Preprints of the 18th IFAC World Congress
Milano (Italy) August 28 - September 2, 2011

Medical Decision Support Systems based on Soft Computing techniques

Chrysostomos D. Stylios* and Voula C. Georgopoulos**

**Knowledge and Intelligent Computing Laboratory, Dept. of Informatics and Telecommunications Technology, Technological Educational Institute of Epirus, 47100, Artas, Greece (+302681050330, email: stylios@teiep.gr)*

*** Department of Speech and Language Therapy, Technological Educational Institute of Patras, Koukouli 26334, Patras, Greece (email: voula@teipat.gr)*

Abstract: Medical Decision Support Systems (MDSS) are very important constructions that are incorporated into Intelligent Information E-Health Systems aiming to produce warnings or to consult and suggest clinical judgments either to inexperienced medical professionals or in their lighter versions to the general public through medical advisors websites. Soft Computing (SC) techniques, especially those that are based on exploiting human knowledge and experience, are extremely useful to model complex decision making procedures and thus, they have a key role in development such MDSS. Such a modeling methodology is Fuzzy Cognitive Maps which is suitable to represent human reasoning and to infer conclusions and decisions in a human-like way. In order to develop an integrated stand alone MDSS, Fuzzy Cognitive Maps could be complemented by other Soft Computing techniques such as Genetic Algorithms and/or Case Based Reasoning and so to construct more efficient advanced Medical Decision Support Systems. The synergism and complementary of these methodologies may pave the way to new sophisticated systems.

1. INTRODUCTION

Medical Decision Support Systems are mainly used to consult and support medical professionals. Most of the times they are developed in methodologies to resemble human-like decision making procedures. Soft Computing modeling methodologies such as Fuzzy Cognitive Maps (FCMs) are similar to the human reasoning approach and they have been successfully employed in the development of sophisticated systems that have been effectively applied in a variety of application domains. Human knowledge and experience is reflected in the creation procedure and the infrastructure of FCMs making them suitable for modeling the decision-making and reasoning approach in a human like manner. Human experts that have observed and know the operation of system and its behavior under varying circumstances develop the FCM structure. Especially, in the medical field, the decision making procedure is often crucial and must be achieved in a timely manner.

Fuzzy Cognitive Maps is a modeling approach to resemble human reasoning and so, it relies on the human expert knowledge for a domain, making associations along generalized relationships between domain descriptors, concepts and conclusions. FCMs are an illustrative causative representation for the description and modeling of any system. Fuzzy Cognitive Maps model any real world system as a collection of concepts and causal relations between concepts. An FCM is illustrated as a causal graphical representation consisting of interrelated concepts (Kosko, 1986). FCMs are fuzzy signed directed graphs permitting feedback, where the weighted edge w_{ij} from causal concept C_i to affected concept C_j describes the amount by which the first concept influences the latter, as is illustrated in Fig. 1.

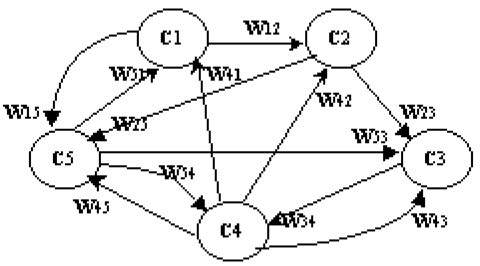

Fig. 1. The Fuzzy Cognitive Map model.

Soft Computing and Computational Intelligence techniques such as Fuzzy Cognitive Maps (FCMs), Genetic Algorithms (GAs) and others have been proposed and successfully employed for developing intelligent systems. These kinds of approaches can be used complementary so that they can be effectively applied in many different application domains. Both techniques incorporate knowledge, experience and historical information and data in order to handle and solve real world problems. Knowledge and experience is reflected in the developing procedure and the infrastructure of FCMs, which are suitable to model the reasoning process of making decisions or, more specifically in the medical field, for reaching a diagnosis. On the other hand, GAs belong to adaptive methods exploiting existing data which are mainly used to solve search and optimization problems. They originate from the genetic processes of biological organisms. Genetic algorithms (GAs) represent an advanced methodology based on a random selection within a defined search space to solve a problem.

Fuzzy Cognitive Maps have been successfully used to develop Decision Support Systems (FCM-DSS) for differential diagnosis (Georgopoulos, *et al.*, 2003), to determine the success of the radiation therapy process estimating the final dose delivered to the target volume (Papageorgiou *et al,* 2003) and many other applications. FCMs are particularly well suited for such applications, since medical systems are complex systems involving inexact, uncertain, imprecise and ambiguous information (Sprogar *et al.,* 2002). For the paradigm from obstetrics, where, in essence, there are two opposing decisions, a FCM approach could support the obstetrician, particularly in situations where there are associated risks to the mother and/or baby. This is due to that fact that: a) there are many physiologic parameters (for “each” patient) and b) there is a high degree of subsystem interactivity.

In obstetrics the potential risks of an adverse outcome often affect 2 patients (mother and infant) and a perinatal injury affecting an infant can have considerable long-term consequences. A recent study (Pettker, 2011) reports that is estimated that adverse events involve 2% to 10% of obstetrical cases.

However, there are problems where the input information is not adequate and FCM-DSS cannot discriminate and reach a decision; this surfaces the need of a mechanism to supplement the FCM-DSS. For such systems exploitation of the optimization properties of Genetic Algorithms for selected weighted edges w_{ij} of the FCM-DSS may lead to more confident decisions.

2. FUZZY COGNITIVE MAPS FOR MEDICAL DECISION SUPPORT SYSTEMS

Fuzzy Cognitive Maps have been used to develop Medical Decision Support System (MDSS). A specific type for Medical Diagnosis is the Competitive Fuzzy Cognitive Map (CFCM) (Georgopoulos and Stylios, 2003, 2004) and it consists of two main types of concepts: diagnosis-concepts and factor-concepts. Fig.2 illustrates an example CFCM model which is used to perform medical diagnosis. Here the concepts of the FCM and the causal relations among them that influence concepts and determine the value of diagnosis concepts indicating final diagnosis are illustrated.

Here in the CFCM model each diagnosis concept represents a single diagnosis, which means that these concepts must be mutually exclusive because the main intention is to infer always only one diagnosis. This is the case of most medical applications, where, according to symptoms, medical professionals conclude to only one diagnosis and then decide accordingly concerning the treatment. The general diagnosis procedure is a complex process that has to take under consideration a variety of interrelated factors and functions. Usually, in any real world diagnosis and decision problem, many different factors are taken into consideration. In accomplishing any diagnosis process, some of these factors are complementary, others are similar and even others are conflicting.

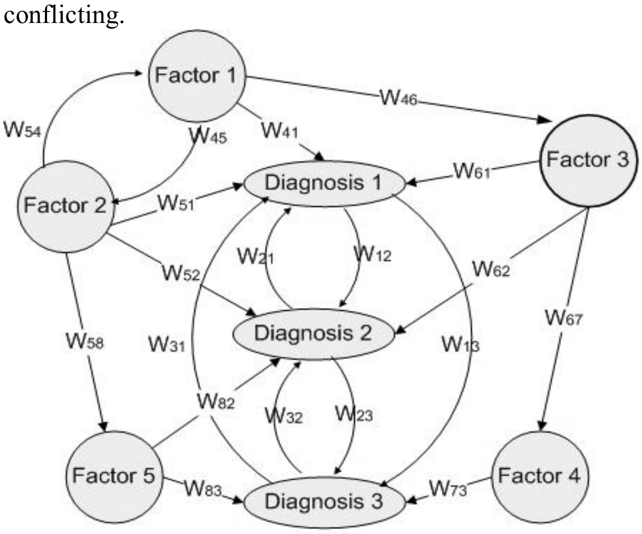

Fig. 2. A CFCM model for Medical Diagnosis.

The factor-concepts can be considered as inputs of the MDSS from patient data, observed symptoms, patient records, experimental and laboratory tests etc, which can be dynamically updated based on the system interaction, whereas the decision-concepts are considered as outputs where their estimated values outline the possible diagnosis for the patient. However, the real strength of FCMs is their ability to describe systems and handle situations where there are feedback relationships and relationships between the factor concepts. Thus, interrelations between factor-concepts can be included in the proposed medical decision-support model. Such interconnections are shown in Fig. 2 where the “competitive” interconnections between diagnosis concepts are also illustrated.

3. GENETIC ALGORITHMS

Genetic algorithm (GAs), based on the genetic evolution of a species were introduced by Holland (1975). They are adaptive methods, based on the genetic processes of biological organisms, which may be used to solve search and optimization problems. Potential solutions to specific problems are encoded using simple data structures similar to chromosomes. These chromosomes make up an initial population where each individual chromosome is assigned a "fitness score" according to how good a solution to the problem it is. The higher the fitness score the more opportunity they have to produce “offspring” through mechanisms of mutation, selection and crossover as defined in (Goldberg, 1989) retaining some desirable properties from the parents. In this way, the population members cover the search space based on selection rules and parameters specified and convergence towards the optimal solution occurs, with a tendency to detect local optima and ultimately to find the global optimum. Genetic algorithms are particularly effective for problems where i) the cost function or its gradient are not defined analytically, ii) the cost function has many local minima, iii) there is a large number of variables is large, or iv) there is requirement for application of many and/or complex constraints.

Originally, genetic algorithm populations were only binary valued but other coding types have been considered, such as Real Coded Genetic Algorithms (RCGA) (Janikow and Michalewicz, 1991), for optimization problems of parameters with variables in continuous or discontinuous domains. The theory and workings of genetic algorithms is beyond of the scope of this paper and can be found in (Whitley, 1994).
Genetic Algorithms have been successfully employed to Fuzzy Cognitive Maps by (Stach et al., 2005; 2007) to optimize the learning process.

Genetic Algorithms have also been successfully used for Medical Decision Support either alone or in combination with other techniques, particularly in the area of diagnosis (Dybowski *et al.,* 1996; Vinterbo, S. Ohno-Machado, 2000; Liang *et. al* 2000; Tan *wt al,* 2000). GAs are designed to evaluate existing potential solutions as well to generate new (improved) solutions to a problem for evaluation. Thus, GAs can improve the quality of decision making.

In previous work the synergy of the two techniques resulted in a Genetic Algorithm Factor Interaction Competitive Fuzzy Cognitive Map (GAFI-CFCM) Diagnostic Support Model (Georgopoulos and Stylios, 2009) which was developed and employed for the differential diagnosis of language impairments.

The following section discusses the extension of the GAFI-CFCM for a .Medical Decision Support System in labor.

4. ADVANCED MEDICAL DECISION SUPPORT SYSTEM

It is concluded from the previous sections that both FCM and GA techniques have been successfully used in the medical domain to perform diagnosis tasks and develop Medical Decision Support Systems. Here, an advanced MDSS is proposed based on the complementary use of FCMs and GA that constitutes an advanced hybrid inferring methodology. When the CFCM has difficulty to infer a decision with great certainty, then the GA is called to assist the CFCM, so that the hybrid MDSS can recommend a decision.

Figure 3 diagrammatically shows the GA enhanced CFCM Medical Decision Support Model. Here the patient data is input to the CFCM and the factor concepts take their initial values from this input data. Patient information are experimental results, test results, physical examinations and other descriptions of symptoms and measurements of physical qualities. This information can be described either in numerical values or in fuzzy linguistic weights which are then transformed into a numerical weight in the range [0,1], i.e. the allowable values for the CFCM concepts. The CFCM runs according to the algorithm described in (Georgopoulos and Stylios, 2003) and when an equilibrium region is reached the CFCM ceases to interact. Then the values of the decision concepts are examined to determine if there is a distinct recommended decision or not. A distinct outcome is inferred, if the value of a decision concept is surpassing the others by at least 10%. In this case the leading competitive node is the suggested decision. Otherwise, when the percent difference between the two leading competitive nodes is less than 10%, then the comparison made in the “Distinct Outputs” box leads to a “NO” result, activating the GA component. The GA component is used to “manipulate” weights that correspond to between factor interactions and do not involve decision concepts. These weights are usually the most difficult to assess by experts in medical decisions since on one hand, the interactions are complex and in many cases two-way while on the other hand, there can be a wide variation (even disagreement) between experts. In order to activate the GA component, the “reduced” weight matrix is formed from the original weight matrix W by removing the first *m* rows and columns which involve connections to diagnosis nodes:

$\mathrm{Wr} = \{wr_{i,j}\}_{i,j=1,\ldots,n-m} = \{w_{kl}\}_{k,l=m+1,\, m+2,\, ..n}$

where: n is the total number of nodes
m is the number of decision nodes.

Therefore, Wr contains only the weights between factor cause–effect relationships; where the column vector wr_j, corresponds to the causative effects on factor j from other factor concepts. Thus, each column vector wr_j, makes up a real-coded chromosome, which is allowed to mutate/reproduce. Whether each mutation/reproduction becomes part of the new population relies on whether a criterion is met as follows: Each new weight matrix resulting from mutations/reproductions of Wr is then placed in the correct elements of initial weight matrix W forming a new matrix $\mathbf{W}^{\mathbf{new}}$ which is now used to run the CFCM again. If one of the two “leading” decision concepts is not the result of the new GAFI-CFCM or if again the 10% rule above is not met, then the new chromosomes are discarded. Otherwise, the new result (interim inferred decision) is recorded, “chromosome” weights are kept as part of the population and the algorithm is repeated for a large number of iterations. The final decision corresponds to the decision concept with the highest probability as a result of the iterations. The detailed algorithm is described in (Georgopoulos and Stylios, 2009).

5. FUZZY COGNITVE MAP FOR MODELING LABOR

During the crucial period of labor, obstetricians evaluate the whole situation and they take into consideration a variety of factors in order to conclude. The decision is because the infant will be safer if delivered or the risk to the maternal health of continuing with the pregnancy outweighs the risk to the baby delivery.

Decision Support Systems and particularly those based on Fuzzy Cognitive Maps are well suited for labor modeling since there are clinicians that are not always in agreement on the importance of parameters for example for normal uterine activity, especially in situations involving induction or augmentation of labor. Clinical disagreements exist as well as to what constitutes excessive uterine activity and what management strategies to undertake when it occurs (Simpson and Miller, 2011).

A very significant decision of obstetricians is to determine whether they will proceed with a Caesarian section or a natural delivery based on the physical measurements, FHR and the intepretation of and other essential indications and measurements. The decision, in essence, is based on "weighing" the risks of maternal and/or fetal health complications. Here, is not considered the case of a routine Caesarean section but the case of an emergency Caesarean section when there is a fetal distress (because of abnormal CTG, acidosis, cord prolapse or abruption) or obstructed labor or prolonged labor or delivery at maternal risk. The factors that are taken into consideration in many cases have intrinsic fuzziness, they are described by obstretricians using liguistic terms and they are characterised such as: stable, moderate, intense, increased etc. are used to describe them.

Cardiotocography was introduced into obstetrics practice and it has been widely used for antepartum and intrapartum fetal surveillance. Cardiotocogram (CTG) consists of two distinct signals, i.e. the recording of instantaneous Fetal Heart Rate (FHR) and Uterine Activity (UA), which are two biosignals corresponding to fetal condition and progress of the labor. FHR variability is believed to reflect the interactions between the sympathetic nervous system (SNS) and the parasympathetic nervous system (PSNS) of the fetus. Considerable research efforts have been made to process, evaluate and categorize FHR either as suspicious, or pathological or normal. Integrated methods based on Support Vector Machines, Wavelets and other computational intelligence techniques have been proposed to interpet the FHR (Georgoulas *et al,* 2006).

Here, the development of a Fuzzy Cognitive Map to model the way by which the obstetrician makes a decision for a normal delivery or a caesarean section is investigated. It is a dynamic procedure, where the obstetrician evaluates whether

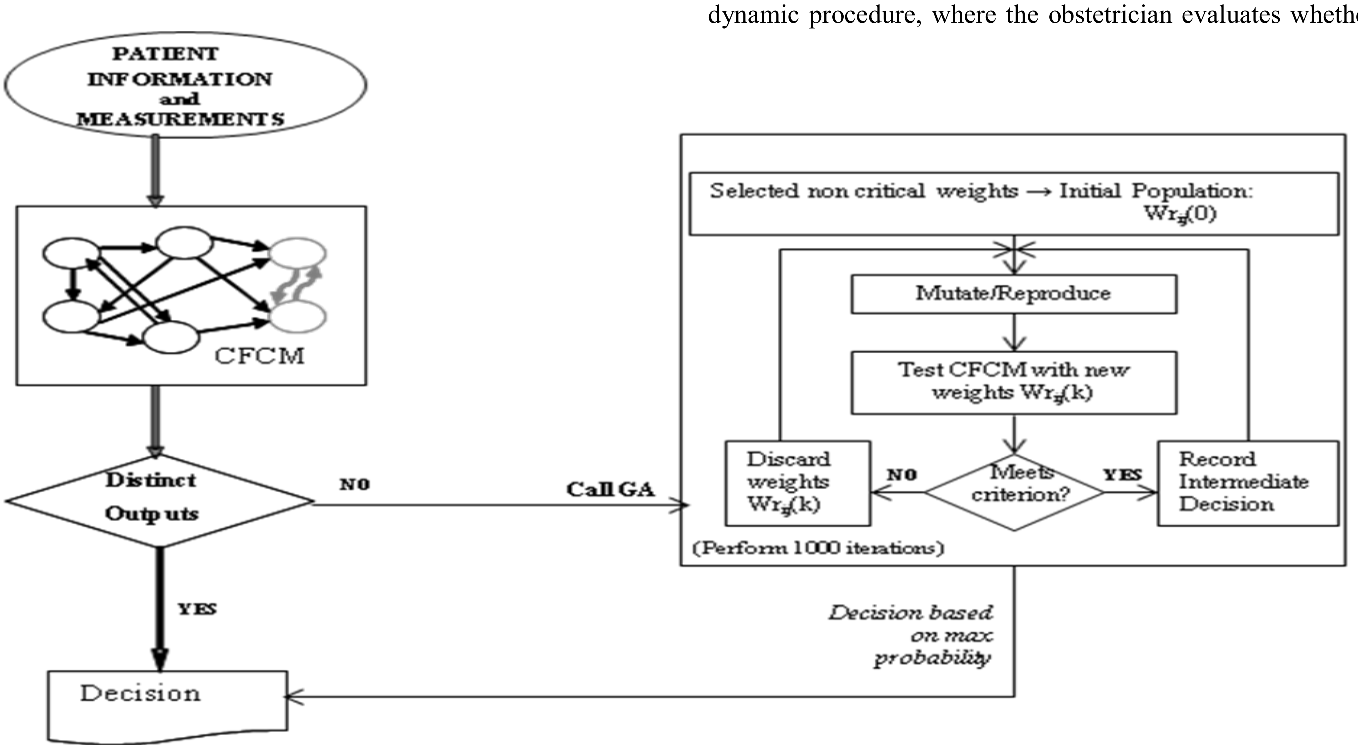

Fig. 3. The overall MDSS Structure consisting of FCM and GA

either the mother or the fetus are at serious risk and thus, he/she has to intervene by stopping the physiological delivery and performing an emergency caesarean section instead of continuing with natural delivery. According to evidence based practice, labor abnormalities and unnecessary cesarean birth, can be associated with risks to the mother and baby, whereas excessive uterine activity may have a negative effect on fetal oxygenation during labor and fetal acid-base status at birth (Simpson and Miller, 2011). Decision support procedures developed by Warrick et al. (2010) focus on hypoxia detection based on recordings of the uterine pressure and fetal heart rate, which are routinely monitored during labor.

Obstetricians consider a variety of maternal indications and fetal indications; the labor surveillance monitoring has three main components: fetal condition, progress of labor and maternal conditions. These are the subsystems on the sense of section II. Fetal condition is mainly reflected in the interpretation of the Fetal Heart Rate (FHR) signal and some physiological measurements, e.g. color of liquor (meconium) and vaginal examinations. Progress of labor is based on physiological examinations (descent of head, dilatation of the cervix) measurement of the strength and frequency of uterine contractions, the drugs given to augment/induce the labor and the time passed. Maternal conditions are measured by well-being pulse and blood pressure and etc.

The model described here takes into consideration more factors based on the main parameters that an obstetrician evaluates. These parameters constitute the 13 concepts of the FCM model which are:

- Concept 1 Decision for Normal Delivery
- Concept 2 Decision for Emergency Caesarian section
- Concept 3 Fetal Heart Rate (FHR) evaluation
- Concept 4 Meconium (Color of liquor) (from clear to mild blood staining and to heavier bleeding)
- Concept 5 Time duration of labor in comparison to progress of the delivery
- Concept 6 Contractions of the uterine (strength and frequency)
- Concept 7 Medication (quantity of oxytocine given to mother)
- Concept 8 Diastole of Cervix (measurement)
- Concept 9 Evaluation of Cervix commendation (4 linguistic values)
- Concept 10 Position of placenta (3 linguistic values)
- Concept 11 Position of fetus (5 linguistic values)
- Concept 12 Contraindication
- Concept 13 Fetal weight estimation (3 linguistic values)

It is important to note that concepts are interrelated. For example, recent research (Balchin et al. 2011) has shown that meconium is related to the duration of labor, the fetal position (breech), abnormal FHR.

After the determination of the main aspects that affect the obstetricians' decision on delivery, which are the concepts of the FCM, a team of three experienced obstetricians estimated the degree of influence from one concept to the other. Thus, the Obstetrics Fuzzy Cognitive Map model was constructed, for evaluating labor, as is represented in Fig 4.

Enhanced CFCM model, shown in block diagram form in Figure 3.

Here is an illustrative example where the FCM-MDSS is applied. A 27 year old woman patient was admitted to the labor ward in a spontaneous labor at 39 weeks' gestation. Her pregnancy had been uncomplicated. She reported good fetal movements and a 30- minutes fetal heart tracing was reactive with a rate of 140 beats per minute (bpm). On abdominal examination the symphysis- fundal height was 39 cm, the lie was longitudinal, and the presenting part was cephalic with two-fifths of the fetal head palpable. On vaginal examination the cervix was 5 cm dilated. An amniotomy was performed and clear liquor drained.

The patient requested an epidural and this was sited. Four hours after admission the vaginal examination was repeated and the cervix was found to be 8 cm dilated. When she was re-examined a further 2 hour later, the fetal was one-fifth palpable abdominally and, on vaginal examination, the cervix was fully dilated with the fetal head in the left occipitotransverse position. Throughout labor, the liquor remained clear and no fetal heart rate abnormalities were recorded. Active pushing was commenced.

After just over 1 hour of active pushing, maternal effort was diminishing and the patient was requesting assistance in delivering her baby. On examination the fetal head was no palpable abdominally. On the vaginal examination the fetal position remained left occipitotransverse and the fetal heart tracing remained normal and reactive.

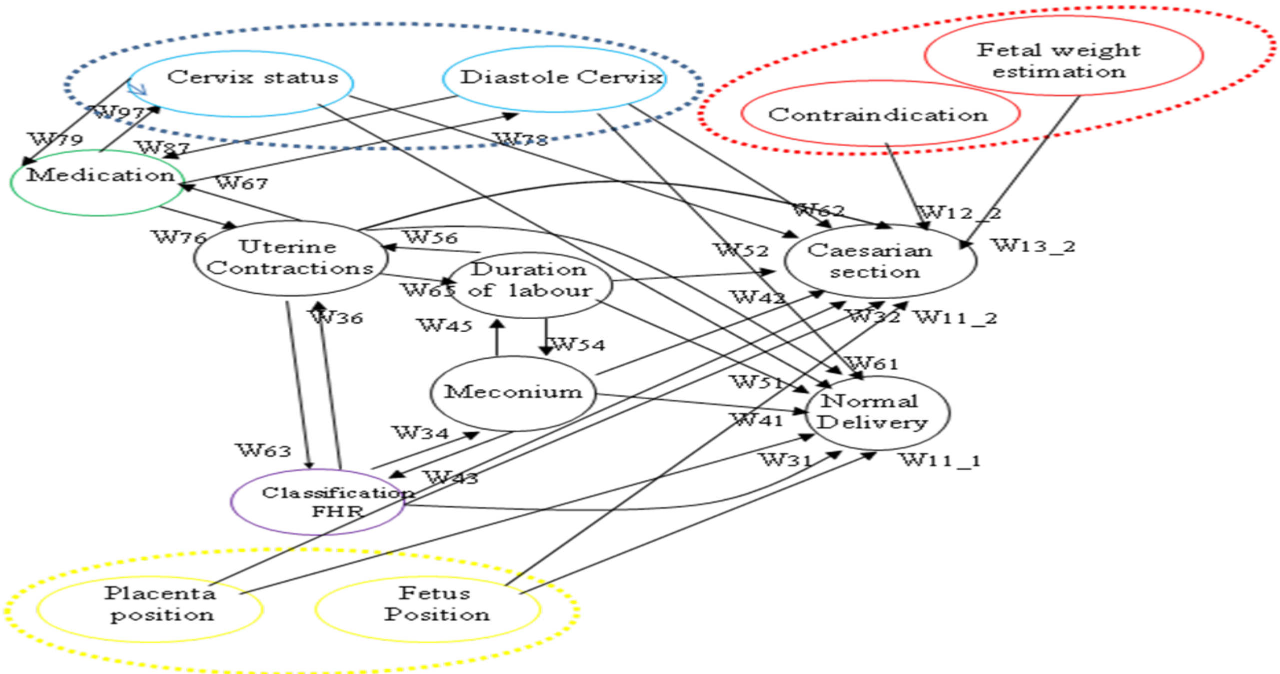

Figure 4 FCM model for delivery decision

In the event that this model does not reach a conclusion, it may require information and suggestion from the GA-

The decision that was made by the obstetrics team was to deliver the baby by Caesarian section which was also the decision proposed by the FCM-MDSS.

6. CONCLUSIONS

This research work presents a new hybrid architecture consisting of two complementary techniques the soft computing technique of FCMs and the computational intelligence technique of GAs. Both are incorporated synergistically in order to overcome the situation where one technique does not infer a unique decision/diagnosis. The incorporation of the two complementary methodologies develops the FCM-MDSS architecture that could be successfully applied to medical applications. This promising approach is tested in a real complicated case and it has proved to reach the correct conclusion and it infers the best decision. Moreover, this approach will be tested on other decision support problem where the possible outcomes are more than two, thus increasing the complexity of the problem.

Acknowledgments. Authors would like to thank the Operational Programme Education and Lifelong Learning of the Greek Ministry of Education, Lifelong Learning and Religious Affairs co-financed by the Greece and the European Union for its sponsoring.

REFERENCES

Balchin, I., J.C. Whittaker, R.F. Lamont, and P.J. Steer (2011). Maternal and Fetal Characteristics Associated With Meconium-Stained Amniotic Fluid. *Obstet Gynecol.,* **117**,828-835.

Dybowski, R., P. Weller, R. Chang, and V. Gant (1996). Prediction of outcome in critically ill patients using artificial neural network synthesised by genetic algorithm. *Lancet*, **347**, 1146–1150.

Georgoulas, G., C.D. Stylios, and P.P. Groumpos (2006). A Novel methodology for Fetal Heart Rate Signal Classification During the Intrapartum Period. *IEEE Trans. Biomedical in Engineering,* **53**, 875-884.

Georgoulas, G., C.D. Stylios, and P.P. Groumpos (2006). Feature extraction and classification of Fetal Heart Rate using Wavelet analysis and Support Vector Machines. *International J. of AI Tools,* **15**, 411-432

Georgopoulos, V.C., G. A. Malandraki, and C.D. Stylios (2003). A fuzzy cognitive map approach to differential diagnosis of specific language impairment. *Journal of Artificial Intelligence in Medicine*, **29**, 261–278.

Georgopoulos V.C. and C.D. Stylios (2004). Augmented fuzzy cognitive maps supplemented with case based reasoning for advanced medical decision support. In: *Soft Computing for Information Processing and Analysis Enhancing the Power of the Information Technology*. (M. Nikravesh, L. A Zadeh, J. Kacprzyk (Eds)).

Georgopoulos V.C. and C.D. Stylios (2009). Diagnosis Support using Fuzzy Cognitive Maps combined with Genetic Algorithms. *Proc. 31st IEEE Eng. in Medicine and Biology Society (EMBC'09).*Minneapolis, MN.

Goldberg, D.E. (1989). *Genetic algorithms: search, optimization and machine learning*. Addison-Wesley, Reading MA.

Holland, J.H. (1975). *Adaptation in natural and artificial systems*. University of Michigan press, Ann Arbor, MI.

Janikow, C. Z. and. Z. Michalewicz (1991). Experimental comparison of binary and floating point representations in genetic algorithms. In: *Proc. of the 4th Int. Conference on Genetic Algorithms* (R. K. Belew and L. B. Booker. (Eds.)). Morgan Kaufmann Publishers Palo Alto, CA.

Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*. **24**, 65-75.

Liang, H.. Z. Lina and R.W. McCalluma (2000). Application of combined genetic algorithms with cascade correlation to diagnosis of delayed gastric emptying from electrogastrograms. *Med. Engin. & Physics*, **22**, 229-234.

Papageorgiou, E., C. Stylios, and P. Groumpos (2003). An integrated two-level hierarchical system for decision making in radiation therapy using fuzzy cognitive maps. *IEEE Trans. on Biomedical Engineering*. **50**, 1326-1339.

Pettker, C.M. (2011). Standardization of intrapartum management and impact on adverse outcomes. *JF - Clin Obstet Gynec.,* **54**, 8-15.

Simpson, K. R. and L. Miller (2011). Assessment and Optimization of Uterine Activity During Labor. *Clinical Obstetrics and Gynecology,* **54**, 40–49.

Sprogar, M., M. Lenic and S. Alayon (2002). Evolution in medical decision-making," *Journal of Medical Systems,* **26**, 479-89.

Stach, W., L. Kurgan, W. Pedrycz, and M. Reformat (2004). Learning Fuzzy Cognitive Maps with Required Precision Using Genetic Algorithm Approach. *Electronics Letters*, **40**, 1519-1520.

Stach, W., L. Kurgan and W. Pedrycz (2005). A Survey of Fuzzy Cognitive Map Learning Methods. In:*Issues in Soft Computing: Theory and Applications* (Grzegorzewski, P., Krawczak, M., Zadrozny, S. (Eds.)), 71-84.

Stach, W., L. Kurgan and W. Pedrycz (2007). Parallel Learning of Large Fuzzy Cognitive Maps. *Int. Joint Conf on Neur. Nets (IJCNN 2007),* Orlando, FL.

Stach, W., L. Kurgan, W. Pedrycz, and M. Reformat (2005). Evolutionary Development of Fuzzy Cognitive Maps. *Proc. 14th International Conference on Fuzzy Systems (FUZZ-IEEE 2005),* Reno, NV.

Stylios C. D. and P.P. Groumpos (2004). Modeling Complex Systems Using Fuzzy Cognitive Maps. *IEEE Trans. on Systems, Man and Cybernetics: Part A Systems and Humans.* **34**, 155-162.

Stylios, C.D. and V.C. Georgopoulos (2010). Fuzzy Cognitive Maps for Medical Diagnosis Support- A paradigm from Obstetrics. *Proc. 32nd Annual International Conference of the IEEE EMBS EMBC'10.* Buenos Aires, Argentina.

Tan, K. C., Q. Yu, C.M. Heng, and T.H. Lee (2003). Evolutionary computing for knowledge discovery in medical diagnosis. *Artificial Int in Medicine*. **27**, 129-154.

Vinterbo, S. and L. Ohno-Machado (2000). A genetic algorithm Approach to multidisorder diagnosis. *Artificial Intelligence in Medicine*. **18**, 117-132.

Warrick P., E. Hamilton, R. Kearney, and D. Precup (2010). A machine Learning Approach to the Detection of Fetal Hypoxia during Labor and Delivery. *Proc. 22th Innovative Applications of Artificial Intelligence Conference (IAAI-10)*. 1865-1870.

Whitley, D. (1994). A Genetic Algorithm Tutorial. *Statistics and Computing.* **4**, 65--85.