision Support Systems (DSS) are powerful tools integrating methods from different scientific fields for supporting difficult decisions been made when problems for complex systems are investigated. DSS are gaining an increased popularity in many domains. More and more people have the need to use DSS software tools in their everyday life. They are especially valuable in situations in which the amount of available ‘’information’’ or ‘’scientific data’’ is prohibitive for the human mind to reach an ‘’optimal’’ and/or ‘’acceptable’’ decision. However in this process ‘’precision’’ and ‘’optimality’’ are of great importance to the decision maker.

In this chapter the historical commentary, starting from the Delphi Oracle to present DSS is less prescriptive than other works on other scientific fields. However it highlights the plethora of DSS theoretical research and their application to various scientific fields for the last 50 years or so. Nevertheless in this chapter a critical overview of the theoretical, research and application results been published in the broad field of DSS has been provided. It is very interesting to follow the development of the field of DSS, which in less than 20 (last) years has shown a great research interest, in order to embed to the whole procedure the philosophy of the ‘’Decision Making’’ and not just the ‘’Decision Support’’. Expansion of Internet and Communications is a promising environment for developing a Decision Making Support System (DMSS) tool/software for professionals and researchers in many scientific fields.

This chapter revealed the need of Decision Making (DM) and not only Decision Support Systems (DSS). The conventional DSS rarely contained the ‘’Decision Making’’ part as an integrated step in the overall decision making loop. One of the major obstacles of the effectiveness of this process is uncertainty. Combination and collaboration of Fuzzy Cognitive Maps (FCMs), experts, data base, learning algorithms and the decision making process leaded us to the proposed Decision Making Support System (DMSS). This could provide a new step towards the minimization of the uncertainty.

Rapid growth of Internet and other networking technologies such as broadband WAN's, LAN's and WIP provide full and easy accessibility in data-base of many scientific fields. This way we don't just trust experts' knowledge but we can also compare it with past data-base and historical facts in order to make the experts selection procedure more reliable and interactive.

Given problems of complex systems in the presence of nonlinearities, uncertainties, impression or complexity can now be investigated in a new promising way through the proposed DMSS. Future direction of this research could be the development of a DMSS-FCM tool for daily use under real-time data. In this way the new FCM model will become more dynamic and flexible. The included nodes/concepts will tend to behave more and more like neurons of a real nervous system. This will further improve Decision Making of humans taking into consideration the various human factors of different experts but with one main objective: to improve the human performance.

However, there is an important difference: single man's nervous system provides only decisions in limited scientific fields and not always an acceptable and implementable one. The proposed DMSS-FCM model will provide decisions in any scientific field with certainties of acceptability and feasibility.

This chapter, therefore, can be useful to a broad spectrum of professionals, researchers and students in many scientific fields. Moreover it can be a starting point for a more interdisciplinary research work on all these different fields.

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