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Modeling Complex Logistics Systems using Soft Computing Methodology of Fuzzy Cognitive Maps

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***Abstract*—Fuzzy Cognitive Maps (FCMs) is an abstract soft computing modeling methodology that has been applied in many areas quite successfully. In this paper we discuss its modeling applicability to complex logistics systems involved in an intermodal container terminal and the way it could represent and handle the vast amount of information by an abstract point of view based on a decentralized approach, where the supervisor of the system is modeled as an FCM. We also investigate its applicability as a metamodel of the intermodal terminal in a simulation-optimization framework. Experts have a key role in developing the FCM as they describe a general operational and behavioral model of the system using concepts for the main aspects of the system, and weighted directed edges to represent causality. On the other hand, when data is available, data driven approaches have also been proposed for the development of FCM models. The FCM representation and implementation is discussed to develop a behavioral model of any complex system mainly based on a hierarchical structure, as well as its use as a metamodel of the system.**

I. Introduction

Modern systems such as logistics systems are characterized by uncertainties with high degree and great complexity as it is observed in any production, logistics and enterprise structures [1]. A quite common approach in modeling complex systems is their description as a system of connected agents that exhibits an emergent global behavior not imposed by a central controller but resulting from the interactions between the agents [2]. Complexity and large scale characterize modern logistics systems involved in intermodal container terminals that usually are described as systems-of-systems, which are non-monolithic entities characterized by geographic distribution, operational and management independence of their subsystems and presenting emergent behavior and evolutionary development.

Scale and complexity of logistics systems and their modeling requirements and organizational needs continuously increase. In addition to this, new practices, structures, models, techniques and methods are emerging as complements to increased needs. Models of advanced logistics systems in intermodal container terminals have to cover all modes of transportation and related functions involving storage and cargo handling. Their requirements are high autonomicity, great efficiency and intelligence, which force engineers to investigate new techniques that can integrate and combine well-known advanced methodologies that will be the core of these sophisticated systems.

Any effective knowledge representation is based on advanced modeling methods. Moreover, the requirements in modeling and adequate description of systems cannot be met only with the existing methodologies and theories. Therefore, it is necessary to investigate and use new methods that will exploit human experience, will have learning capabilities and will take into account the imprecision and uncertainty, which characterize real world systems [3]. The flourishing of new theories that exploit the synergy of discipline theories: such as Fuzzy Logic, Neural Networks, Genetic Algorithms, Probabilistic Reasoning and Knowledge Based Systems, known as Soft Computing Techniques and/or Computational Intelligent techniques motivate researchers to utilize them in order to create and develop new models and sophisticated systems based on knowledge exploitation [4]. Such advanced representation techniques will use effectively all the knowledge of the complex system resources, especially the insights and experience of front-line operators and experts, in order to achieve continuous improvements.

In the 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 such 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 for any procedure includes uncertain description and can have subtle variations in relation to time and space; in such situations Fuzzy Cognitive Maps (FCMs) can be a very suitable tool.

FCM were introduced by Kosko as a synergism of Fuzzy Logic and Neural Networks [5][6]. Kosko 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 expressions [7].Fuzzy values are introduced in FCMs to better represent causal reasoning [8] forming a network of interconnected concepts that can be used to model situations by classes and their causal links between them.

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FCMs have been used to make decision analysis and coordinate distributed agents [9], to develop Medical Decision Support Systems (DSSs) [10], and to accompany case-based reasoning approaches [11]. FCMs have also been used as structures for automating human problem solving skills [12] and to represent complex social systems where relationships between social forces demand feedback [13]. They have also been used to model and support plant control systems of a water distribution system [14] and to perform Failure Modes and Effects Analysis in the process industry [15]. FCMs have been proposed to model the Supervisor of complex manufacturing systems [16], concerning hierarchical systems, where the supervisor incorporates knowledge [17] and is capable of learning relational structures and evidential reasoning [18].

It is believed that FCMs can improve model representation and development of sophisticated systems, combining characteristics from Fuzzy Logic and Neural Networks and can contribute from a behavioral point of view, first to model sub-systems at a lower level and, second, at the supervisory decision and coordination level [19]. Moreover, new hybrid methods based on complementary approaches for enhancing FCMs construction abilities make FCMs potential candidates to be used as metamodels in a simulation-optimization framework.

In the rest of this paper, section II will briefly introduce FCMs, presenting the main aspects of this modeling approach. Section III discusses the main requirements for modeling complex logistics systems and how FCMs meet their requirements. Section IV presents how FCMs could be used to develop DSSs for logistics systems and Section V introduces for the first time the usage of FCMs as metamodel of a system. Finally section VI concludes the paper and gives future research directions.

II. Fuzzy Cognitive Maps

FCMs belong to the neuro-fuzzy systems that aim at solving real world decision-making problems, modeling and control problems [17]. 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 role in the conception and design of hybrid intelligent systems [20]. An FCM is a conceptual network, which is in most of the cases built by experts, using an interactive procedure of knowledge acquisition.

FCMs are dynamical systems that have the topology of a directed fuzzy graph (Figure 1) consisting of nodes and edges and permitting cycles and feedback. 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 among concepts (Figure 1). It must be mentioned that all the values in the graph are fuzzy, so concepts take values in the range between [0, 1] and the weights of the interconnections belong in the interval [-1, 1]. The concept nodes C_i have fuzzy nature [21]. The edges w_{ij} define rules or causal flows $C_i \rightarrow C_j$ between the concept nodes. At time t the state of the FCM is the $1 \times n$ concept vector $\boldsymbol{A}^t$ gathering the values of concepts $\boldsymbol{A}^t = [C_1, \ldots, C_n] \in [0,1]$ or a point in the fuzzy n-cube state space. The n-by-n matrix $\boldsymbol{W}$ lists the n^2 rules or pathways in the causal web, represented by the corresponding weight. FCM dynamics depend on the dynamics of the concept nodes and causal edges. These adaptive feedback fuzzy systems are nonlinear function approximations with even more complex dynamics than feedback neural networks [6].

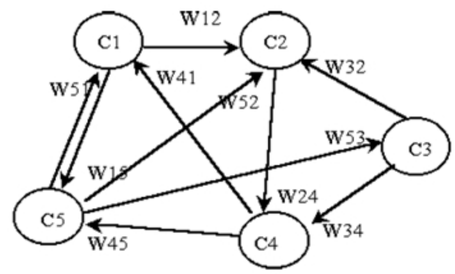

Fig. 1. The Fuzzy Cognitive Map model

With the graphical representation it becomes clear, which concept influences other concepts, showing the interconnections between concepts and permitting thoughts and suggestions in the construction of the graph, as the adding or deleting of an interconnection or a concept. In conclusion, FCMs are fuzzy-graph structures, which allow systematic causal propagation, in particular forward and backward chaining. The simplest FCMs act as asymmetrical networks of threshold or continuous concepts and converge to an equilibrium point or limit cycles. They have non-linear structure of their concepts and differ from Neural Networks in their global feedback dynamics.

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, they determine the structure and the interconnections of the network using fuzzy conditional statements. Experts use linguistic variables in order to describe the relationship among concepts, and then all the variables are combined and the weights of the causal interconnections among concepts are determined. On the other hand, the fuzzy graph structure can emerge through a learning process based on accumulated historical data [22].

The mathematical model of an FCM can be described by the matrix $\boldsymbol{W}$, which gathers the weight values of the interconnections between the n concepts of the FCM; and the vector $\boldsymbol{A}$, which gathers the values of the n concepts.

The value A_i for each concept C_i is calculated by the following rule, presented in equation 1:

$$A_i = f\left(\sum_{\substack{j=1 \\ i \neq j}}^{n} A_j^{t-1} W_{ji} + A_i^{t-1} \right) \qquad (1)$$

Namely, A_i is the value of concept C_i at time t, A_i^{t-1} the value of concept C_i at time t-1, A_j^{t-1} the value of concept

C_j at time *t*-1, and the weight W_{ji} of the interconnection from concept C_j to concept C_i and *f* is a threshold function.

The unipolar sigmoid function is the most used threshold function, [23] where $\lambda \succ 0$ determines the steepness of the continuous function *f*. The sigmoid function ensures (equation 2) that the calculated value of each concept will belong to the interval [0, 1].

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

A more general and compact mathematical model for an FCM is presented by the following equation:

$$\mathbf{A}^{t} = f\left(\mathbf{A}^{t-1} \circ \mathbf{W} + \mathbf{A}^{t-1}\right) \tag{3}$$

Thus, equation 3 computes the new state vector $\mathbf{A}^t$, which results from the multiplication of the previous, at time t-1, state vector $\mathbf{A}^{t-1}$ by the weight edge matrix $\mathbf{W}$. The new state vector holds the new values of the concepts after the interaction among concepts of the FCM. Values of concepts are calculated and when the FCM reaches an equilibrium point or a limit cycle, values of concepts stop to change.

An FCM can represent the human knowledge on the operation of the system. The developed FCM is a behavioral model of the system, which is based on the knowledge, and experience of the expert who described the model of the system in terms of concepts and inter-relationships among concepts. Using the FCM model the operation of the system can be simulated and in each step of the interaction, the new state vector $\boldsymbol{A}$ is computed according to equation 3. Moreover, when the relationship between the main factors/concepts of a system cannot be exactly extracted from the knowledge and experience of experts or could be further improved, then data driven approaches can be employed such as the inclusion of learning algorithms. Then, an FCM exploiting its universal approximation capabilities can successfully be used to model the system.

III. Logistic Complex Systems and Fuzzy Cognitive Maps

Logistics Systems are complex systems requiring new models, based on the combination of knowledge based techniques and methodologies from various areas. Usually it is very difficult for both researchers and managers to achieve a clear, coherent picture of how such logistics systems work. In most cases it requires a lot of effort and time to obtain satisfactory solutions to the technical problems inherent in complex logistics systems. Furthermore, we continue to witness the development of fundamentally new approaches to the subject, mainly because the practical world of logistics is continuously changing over the past few decades with the explosion of information technologies [24]. They are characterized with high complexity and for most of them it is more practical and convenient to construct an abstract qualitative model rather than a mathematically accurate one. Thus, the use of concepts from information theory, neural networks and fuzzy logic [25] to represent and process information in a hybrid and hierarchical methodology could be useful [26].

In addition to this, there is a great deal of emphasis placed on the development of integrated and holistic solutions, it would be therefore interesting to design efficient logistics systems considering simultaneously all integral aspects of their operation. Especially an approach more abstract rather mathematical one, which will require not detailed huge amount of data or a mathematical formulation with thousands of variables but only structured information, could come handy in such a complex domain. Such an approach based on the understanding of the logistics systems, would be particularly useful when decisions have to be made with incomplete or uncertain information; e.g. when evaluating a business plan, or designing a system for a long time horizon [27].

FCMs use a symbolic representation for the description and modeling of systems. FCMs model any system from a behavioral point of view and can utilize an abstract methodology to describe and model the behavior of the system. An FCM integrates the accumulated experience and knowledge on the operation of the system, using mainly human experts that know the operation of system and its behavior. They represent the human accumulated knowledge on the operation and behavior of the system, using concepts to stand for each characteristic of the system. Experts are actively involved in the creation of models and they interact with the models and so their understanding for the benefits of models will increase the quality of models, the inherent knowledge in the model will be used more frequently and models will be widely accepted [28].

Furthermore, complex systems operate in changing and unknown environments. When the environment changes, the system has to adapt and the input-output characteristics of the system will be altered [29]. If a single model is identified, it will have to adapt itself to the new environment. In non-linear systems, a single model may not be adequate to identify the changes in the process behavior (i.e. a model may not exist in the assumed framework to match the environment). Hence, multiple models could be used to identify the different environments. In some environments different models may be available whose validity (or accuracy) depends upon the region in the state space where the system trajectories lie. All the above considerations suggest that multiple models may be preferable to a single model, in many different situations (Figure 2).

A set of separate models is used to form hybrid models. The rationale for using multiple models is to ensure that there is at least one model with parameters sufficiently close to those of the unknown process. This “multiple models” approach possesses different modeling strategies to accommodate different operating conditions, adaptive behavior to perform model design under uncertain or unfamiliar situations and the capability to co-ordinate separate models to accomplish the system task.

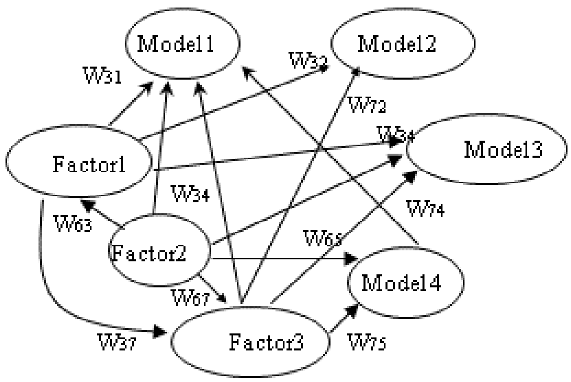

Fig. 2. An FCM aggregating multiple models

FCMs are used to aggregate the separate models and to perform a sophisticated approach by integrating alternative modeling techniques. An augmented FCM can accomplish identification of the different models and cope with limited uncertainty situations.

IV. Fuzzy Cognitive Map Decision Support System for Logistics Systems

DSSs are available for various stages of supply chain management including logistics planning, production planning, demand management and pricing decisions. DSSs have to cope with the overwhelming flow of data, information and knowledge. These applications involve a large number of dynamic objects that change their state in time and are engaged in complex spatio-temporal relations. It is important to understand the situation in which these objects participate, to recognize emerging trends and to undertake protective actions that will lead to a predefined goal situation.

Container terminals and more specifically intermodal container terminals involve a number of complex logistics processes such as the spatial allocation of the containers on the terminal yard, the allocation of resources (cranes, tracks, personnel) and the scheduling of operations in order to maximize some performance indicators [30],[31]. Managing such a complex systems in an integrated manner is very demanding and usually a “hierarchical decomposition approach” is employed. Capturing and utilizing the expert’s knowledge, effectively and efficiently, promises to improve modeling operational conditions [32].

For this kind of intermodal container terminals there is a need to design and develop DSSs, which will be able to interpret the huge amount of data arising from the intermodal transport system and to suggest the optimal decisions so as to support operators in performing complex management tasks.

An FCM could be built to model the interaction of the different concepts comprising the processes in the terminal along with the key performance indicators (e.g. berthing time of vessels, the resources needed (cranes, trucks, etc), the waiting time of customer trucks, road congestion) (Figure 3). This approach [33] could be used to develop a DSS.

The main FCM-DSS task is the co-coordination of the whole system of systems. It supervises the local subsystems, co-ordinates the sharing of the resources, it schedules, choosing between different distribution sequences and the right command to the right agent [34]. The role of the FCM is to extend the range of application of a conventional modeling approach by using a more abstract representation, general knowledge and adaptation heuristics and to enhance the performance of the whole system. Symbolic representation and processing of the supervisor of a hierarchical system using FCMs or any other similar approach will undoubtedly play an important role in the construction of Intelligent Systems. Using human knowledge and experience of the system, can lead to the creation of a higher degree of autonomous systems.

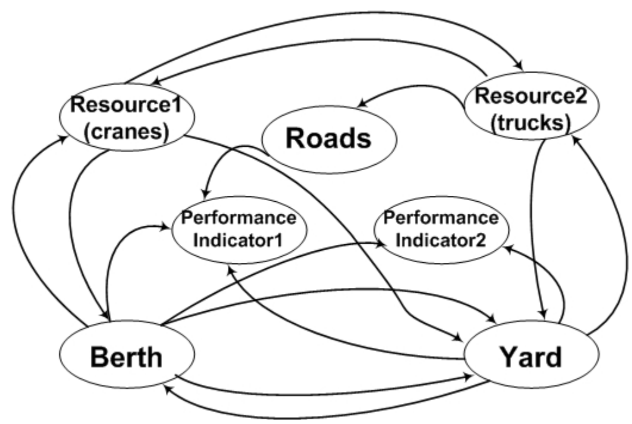

Fig. 3. A hypothetical FCM model for an abstract logistic system for a container terminal

In the case of intermodal container terminals, each logistics IT centre copes with a specific process taking place within the terminal “limits”. It is well known that the questions concerning transportation modeling and optimization are in most cases difficult mixed integer programming problems making it sometimes unrealistic to solve them to optimality let alone to “attack” them in an integrated fashion analytically. Therefore the overall problem of optimal terminal management is broken down into subsystems. Each one of those logistics and informatics subsystem manages are modeled by the local model for each logistic center with each one of them capable to “solve” the various resource allocation and scheduling problems that arise within its “authority”.

Since many needs in an establishment such as a container terminal, are already satisfied by existing systems in logistics, it is not very useful to rebuild or re-engineer the complete IT system [35]. Therefore a hierarchical structure can be adopted for the development of sophisticated DSSs for intermodal container terminals in an integrated manner.

In addition, an FCM could be used as a metamodel of an existing DES of a logistic system and more specifically of an intermodal container terminal. Given such a metamodel, unsatisfactory solutions/decisions can be filtered out whereas, on the other hand, promising solutions could be pinpointed and returned to the DES for verification and sensitivity analysis.

V. INTRODUCING FUZZY COGNITIVE MAPS AS METAMODELS

As already explained, many real world problems are too complex to be given tractable mathematical formulations [36]. Especially in the area of manufacturing, supply chain management, financial management and logistics, the systems under investigation cannot be modeled analytically in most of the cases [37]. For such cases, a well known approach is Discrete Event Simulation (DES) that has been extensively used to evaluate the behavior/performance of a system. However the use of DES comes with a cost: each simulation cycle can last from a few seconds up to some minutes and since a simple evaluation (run) is often insufficient to evaluate the system, the computational burden and the required time can be significant. Therefore a more exploratory process is needed in the form of simulation optimization that can provide the operator or the decision maker with the “optimum” decision.

Since a DES run quite slowly, one of the potential solutions is the use of a metamodel, which is a “model of the model” and use the metamodel to search for the optimal decision set. Since any metamodel can run much faster than the underlying simulation model, it can be used as a substitute/complement to the simulation optimization problem [38]. In this way the metamodel could become the prediction model for the simulation in the same way that the simulation is the prediction model for the real system [39],[40].

Metamodels can be built using “simple” linear, quadratic and higher order polynomials, splines, spatial correlation (kriging) models, or more recently novel advanced methods such as neural networks, support vector regression models etc [40].

FCMs can be used as metamodels due to their universal approximation property, incorporating both expert knowledge about the system as well as data driven approaches. FCMs can also be used along with a DES if such a model has already been developed for a particular system. Therefore the FCM acts as a metamodel and an appropriate optimization procedure (depending on the nature of the problem) can be utilized to conduct a much more effective search of the parameter/decision space.

Especially in the case of problems involving metaheuristic optimizers [41], as it is the case in most container terminals, an FCM metamodel could be used to filter out solutions that are expected to be inferior than the current best solution and also be used as a means for generating new trial solutions.

VI. CONCLUSIONS

The soft computing modeling methodology of FCMs has been briefly reviewed and presented. It offers essential opportunities for design and implementation of new advanced models suitable for complex systems such as logistics systems. Taking advantage of the characteristics and the abilities of the FCMs, the main needs that have to be addressed are discussed. An important question is what methodologies might be further developed in order to meet the requirements of modern complex systems and at the same time take advantage of existing and future technologies.

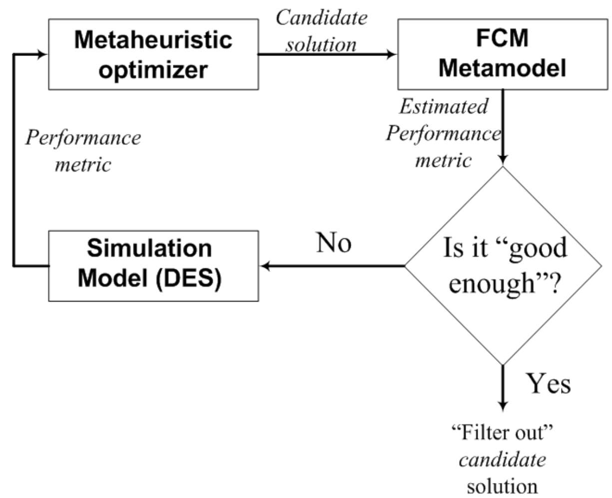

Fig. 4. FCM metamodel filter combined with a metaheuristic optimizer and a DES

The increase in the complexity and sophistication of large scale logistics systems requires the implementation of new intelligent strategies. Human experts have a key role in the supervision of any system. Capturing the heuristic knowledge of experts, representing, modeling and exploiting it using FCMs may provide the foundation of new directions in modeling complex logistics systems. The main requirements for sophisticated systems are the possession of human-like expertise within a specific domain, adaptation and learning to do better in changing environments. An FCM is a symbolic representation for the modeling of complex systems, describing different aspects in their behavior in terms of concepts and interactions among them. An interesting approach is the hierarchical one, where the supervisor of systems is modeled as an FCM that follows the principle of "decreasing precision and increasing intelligence" [42].

Within this framework FCMs seems a very promising tool for the development of intelligent DSSs either by constructing an abstract model of the whole process or as a two stage hierarchical system. The latter approach could take advantage of the already (mature) existing technologies that are installed in most of container terminals world-wide, dedicated for a specific process within the terminal limits.

Furthermore FCMs can be combined with existing DES systems offering a flexible tool to speed up the simulation optimization procedure. To the best of our knowledge FCMs have not yet been used within this context, even though other members of the soft computing family (neural networks, support vector regression models) have already proven the potential use of such tools.

In future work we will try to develop a hierarchical system using an FCM at the supervisor level and test it for the case of a port in the Adriatic sea. Another candidate direction will be to develop and train an FCM metamodel for an already existing DES for the same port [42].

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