Fuzzy Cognitive Map Control on Room Temperature in A Smart House

Kung-Jeng Wang[1],Chih-Yung Wu[1,2], Wei-Lung Ning[1]

1.Department of Industrial Management

National Taiwan University of Science and Technology

Taipei, Taiwan, ROC

2. Department of Information Management
Dahan Institute of Technology
Hualien, Taiwan, ROC

john5dudu@gmail.com

Abstract - A smart house aims at building intelligent automation with a goal to provide its inhabitants with maximum possible comfort, minimum resource consumption and thus reduced cost of home maintenance. However, thermal comfort is an essential property in many applications that support a smart house. In this study, we develop a temperature prediction and control model based on fuzzy cognitive map (FCM) and construct a genetic algorithm for finding the connection matrix of FCM. The proposed model successfully conducts temperature prediction and control. Finally, we have investigated the prediction accuracy of the proposed model against a variety of system parameters, such as different number of inhabitants.

Keywords - Smart house, Simulation, Fuzzy cognitive map, Genetic algorithm.

I. INTRODUCTION

Due to increasing life expectancy and decreasing birth rates, the aging society is the major trend throughout the world. To improve the quality of life for the increasing elderly people is becoming a more essential task. One way to improve the quality of life is by making a more comfortable smart home environment to live in. A "smart environment" is one that is able to autonomously acquire and apply knowledge about its inhabitants and their surroundings, and adapt to the inhabitants' behavior or preferences with the ultimate goal of improving their experience in that environment[1, 2]. It must have some kinds of abilities of perception, cognition, analysis, reasoning and anticipation about a user's existence and surroundings, on which it can accordingly take proper actions [3].

With the rapid development and popularity of the information and communication technology (ICT) in recent years, smart house equipped with the integration of technology and services through home networking for a better quality of living. Advances in smart devices, mobile wireless communications, sensor networks, pervasive computing, machine learning, middleware and agent technologies, and human–computer interfaces have made the dream of smart environments a reality [4]. Thus, people's daily life has closely connected to the ICT.

"Context awareness" is indeed a key to building a smart environment and associated applications [5]. Studies on context-aware information services have become popular, such as the Aware Home [6], The Neural Network House [7], the Intelligent Home [8], the Intelligent House n [9] and the MavHome [10]. By embedding wired and wireless sensors and various types of computers in the daily environment, we can create a context-aware environment inside the smart house.

"Thermal comfort" is defined as "that condition of mind which expresses satisfaction with the thermal environment" [11].Thermal comfort is a result of a combination/adaptation of parameters of both the environment and the human body itself [12]. Finger [13] stated that the condition for thermal comfort is thus that skin temperature and sweat secretion lie within narrow limits.

It is reasonable to assume that room temperature changing is mainly caused by thermal energy of inhabitant movement and environment temperature continuously in smart house. The optimal-based temperature control rule is a dynamic system that reflects immediately the appropriate adjustment throughout the interaction of environment. The FCM operation is same to the control rule. FCM is applied for the dynamic system that analyzes the changing during time. Therefore, this study uses FCM to find out the causal-effect relationship between inhabitant and smart house to predict the changing in room temperature during time.

This research aims at developing a temperature control model for a smart house. It develops the model based on a smart house simulation system developed by Hong [14]. The proposed model possesses abilities of cognition through simulated RFID facilities (readers, tags and other wireless sensors). Specifically speaking, those facilities can handle messages of the movement, location and body temperature of inhabitants. This study develops an adaptive temperature predictor and controller to dynamically conduct optimal temperature control in a smart house.

II. LITERATURE REVIEW

Fuzzy cognitive map (FCM) is a convenient, simple, and powerful tool for simulation and analysis of dynamic systems [15]. It was originally developed in 1988 by Kosko [16], and since then successfully applied to numerous domains, such as information retrievals [17], modeling of plant control [18], analysis of electrical circuits [19], supervisory systems [20], organization and strategy planning [21], analysis of business performance indicators [22], modeling virtual world [23], medicine [24], software project management [25] and system dynamics and complex systems [26], etc. However, applying FCM to the smart house fields has not been attempted yet.

Most applications of FCM have been made for what-if analysis, and the research on backward analysis has been rarely performed. Khan [27] showed as an example that backward analysis using genetic algorithm is possible in the decision making of purchasing equipment and the cause analysis of public health problem. However, the research assumed that weight matrix is given.

Presently, weight connection methods which are a kind of artificial neural network connection algorithms have been presented [28-30]. The algorithm changes the weights gradually toward reducing the differences between actual state vectors and the state vectors predicted by FCM. Papageorgiou [31] presented a two-step FCM weight learning methodology where varied evolution algorithm decides the ending point of the learning, and a nonlinear hebbin learning algorithm executes the weight learning during the interval. Furthermore, Parsopoulos [32] performed a research on the weight learning using particle swarm method, a heuristic algorithm for seeking optimal solutions. Kurgan [33] generates FCM models by genetic algorithm from input historical data, and without human intervention.

III. THE SIMULATION OF SMART HOUSE

The original temperature control rule of Hong [14] performs optimization-based evaluation. This rule controls individual inhabitant in thermal environments. It includes five components:

1. Modeling of a virtual human (its physical movement and physiological status.)
2. Modeling of the smart house environment (i.e., space and partition of a smart house with walls, stairways, and elevators in Figure 1)
3. Modeling of sensors and their fuzzy-based characteristics.
4. Design of optimization-based intelligence to control environment settings (e.g., room temperature) in the smart house.
5. Performances evaluation of the house-controlling intelligence detected by thermal comfort, context-awareness and security in the smart house

It consists of ten physical parameters:

1. t_{now}: The current temperature
2. m: The metabolic rate (Watt/m^2).
3. pa: The pressure of water vapor in ambient air (mmHg)
4. ta: The air temperature
5. tr: The mean radiant temperature
6. fcl: The ration of the surface area of the clothed body to the surface area of the nude body.
7. hc: The convection coincident (Watt/m^2*K).
8. tb_i: Body temperature of human i
9. wi: A mechanical work by human i (Watt/m^2).
10. k: Range of PMV.

Hong [14] suggested that we can use Newton or gradient search method to solve the minimization function, and the corresponding optimal room temperature. Then we can get optimization of environment temperature.

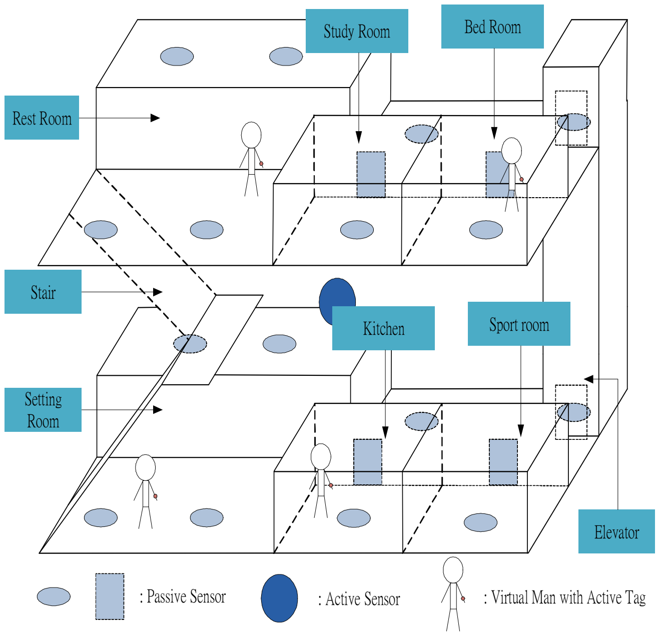

Fig. 1 The sample smart house under investigation Hong[14]

In terms of simulation, Hong [14] addressed that the most important significant factors on three performance indexes are the number of inhabitant, sensor setting and temperature setting. These factors are fixed state during simulation. In reality, the number of inhabitant is dynamic state, and the other setting will be changed corresponding to the number. Therefore, after we review the definition of each performance index, it is understandable that the complex operation and a lot of parameters have to simplify with the new analysis method.

IV. FCM MODELING FOR SMART HOUSE

It is reasonable to suppose that room temperature changing is mainly caused by thermal energy of inhabitant movement and environment temperature continuously in smart house. Let us look more carefully into temperature changing in simulation modeling. The aspect of inhabitant, the age of inhabitant is differentiated into children, adult and old. Different age of inhabitants cause different velocity to move, the velocity brings thermal energy, more velocity leads to more thermal energy. The aspect of environment temperature, the facility operation also brings waste heat to increase room temperature. The question then arises about balance the room temperature throughout these interactions.

If we assume that room temperature changing is a dynamic system, fuzzy cognitive maps can help us to analyze the appropriate temperature adjustment. But, before we come to the modeling, the application of FCM must be clarified. The FCM operation procedure is that FCM module receives the data from simulator and sends the predicted temperature to simulator before evaluating the temperature control rule, and then simulation evaluates the temperature control rule in the end of stage, and goes to next stage. The predicted temperature operation is shown in Figure 2.

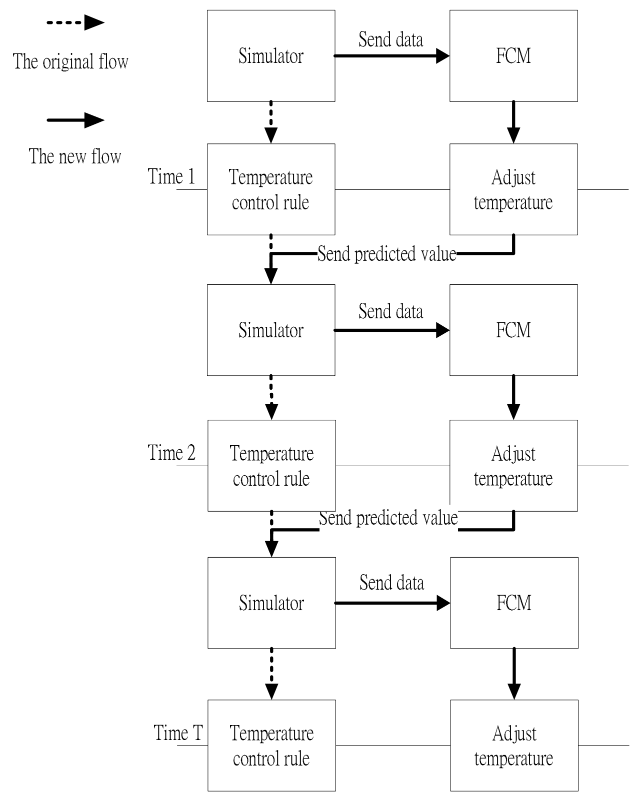

Fig. 2 The predicted temperature operation

FCM operation procedure is that FCM module receives the data from simulator and sends the predicted temperature to simulator before evaluating the temperature control rule, and then simulation evaluates the temperature control rule in the end of stage, and goes to next stage.

As seen Figure 3, the FCM has four types of states - external states, group states, internal states and predicted objective. The definitions of states are given below:

1. External states: Variables such as thermal comfort, context awareness and security which have definitive effect on the performance in smart house. These states are determined through complex causal relationships among internal and group states.
2. Group states: Group variable to show the number of inhabitant in smart house, it concerns with the change of "Sensor range", "Sensor decision interval" and "Stationary Temperature". When "Group" change in simulation, the related states will change correspondingly.
3. Internal states: Internal states are generated from the original simulator, they are determined by inhabitants' activities, and the changes in the internal states are also uncertain. In FCM, internal states are mediums between the group states and external states.
4. Predicted objective: The concept is to substitute original temperature control rule. It is a predicted temperature generated from FCM for next iteration.

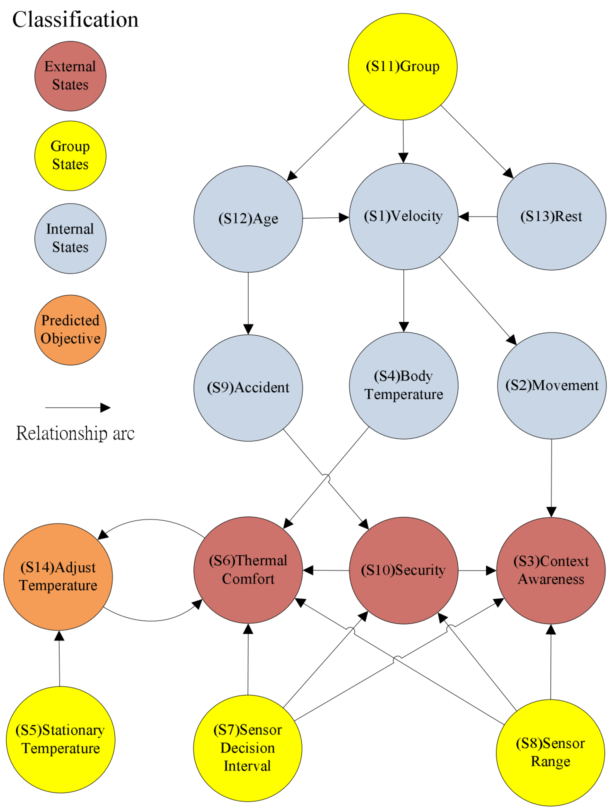

Fig. 3 The cognitive map of the smart house

This research makes it clear what states of fuzzy cognitive maps intend by these expressions. After constructed the FCM of smart home, the next step is using data of the smart house simulator calculates "Connection Matrix" through genetic algorithm. Connection matrix is a medium that connects nodes with weighted edges.

Recently, some FCM studies have attempted to get the accurate weight through heuristic algorithms. This research will attempt to use genetic algorithm to obtain connection matrix. The procedure is collecting a lot of iteration data to train the connection matrix. The goal of the operation model wants to minimize the total prediction error.

Connection matrix calculates through genetic algorithm, the number in diagram is process sequence. Details of genetic algorithm operation are shown as Figure 4.

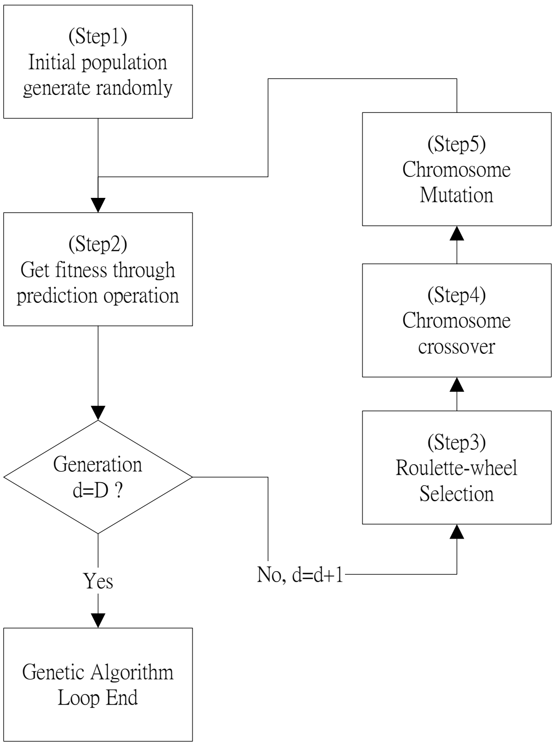

Fig. 4 The forward predicted steps of genetic algorithm

V. EXPERIMENT AND ANALYSIS

In order to create a robust connection matrix, this study sets the variables combination as Table I, which predicts in different Group states and related variables. Afterward, connection matrix is calculated through the data which group states and related variables are changed periodically in simulation. Settings of genetic algorithm parameter are shown in Table II.

Connection matrix trained through 1000 unit times of normalized data and every 200 unit time changed "Group states" randomly. The total CPU time required for the connection matrix is 5 minutes. The minimized prediction error achieve by the GA is 102.

TABLE I
GROUP STATES PARAMETER SETTING IN CONNECTION MATRIX

Group / Corresponding value	2(Small)	6(Medium)	10(Large)
Sensor decision interval (second)	1(Normal)	0.5(Quick)	0.5(Quick)
Sensor range (meter)	3(Narrow)	4(Medium)	5(Wide)
Stationary temperature (℃)	26(High)	23(Middle)	20(Low)

TABLE II
GENETIC ALGORITHM PARAMETER SETTING

Population size (m)	200	Mutation rate	0.06	Iterations	10000
Crossover rate	0.8	The number of time interval for training			100(

Simulation runs 100 unit times with each scenario (1, 2, 3) as Group (Large, Small, Medium) respectively. Notice, there is no change of "Group states" during simulation time in each scenarios. The predicted error on each scenario are 0.09, 0.14 and 0.12 respectively, and the average error is approximately 0.12. The accuracy of FCM predicted temperature is 0.91, 0.86 and 0.88 respectively. The average predicted accuracy is approximately 88%. Figure 4 shows the ratios of FCM predicted temperature to optimal-based temperature control rule during 100 unit times on each scenario.

The FCM predicted method show an average of 88% accuracy. The reason that the error of FCM predicted value is less than simulation data supposedly because the inhabitant movement was performed very randomly. Also, another source of the inaccuracy may come from the insufficient connection matrix training.

In terms of design of experiment, the result is that all group states affected FCM predicted value, "Group" factor especially. The small "Group" states results in inaccuracy FCM predicted value than the large one. More inhabitant movement data in FCM operation, the proposed "Thermal comfort" can reach more accurate prediction of optimal room temperature as compared to the "Group" states with small scale.

Finally, all factors of group states can make a great impact on FCM predicted value. This study concludes that the factor "Decision interval" taken by FCM operation significantly affects the FCM predicted result. Less inaccuracy of FCM predicted value is using a wide parameter of "Sensor range". The FCM predicted accuracy is declined when high "Stationary temperature" and large "Group" because of interaction.

VI. CONCLUSION

This research has developed a cognitive map model that connects kinds of states in a smart house to conduct intelligent control on temperature of the smart house. The proposed model has reduced the complexity of current temperature control approaches. Experiment results of temperature prediction have demonstrated the accuracy of the proposed cognitive map model against different numbers of inhabitant.

In this study, we have presented a cognitive map model, which includes external states (the performance indexes), group states (the number of inhabitant in response to the setting of sensor range and decision interval and stationary temperature), internal states (the related parameters of inhabitants), and predicted objective (the adjusted value to temperature).

In terms of cognitive map experiment, first, this study has computed the connection matrix through a genetic algorithm, and then the temperature prediction has been conducted to examine the accuracy of the adjusted value to "Thermal Comfort" function. We have compared the prediction outcomes of the proposed cognitive map model with the original model proposed by Hong [11], showing that their output is similar. However, our model needs less information and computation burden in terms of complex physical parameters and optimization effort.

REFERENCES

[1] Sajal K. D., Nirmalya R., and Abhishek R., "Context-aware resource management in multi-inhabitant smart homes: A framework based on Nash H-learning", Pervasive and Mobile Computing 2 (2006) 372–404

[2] Cook, D.J. and Das, S.K., Smart Environments: Technology, Protocols and Applications, John Wiley & Sons, 2004.

[3] Ma, J., Yang, L.T., Apduhan, B.O., Huang, R. Barolli, L. and Takizawa M. (2005) "Towards a smart world and ubiquitous intelligence: a walkthrough from smart things to smart hyperspaces and UbicKids", "International Journal of Pervasive Computing and Communications 1", 53-68.

[4] Hopper, A., Sentient computing, The Royal Society Clifford Patterson Lecture, 1999.

[5] Weiser, M., The computer for the 21st century, Scientific American 265 (3) (1991) 94–104.

[6] Orr, R.J. and Abowd, G.D., The smart floor: A mechanism for natural user identification and tracking, in: Proceedings of Conference on Human Factors in Computing Systems, CHI 2000, ACM Press, NY, 2000.

[7] Mozer, M.C., The Neural Network House: An Environment that Adapts to its Inhabitants, in: Proc. of the American Association for Artificial Intelligence Spring Symposium on Intelligent Environments, 1998, pp. 110–114.

[8] Lesser, V., The intelligent home testbed, in: Proc. of Autonomy Control Software Workshop, January 1999.

[9] House n Living Laboratory Introduction, Web resource available at http://architecture.mit.edu/house n/web/publications.

[10] Das, S.K., Cook, D.J., Bhattacharya, A., Hierman, E., and Lin, T.Y., The role of prediction algorithms in the MavHome smart home architecture, in: Smart Homes, IEEE Wireless Communications (2002) (special issue).

[11] ANSI/ASHRAE 55-2004. Thermal environmental conditions for human occupancy. American Society of Heating, Refrigerating and Air-conditioning Engineers Inc., Atlanta, USA, 2004.

[12] Leen Peeters, Richard de Dear, Jan Hensen, William D'haeseleer, "Thermal comfort in residential buildings: Comfort values and scales for building energy simulation", Applied Energy 86 (2009) 772–780.

[13] Fanger P., Thermal comfort: analysis and applications in environmental Engineering. United States: McGraw-Hill Book Company; 1970.

[14] Hong, Y.S., "Simlation and modeling of wireless sensor and RFID-based samrt house", 2007.

[15] Sadiras, A. K.and Kouskouvelis, I. (2005) Using fuzzy cognitive maps as a decision support system for political decisions: The case of Turkey's integration into the European Union Springer-Verlag Berlin.

[16] Kosko, B. (1992) "Neural networks and fuzzy systems: A dynamical systems approach to machine intelligence.", "Englewood Cliffs, NJ: Prentice-Hall"

[17] Montazemi, A.R. and Conrath, D.W., The use of cognitive mapping for information requirements analysis, MIS Quarterly 10 (1986) 44–55.

[18] Gotoh, K., Murakami, J., Yamaguchi, T., and Yamanaka, Y., Application of fuzzy cognitive maps to supporting for plant control, in: Proc. SICE Joint Symp. 15th Systems Symp. and Tenth Knowledge Engineering Symp., 1989, pp. 99–104.

[19] Styblinski, M.A. and Meyer, B.D., Signal flow graphs versus fuzzy cognitive maps in application to qualitative circuit analysis, Int. J. Man Mach. Studies 35 (1991) 175–186.

[20] Georgopoulos, V.C., Malandraki, G.A., and Stylios, C.D., A fuzzy cognitive map approach to differential diagnosis of specific language impairment, J. Artif. Intell. Med. 29 (3) (2003) 261–278.

[21] Bougon,M.G., Congregate cognitive maps: a unified dynamic theory of organization and strategy, J. Manage. Stud. 29 (1992) 369–389.

[22] Kardaras, D. and Mentzas, G., Using fuzzy cognitive maps to model and analyze business performance assessment, in: J. Chen, A. Mital (Eds.), Advances in Industrial Engineering Applications and Practice II, 1997, pp. 63–68.

[23] Koulouriotis, D.E., Diakoulakis, I.E., and Emiris, D.M., Anamorphosis of fuzzy cognitive maps for operation in ambiguous and multistimulus real world environments, in: 10th IEEE Int. Conf. on Fuzzy Systems, 2001, pp. 1156–1159..

[24] Georgopoulos, V.C., Malandraki, G.A., and Stylios, C.D. A fuzzy cognitive map approach to differential diagnosis of specific language impairment, J. Artif. Intell. Med. 29 (3) (2003) 261–278.

[25] Stach, W. and Kurgan, L., Modeling software development project using fuzzy cognitive maps, in: Proc. 4th ASERC Workshop on Quantitative and Soft Software Engineering (QSSE'04), 2004, pp. 55–60.

[26] Koulouriotis, D.E., Diakoulakis, I.E., Emiris, D.M., and Zopounidis, C.D., Development of dynamic cognitive networks as complex systems approximators: validation in financial time series, Appl. Soft Comput. 5 (2005) 157–179.

[27] Khan, M. S., Khor, S. and Chong, A., "Fuzzy cognitive maps with genetic algorithm for goal-oriented decision support", "International Journal of Uncertainty Fuzziness and Knowledge-Based Systems", 12, 2004, 31-42.

[28] Aguilar, J. Adaptive random fuzzy cognitive maps Springer-Verlag Berlin ,2002.

[29] Papageorgiou, E. I., Stylios, C. D. and Groumpos, P. P., "Active Hebbian learning algorithm to train fuzzy cognitive maps", "International Journal of Approximate Reasoning", 37(3), 2004, 219-249.

[30] Stylios, C. D.and Groumpos, P. P., "Modeling complex systems using fuzzy cognitive maps", "Ieee Transactions on Systems Man and Cybernetics Part a-Systems and Humans", 34(1), 2004, 155-162.

[31] Papageorgiou, E. I.and Groumpos, P. P. (2005) "A new hybrid method using evolutionary algorithms to train Fuzzy Cognitive Maps", "Applied Soft Computing", 5(4), 409-431.

[32] Parsopoulos, K. E., Papageorgiou, E. I., Grumpos, P. P.,Vrahatis, M. N. (2003) "A first study of fuzzy cognitive maps learning using particle swarm optimization.", "In Proceedings of IEEE congress on evolutionart computation ", 1440-1447.

[33] Khan, M. S., Khor, S.and Chong, A., "Fuzzy cognitive maps with genetic algorithm for goal-oriented decision support", "International Journal of Uncertainty Fuzziness and Knowledge-Based Systems", 12, 2004, 31-42.