Introducing a Fuzzy Cognitive Map for Modeling Power Market Auction Behavior

Denise M. Case
Intelligent Systems Laboratory
School of Computer Science and Information Systems
Northwest Missouri State University
800 University Drive, Maryville, MO 64468, USA
dcase@nwmissouri.edu

Chrysostomos D. Stylios
Knowledge and Intelligent Computing Laboratory
Dept. Computer Engineering
Technological Educational Institute of Epirus
Arta, Greece
stylios@teiep.gr

***Abstract*—The power market is becoming more complex as independent small producers are entering it but their energy offerings are often based on alternative sources which may be dependent on transient weather conditions. Power market auction behavior is a typical large-scale system characterized by huge amounts of data and information that have to be taken into consideration to make decisions. Fuzzy Cognitive Maps (FCM) offer a method for using the knowledge and experience of domain experts to describe the behavior of a complex system. This paper discusses FCM representation and development, and describes the use of FCM to develop a behavioral model of the system. This paper then presents the soft computing approach of FCM for modeling complex power market behavior. The resulting FCM models a variety of factors that affect individual participant behaviors during power auctions and provides an abstract conceptual model of the interacting entities for a specific case problem.**

Keywords—Power market; modeling; Fuzzy Cognitive Maps; decision support; soft computing; cyberphysical systems; distributed generation

I. Introduction

Modeling is the basis for effective knowledge representation. It is accepted that the requirements in the modeling and adequate describing systems cannot be met only with the existing methodologies and theories. It is necessary to investigate and use new methods that will exploit human experience, will have learning capabilities and identification characteristics, and will take into account imprecision and uncertainty, which characterize real world systems [1]. The flourishing of new theories and approaches capable of synergizing multiple mature discipline theories such as Fuzzy Logic, Neural Networks, Genetic Algorithms, Probabilistic Reasoning and Knowledge Based Systems, is known as Soft Computing and/or Computational Intelligence. These new techniques enable engineers to utilize them to create and develop new models and sophisticated systems based on domain knowledge [2]. Such advanced techniques effectively utilize the knowledge of the complex system resources, especially the insights and experience of front-line operators and experts, to achieve continuous improvement in productivity and understanding.

In past years, conventional methods have been used successfully in modeling and control systems but their contribution is limited in the representation and solution of complex systems. In complex systems, their operation, especially in the upper level, depends on human leadership. Generally, there is a greater demand for autonomous systems, which may be achieved by taking advantage of human-like reasoning and description of systems. Human reasoning often includes uncertain descriptions and can have subtle variations in relation to time and space; in such situations, Fuzzy Cognitive Maps (FCM) and modeling can offer a capable approach.

FCM modeling offers a synergism of Fuzzy Logic and Neural Networks. FCM is a network of interconnected concepts that can be used to model situations by classes and the causal links between them. FCM have been introduced by Kosko [3,4], who enhanced the cognitive maps theory that had been used in social and political sciences to analyze social decision-making problems; showing a causal relationship between different factors, where the causal relationship is expressed by either positive or negative sign of knowledge expression [5]. Fuzzy values introduced in cognitive maps and FCM were used to represent causal reasoning [6]. FCM have been used to provide decision analysis and cooperation among distributed agents [7], to model Medical Decision Support Systems [8], and have been accompanied with case-based reasoning approaches [9]. FCM have been used as structures for automating human problem-solving skills [10] and to represent complex social systems where relationship between social forces demand feedback [11]. In addition, FCM have been used to model and support plant control systems for water distribution [12] and to perform Failure Mode and Effects Analysis (FMEA) in the process industry [13]. FCM have been proposed in modeling supervisor functionality in complex manufacturing systems [14], and for investigating concerns in hierarchical systems, where the supervisor incorporates knowledge [15] and is capable of learning relational structures and evidential reasoning [16].

Soft Computing approaches have been suggested as a means to improve model representation and development of sophisticated systems. By employing a modeling methodology that combines characteristics from fuzzy logic and neural networks, FCM models can employ a behavioral point of view to model systems first at the initial base level and second at the supervisory control level [17].

The aim of this work is to introduce FCM in the specific application of modeling the availability and pricing behavior in distributed power auctions. As distributed generation continues to increase, understanding the factors affecting distributed markets will continue to grow in importance, affecting policy makers, utilities, investors, and advisory services [18]. The number of factors and complexity of the relationships between them make direct numerical analysis challenging [19]. The flexibility of a neuro-fuzzy approach enables engineers to identity a broad range of contributing factors that arise due to the environment, the behaviors and preferences of different human participants, and the emergent properties of the auctions as they unfold. FCM allows us to capture the relationships between numerous factors and identify specific complementary and contradictory concepts influencing auctions that should be included in the model. Capturing the concepts and identifying the causal relationships provides a foundation for applying a soft computing approach to designing configurable cyberphysical agents to assist in distributed power auctions.

The distributed power application area in general meets the requirements for a complex system. Distributed and renewable generation are often variable, and the specific area of distributed generation with which we concern ourselves in this effort, distributed power production from residential, roof-top, solar photovoltaic (PV) panels, may be highly variable, resulting from a large number of interconnected, interdependent, and dynamic factors [20]. It is highly dependent on weather-related factors, and weather is recognized as a dynamic, complex, chaotic system. Other contributing factors include those related to the availability and reliability of the associated PV equipment and the necessary transmission and distribution connections to other auction participants [21]. These factors are further influenced by the financial, economic, social, community, and environmental considerations, objectives, and inclinations of the participating homeowners that affect their behaviors while acting as auction participants.

The complexity of the interrelated systems and shareholders acting in a dynamic environment and the desire to have autonomous cyberphysical agents engage in a challenging combination of planning, scheduling, risk management, estimating, and bidding, given approximate and incomplete information provides a potential application area for soft computing and FCM [22]. FCM was chosen for its combination of fuzzy thinking (addressing the incomplete and approximate knowledge available) and the ability to model the approximate direction and level of influence of multiple interrelated concepts (through directed, weighted concept maps).

In the following paper, we provide this introduction, offer background on the FCM modeling approach (Section II) and introduce the specific domain of distributed power auctions associated with residential rooftop solar PV panels (Section III). In Section IV, we describe the specifics of our proposed modeling approach, and in Section V and Section VI, respectively, we present our results and conclusions.

II. FUZZY COGNITIVE MAPS

FCM can be categorized as neuro-fuzzy systems, which aim at solving real-world decision-making problems, modeling challenges, and control problems [23]. Thus, neuro-fuzzy systems with their ability to incorporate human knowledge and to adapt their knowledge base via new optimization techniques are likely to play increasingly important roles in the conception and design of hybrid intelligent systems [24]. Each FCM developed is a conceptual network, which is built by experts, using an interactive procedure of knowledge acquisition [6].

The graphical illustration of an FCM is a signed directed graph with feedback, consisting of nodes and weighted arcs [25]. Each node in the graph represents one of the concepts identified as contributing to the behavior of the system. Concept nodes are connected by signed, weighted arcs representing causal relationships among the concepts. An example FCM is shown in Fig. 1. This model includes four concepts, identified by the four circular nodes, numbered as c_1 through c_4. Six causal relationships have been identified and are depicted with directed connectors. Each connector starts from an originating concept and points to the concept that is influenced by changes in the originating concept. Each relationship arc is assigned a weight as depicted by the six *w* values. All values in the graph are fuzzy. Concepts take values in the range [0,1] and interconnection weights belong in the range [-1,1]. Graphical representation shows which concepts influence other concepts along with the approximate degree of influence. Visualization facilitates discussions during construction of the graph with subject matter experts. The resulting FCM is a fuzzy-graph structure which allows systematic causal propagation, with both forward and backward chaining.

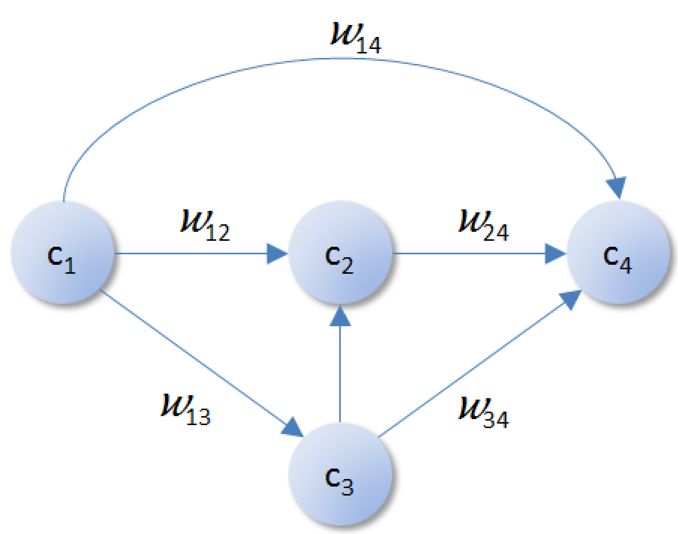

Fig. 1 Fuzzy Cognitive Map model

Experts design and develop the fuzzy graph structure of the system, consisting of concepts-nodes that represent the key principles-factors-functions of the system operation and behavior. Then, experts determine the structure and the interconnections of the network using fuzzy conditional statements. Experts use linguistic variables in order to describe the relationship between concepts. Finally, all the variables are combined and the weights of the causal interconnections among concepts are determined.

FCM modelers employ symbolic representation for the description and modeling of systems [4][22]. FCM models critical concepts and illustrates different aspects in the behavior of the system. The manner in which these concepts interact with each other describes the dynamics of the system. An FCM offers a means to integrate the accumulated experience and knowledge of the operation and behavior of the system based on the method by which it is constructed, i.e., using human experts that know the operation of system and its behavior. Development of the FCM is an attempt to represent the human accumulated knowledge describing the operation and behavior of the system, using concepts to represent each characteristic of the system. Experts are actively involved in the creation of FCM models and as they interact with the models and their understanding of the benefits of models increase, the quality of FCM models and the knowledge inherent in the models increases, and the models are more likely to be accepted and employed on a regular basis [24].

FCM is used to model any system from a behavioral point of view and it utilizes an abstract methodology to describe and model the behavior of the system. To start modeling complex systems, it can be helpful to consider groups of factors at a higher level initially. Here, each node in the graph depicts a conceptual group and each of these nodes can be further decomposed into an FCM that models just that group as shown in Fig. 2. In this illustration, each node serves as a high-level concept group, identified by a circle with a single letter. In this diagram, for example, the concept node T represents the set of temporal, time-based nodes, such as time of day and day of the week. The temporal concept group is not influenced by any factors and is therefore depicted with no incoming arcs. However, temporal factors do influence other concept groups, such as the weather concept group, a set of concepts in the external environment that influence still other concept groups. This approach was employed to assist with identifying the many interrelated concepts that drive behavior in our test case of distributed power auctions. Each conceptual group can be broken down to determine individual concepts for the final working model (e.g. time of day from the temporal concept group and ambient temperature from the weather concept group). When the temporal group is expanded, all sub nodes (such as time of day) will also have no incoming nodes, but at least one of the sub nodes will have an arc to at least one of the weather sub-concepts (such as ambient temperature).

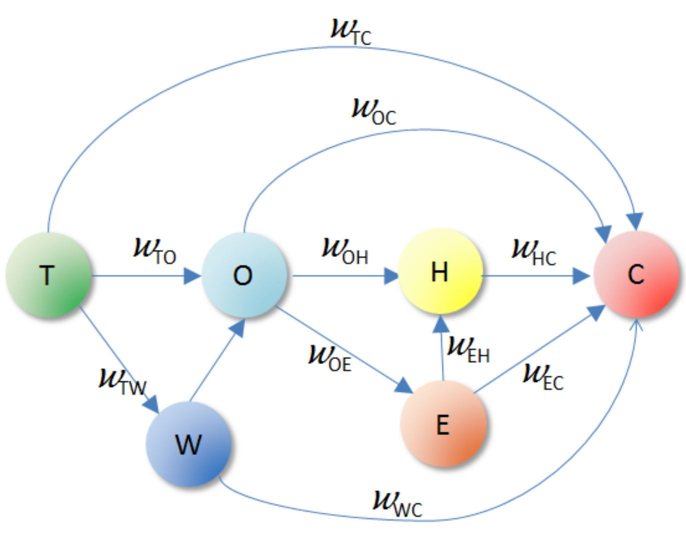

Fig. 2 FCM aggregating multiple models

III. DISTRIBUTED POWER AUCTIONS

The future distributed power market auction system will be a complex system that will include weather, complex devices, and cyberphysical systems (CPS), as well as humans and customizable intelligent agents authorized to act on the specific preferences of the homeowner participating in the auction [24]. While individual homeowner preferences, objectives, and behaviors vary considerably across participants, they may generally respond somewhat consistently over time when aggregated geographically. Conversely, weather systems are likely to highly geographically correlated, but may be highly dynamic in the temporal domain. Affecting the systems in still a different way are the planned and scheduled maintenance provided on the CPS, devices, and electrical conduits and equipment. In turn, different assumptions and provisions for planned maintenance (as well as other factors, such as usage and cycling) affect the likelihood, severity, and time-to-repair of unplanned events, as well as the reliability of various aspects of the system. All these characteristics combine to affect the amount, timing, and confidence that a given amount of distributed generation will be available in any particular area at any particular time. Pricing, too, is a result of the complex interrelationship of many contributing factors, including time of day, weather conditions, availability, and consumption flexibility.

We describe our problem as one of determining a flexible, extensible mechanism for modeling this complex system and relating these various interdependent factors using an approach that is will be easy to evolve, enhance, develop, and tune as our understanding grows.

Several approaches to modeling dynamic renewable distributed energy systems and/or their associated online auctioning systems have been proposed including agent-based modeling and simulation techniques [27][28]. As far we know, an FCM approach has not yet been proposed to the particular problem domain of distributed generation based on residential PV panels. Because of the complex nature of the associated distributed market and the complex interplay of factors, we believe that an FCM approach provides unique value for identifying and characterizing the interrelationships between the various contributing factors.

IV. PROPOSED MODELING APPROACH

First, we begin defining the main concept groups identified. Factors affecting the location, amount, and timing of available distributed generation from rooftop solar PV panels were identified in each of the following areas to ensure we had captured many of the necessary concepts. Concepts began as high-level groups to begin with, but the interrelatedness of factors do not support clear segmentation.

Concept groups (CG) were used for identifying major concepts. Each CG identifier (CGID) and the CG description are shown in the following list:

1. T: Temporal (e.g., time of day)
2. W: Weather (e.g., opacity)
3. O: Owner preferences (e.g., green-focus, profit-focus)
4. H: Household (e.g., schedules)
5. E: Equipment (e.g., type, maintenance, reliability)
6. C: Higher-level combined concepts

In one case, Temporal, the concept group is *purely transmitter* and receives no concepts that influence the group. One group, C, the higher-level combined concepts group, has no *transmitters*; all group members are purely group-level *receivers*, although within the CG, specific nodes may be *ordinary* (serving as both transmitters and receivers) locally. All other GC are ordinary at the group level, in that they are both influenced by factors in one or more groups and influence factors in one or more groups. Exploring each GG resulted in a set of concepts, each assigned a unique Concept Identifier (CID), that form the basis for the FCM model (see Table 1).

Table 1. Model concepts.

Concept identifier (CID)	CG ID	High-level concept description*	Node ID
T_1	T	Proximity to daily noon (max sunlight by hour)	7
T_2	T	Proximity to max demand day in week	8
T_3	T	Proximity to summer solstice (max sunlight by year)	9
W_1	W	Ambient temperature	10
W_2	W	Ambient humidity	11
W_3	W	Wind speed	12
W_4	W	Opacity	13
W_5	W	Opacity variability	14
O_1	O	Comfort-focus	15
O_2	O	Green-focus	16
O_3	O	Community-focus	17
O_4	O	Profit-focus	18
O_5	O	Load flexibility (the ability to defer load to a different time)	19
H_1	H	PV installed (yes/no)	1
H_2	H	PV capacity	2
H_3	H	Use of luxury appliances (e.g., pool)	3
H_4	H	Required, inelastic load each hour	4
H_5	H	Elastic load demand each hour	5
H_6	H	Elastic load demand each day	6
E_1	E	PV reliability	20
E_2	E	PV maintainability	21
E_3	E	PV availability (f of R, M)	22
C_1	C	Total load	23
C_2	C	Desire to buy in auction	24
C_3	C	Desire to sell in auction	25
C_4	C	Amount to sell in auction	26
C_5	C	Amount to buy in auction	27

*In each case, identified concepts may be entered or learned over time, and each may still be relatively complex, e.g., the specifics determining the allowable flexibility in the load may require additional characterization. Reliability / availability / maintainability (RAM) is complex enough to warrant its own FCM model, described separately.

The causal relationships among concepts were declared with a variable T(influence) that codifies both the direction and the intensity of the relationship as shown in Table 2.

Table 2. T(influence) options

Relationship	**Intensity**	**T(influence)**	**Membership function**
inverse	very strong	very strongly negative	µnvs
inverse	strong	strongly negative	µns
inverse	medium	moderately negative	µnm
inverse	weak	weakly negative	µnw
no impact	zero	no influence	µz
direct	weak	weakly positive	µpw
direct	medium	moderately positive	µpm
direct	strong	strongly positive	µps
direct	very strong	very strongly positive	µpvs

Relationships among the concepts identified in Table 1 were described to express the direction and degree to which a change in one concept influences another concept. Each active relationship was identified in terms of both the direction of the relationship, either direct or inverse, and a qualitative assessment of direction was provided. When no relationship exists between a concept CID_i and a resulting concept CID_o, the weight was assigned to the µz membership function. Assessments of existing relationships are provided in Table 3.

Table 3. Interconnection weights between concepts (non-μz)

Node ID	Source CID Description	Node ID	Target CID Description	T(influence)
1	Has PV installed	24	Desire to buy	very strongly negative
1	Has PV installed	27	Amount to buy	very strongly negative
3	Use of luxury appliances	25	Desire to sell	very strongly negative
3	Use of luxury appliances	26	Amount to sell	very strongly negative
4	Required Load Each Hour	25	Desire to sell	very strongly negative
4	Required Load Each Hour	26	Amount to sell	very strongly negative
8	Proximity to max demand day in week	25	Desire to sell	very strongly negative
8	Proximity to max demand day in week	26	Amount to sell	very strongly negative
13	Opacity	26	Amount to sell	very strongly negative
13	Opacity	27	Amount to buy	very strongly negative
24	Desire to buy	25	Desire to sell	very strongly negative
25	Desire to sell	24	Desire to buy	very strongly negative
5	Adjustable Load Each Hour	25	Desire to sell	moderately negative
5	Adjustable Load Each Hour	26	Amount to sell	moderately negative
10	Ambient Temperature	25	Desire to sell	moderately negative
12	Wind Speed	26	Amount to sell	moderately negative
12	Wind Speed	27	Amount to buy	moderately negative
14	Opacity Variability	26	Amount to sell	moderately negative
14	Opacity Variability	27	Amount to buy	moderately negative
19	Load flexibility	4	Required Load Each Hour	moderately negative
23	Total hourly load	26	Amount to sell	moderately negative
2	PV capacity	20	PV reliability	weakly negative
2	PV capacity	21	PV maintainability	weakly negative
3	Use of luxury appliances	18	Profit-focus	weakly negative
3	Use of luxury appliances	19	Load flexibility	weakly negative
6	Adjustable Load Each Day	25	Desire to sell	weakly negative
6	Adjustable Load Each Day	26	Amount to sell	weakly negative
12	Wind Speed	20	PV reliability	weakly negative
15	Comfort-focus	19	Load flexibility	weakly negative
15	Comfort-focus	25	Desire to sell	weakly negative
15	Comfort-focus	26	Amount to sell	weakly negative
16	Green-focus	3	Use of luxury appliances	weakly negative
16	Green-focus	5	Adjustable Load Each Hour	weakly negative
16	Green-focus	6	Adjustable Load Each Day	weakly negative
16	Green-focus	23	Total hourly load	weakly negative
10	Ambient Temperature	19	Load flexibility	weakly negative
11	Ambient Humidity	19	Load flexibility	weakly negative
11	Ambient Humidity	25	Desire to sell	weakly negative
14	Opacity Variability	20	PV reliability	weakly negative
11	Ambient Humidity	23	Total hourly load	weakly positive
11	Ambient Humidity	24	Desire to buy	weakly positive
11	Ambient Humidity	27	Amount to buy	weakly positive
17	Community-focus	1	Has PV installed	weakly positive
3	Use of luxury appliances	4	Required Load Each Hour	weakly positive
6	Adjustable Load Each Day	23	Total hourly load	weakly positive
6	Adjustable Load Each Day	24	Desire to buy	weakly positive
6	Adjustable Load Each Day	27	Amount to buy	weakly positive
7	Proximity to daily noon (max sun)	4	Required Load Each Hour	weakly positive
8	Proximity to max demand day in week	5	Adjustable Load Each Hour	weakly positive
8	Proximity to max demand day in week	6	Adjustable Load Each Day	weakly positive
9	Proximity to annual summer solstice	3	Use of luxury appliances	weakly positive
15	Comfort-focus	3	Use of luxury appliances	weakly positive
15	Comfort-focus	4	Required Load Each Hour	weakly positive
15	Comfort-focus	5	Adjustable Load Each Hour	weakly positive
15	Comfort-focus	6	Adjustable Load Each Day	weakly positive
15	Comfort-focus	23	Total hourly load	weakly positive
15	Comfort-focus	24	Desire to buy	weakly positive
15	Comfort-focus	27	Amount to buy	weakly positive
16	Green-focus	1	Has PV installed	weakly positive
16	Green-focus	24	Desire to buy	weakly positive
24	Desire to buy	5	Adjustable Load Each Hour	weakly positive
24	Desire to buy	6	Adjustable Load Each Day	weakly positive
3	Use of luxury appliances	5	Adjustable Load Each Hour	moderately positive
3	Use of luxury appliances	6	Adjustable Load Each Day	moderately positive
5	Adjustable Load Each Hour	23	Total hourly load	moderately positive
5	Adjustable Load Each Hour	24	Desire to buy	moderately positive

5	Adjustable Load Each Hour	27	Amount to buy	moderately positive
8	Proximity to max demand day in week	4	Required Load Each Hour	moderately positive
9	Proximity to annual summer solstice	4	Required Load Each Hour	moderately positive
9	Proximity to annual summer solstice	5	Adjustable Load Each Hour	moderately positive
9	Proximity to annual summer solstice	6	Adjustable Load Each Day	moderately positive
10	Ambient Temperature	23	Total hourly load	moderately positive
10	Ambient Temperature	24	Desire to buy	moderately positive
10	Ambient Temperature	27	Amount to buy	moderately positive
17	Community-focus	24	Desire to buy	moderately positive
17	Community-focus	25	Desire to sell	moderately positive
23	Total hourly load	27	Amount to buy	moderately positive
19	Load flexibility	6	Adjustable Load Each Day	strongly positive
1	Has PV installed	2	PV capacity	very strongly positive
1	Has PV installed	25	Desire to sell	very strongly positive
1	Has PV installed	26	Amount to sell	very strongly positive
2	PV capacity	26	Amount to sell	very strongly positive
3	Use of luxury appliances	23	Total hourly load	very strongly positive
3	Use of luxury appliances	24	Desire to buy	very strongly positive
3	Use of luxury appliances	27	Amount to buy	very strongly positive
4	Required Load Each Hour	23	Total hourly load	very strongly positive
4	Required Load Each Hour	24	Desire to buy	very strongly positive
4	Required Load Each Hour	27	Amount to buy	very strongly positive
7	Proximity to daily noon (max sun)	10	Ambient Temperature	very strongly positive
7	Proximity to daily noon (max sun)	22	PV availability	very strongly positive
7	Proximity to daily noon (max sun)	25	Desire to sell	very strongly positive
7	Proximity to daily noon (max sun)	26	Amount to sell	very strongly positive
8	Proximity to max demand day in week	23	Total hourly load	very strongly positive
8	Proximity to max demand day in week	24	Desire to buy	very strongly positive
8	Proximity to max demand day in week	27	Amount to buy	very strongly positive
9	Proximity to annual summer solstice	10	Ambient Temperature	very strongly positive
9	Proximity to annual summer solstice	25	Desire to sell	very strongly positive
9	Proximity to annual summer solstice	26	Amount to sell	very strongly positive
16	Green-focus	25	Desire to sell	very strongly positive
16	Green-focus	26	Amount to sell	very strongly positive
18	Profit-focus	22	PV availability	very strongly positive
18	Profit-focus	24	Desire to buy	very strongly positive
18	Profit-focus	25	Desire to sell	very strongly positive
18	Profit-focus	26	Amount to sell	very strongly positive
19	Load flexibility	5	Adjustable Load Each Hour	very strongly positive
20	PV reliability	22	PV availability	very strongly positive
21	PV maintainability	22	PV availability	very strongly positive

V. SIMULATION RESULTS

The simulation included 27 concepts, about a third of which were transmitters. Ten percent were receivers and the remaining were ordinary, a combination of transmitters and receivers. The model includes over 100 interconnections.

The results show that the critical combined concepts (those with a CGID of C) are heavily influenced by a variety of different factors. Visualization was employed to further refine and develop the models. In some cases, intensity levels were further subdivided and additional membership functions were employed. After several iterations, the final inputs were selected and the model evaluated. The FCM was visualized by adding colors and line weights to the arcs and minimizing the size of the nodes. The resulting interactive, responsive model allows us to determine the key factors evaluated in this initial case that drive five critical outcomes:

1. Total hourly load demand
2. Amount to sell
3. Desire to sell
4. Amount to buy
5. Desire to buy

The most important factors, their relative degree of influence, and the associated precedents for each are presented in Figures 3-7, respectively. Currently, the interactive model does not explicitly depict the *direction* of influence (either direct or inverse) between nodes.

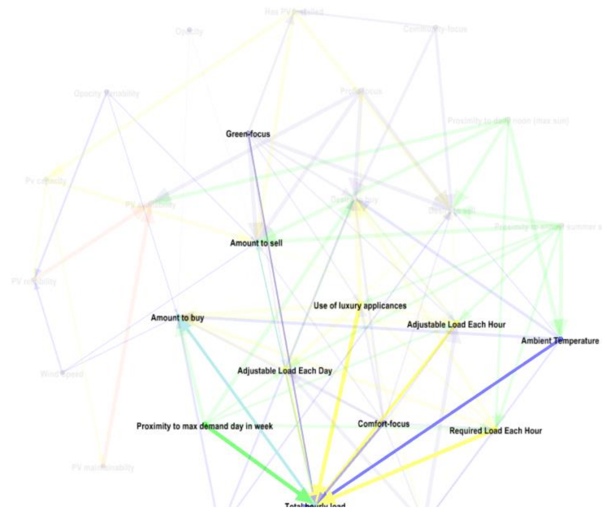

Fig 3. Resulting key factors affecting total hourly load

Fig 4. Resulting key factors affecting amount to sell

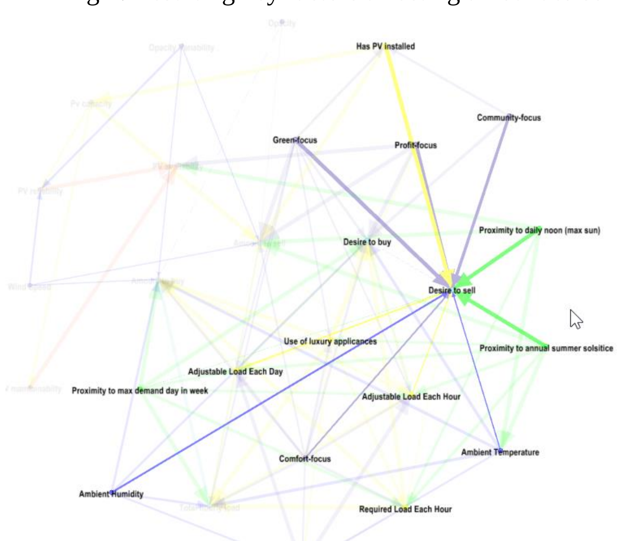

Fig 5 Resulting key factors affecting desire to sell

Fig 6. Resulting key factors affecting amount to buy

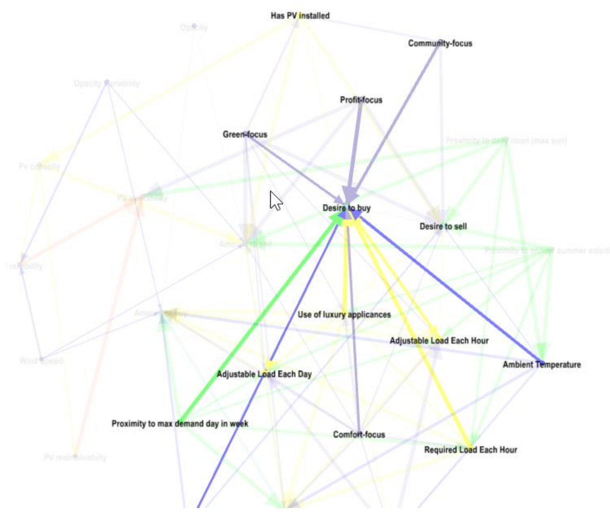

Fig 7. Resulting key factors affecting desire to buy

VI. CONCLUSIONS AND FUTURE WORK

Results from our initial FCM development provide insights into the key factors driving autonomous agent auction execution. Work continues with the development of configurable models, models that will accept necessary inputs and information from a variety of governing sources, including the utility company (e.g., power rates and schedules), the participating owners (e.g., preferences, load scheduling flexibility), and external services including local solar schedules (e.g., dawn, dusk, solar noon) and weather services (e.g., temperature, humidity, opacity). Further, the models continue to evolve, and are being augmented with additional concepts and relationships (e.g., availability of onsite battery storage, electric vehicles, cloud speed, opacity variability, and forecasts).

ACKNOWLEDGMENT

This work was supported by the National funds allocated by the Greek General Secretarial of Research and Development project 2006SE01330025 as continuation of FP7–PEOPLE–IAPP–2009, Grant Agreement No. 251589, Acronym: SAIL

REFERENCES

[1] L. Camarinha-Matos and H. Afsarmanesh, "A comprehensive modeling framework for collaborative networked organizations", Journal Intelligent Manufactiuring, 18, 529-542, 2007.

[2] A. Wierbicki, "Modeling as a way of organizing knowledge", European Journal Operational Research 176, pp. 610-635, 2007.

[3] B. Kosko, "Fuzzy Cognitive Maps," International Journal of Man-Machine Studies, 24, pp. 65-75, 1986.

[4] B. Kosko, Fuzzy Engineering, Prentice-Hall, New Jersey, 1997

[5] R. Axelrod, Structure of Decision: the cognitive maps of political elites. NJ: Princeton, 1976.

[6] M. Hagiwara, "Extended fuzzy cognitive maps," IEEE International Conference, Fuzzy Systems, San Diego, CA, 1992, pp. 795 - 801.

[7] W.R. Zhang, S.S Chen, W. Wang and R.S. King, "A cognitive map based approach to the coordination of distributed cooperative agents" IEEE Transactions Systems, Man, and Cybernetics, 22 (1), pp. 103-114 (1992).

[8] E. Papageorgiou, C. Stylios C. and P. Groumpos, "An Integrated Two-level Hierarchical System for Decision Making in Radiation Therapy based on Fuzzy Cognitive Maps" IEEE Transactions on Biomedical Engineering 50 (12), pp1326-1339, 2003.

[9] V. Georgopoulos and C. Stylios, "Complementary case-based reasoning and competitive Fuzzy cognitive maps for advanced medical decisions," in *Soft Computing*, vol. 12, pp. 191-199, 2008.

[10] B. J. Juliano, "Fuzzy cognitive structures for automating human problem solving skills diagnosis", Proc. 9th Annual NAFIPS Conf., 311-314, 1990.

[11] R. Taber, R. Fuzzy cognitive maps model social systems. AI Expert, 9, pp. 8-23, 1994.

[12] K. Goto, T. Yamaguchi and T. Takagi, "Dynamic Model for a Plant Using Associative Memory System", Proc. of the International Conference on Artificial Neural Networks (ICANN-92), pp. 1517-1520, 1992.

[13] C.E. Pelaez and J. B. Bowles "Using Fuzzy Cognitive Maps as a System Model for Failure Models and Effects Analysis", Information Sciences, 88, pp.177-199, 1996.

[14] C.D. Stylios and P.P. Groumpos, "The Challenge of modeling Supervisory Systems using Fuzzy Cognitive Maps", Journal of Intelligent Manufacturing, 9, pp. 339-345, 1998.

[15] C. Stylios and P. Groumpos, "Modeling Complex Systems Using Fuzzy Cognitive Maps" IEEE Transactions on Systems, Man and Cybernetics: Part A Systems and Humans. 34, (1), pp. 155-162, 2004.

[16] E. Papageorgiou, C. D. Stylios and P. Groumpos, "Active Hebbian Learning Algorithm to train Fuzzy Cognitive Maps," *Int. journal of Approximate Reasoning*, vol. 37, pp. 219-249, 2004.

[17] C.D. Stylios and P. P Groumpos, "A soft computing approach for modeling the supervisor of manufacturing systems", Journal of Intelligent and Robotics Systems, 26 (3-4), pp. 389-403, 1999.

[18] M. Bazilian, I. Onyeji, M. Liebreich, I. MacGill, J. Chase, J. Shah, D. Gielen, D. Arent, D. Landfear, S. Zhengrong, "Re-considering the economics of photovoltaic power" Renewable Energy, 53, pp. 329–338, 2013

[19] T. Sueyoshi and G. Tadiparthi, "Agent-based approach to handle business complexity in US wholesale power trading", IEEE Transactions on Power Systems, 22 (2), pp. 532-543, 2007.

[20] L. Camarinha-Matos, "Collaborative smart grids-A survey on trends", Renewable and Sustainable Energy, 65, pp.283-294, 2016.

[21] L. Suhanthi, S. Iniyan and A. Samuel, "Applications of fuzzy logic in renewable energy systems- A review", Renewable and Sustainable Energy Reviews, 48, pp.585-607, 2016.

[22] A. Voinov and F. Bousquet, "Modelling with stakeholders", Environmental Modelling & Software, 25(11), 1268-1281, 2010.

[23] E. Bourgani, C.D. Stylios, G. Manis, and V.C. Georgopoulos, "Timed Fuzzy Cognitive Maps," in *IEEE International Conference on Fuzzy Systems FUZZ-IEEE 2015*, Istanbul, Turkey, August 2- 2015, pp. 1-6.

[24] J. S. R. Jang, C. T. Sun and E. Mizutani, "Neuro-Fuzzy & Soft Computing", Prentice-Hall, Upper Saddle River, 1997.

[25] D. M. Case and C. Stylios, "Fuzzy Cognitive Map to Model Project Management Problems", in Proceedings of the 2016 Annual Conference of the North American Fuzzy Information Processing Society NAFIPS 2016, El Paso, Texas, October 31-Novemeber 4, 2016,

[26] A. Pahwa, S. A. DeLoach, B. Natarajan, S. Das, A. Malekpour, S. S. Alam, S. S., and D. M. Case, "Goal-based holonic multiagent system for operation of power distribution systems" in *IEEE Transactions on Smart Grid*,*6*(5), 2510-2518, 2015.

[27] E. Guerci, M. Rastegar and S. Cincotti, S. Agent-based modeling and simulation of competitive wholesale electricity markets. In *Handbook of Power Systems II* (pp. 241-286). Springer Berlin Heidelberg, 2010.

[28] D. Case, M. Faqiry, B. Majumder, S. Das and S. DeLoach, "Implementation of a Two-tier Double Auction for On-line Power Purchasing in the Simulation of a Distributed Intelligent Cyber-Physical System", Advances in Artificial Intelligence, 79, 2014.