# Issues on Dynamic Cognitive Map Modelling of Purse-seine Fishing Skippers Behavior

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***Abstract*— This paper focus on obtaining a qualitative dynamic model based on real world data taken from a real world qualitative system: the day to day behavior of purse seine fishing fleet skippers. The model is based on a Dynamic Cognitive Mapping approach (Rule Based Fuzzy Cognitive Maps – RB-FCM) where several developments had to be made in order to obtain a workable system. Most changes were due to timing issues, which are essential in the study of System Dynamics but have traditionally been avoided in most Dynamic Cognitive Maps modelling approaches.**

Keywords: Rule Based Fuzzy Cognitive Maps, Purse-Seine Fishing, Modelling of dynamic qualitative systems.

## I. Introduction

FISHERMEN are the most important predators in marine ecosystems, with a high impact on the mortality on marine populations and destruction of marine habitats. In this paper we focus on the issues involved in obtaining a qualitative dynamic model of this predatory behavior. Such a model could allow simulating and predicting the responses of the skippers of fishing vessels to a wide range of relevant factors, whether of natural or human origin. The work focus on modeling the Portuguese purse-seine fishing fleets, and the model was obtained by combining recent advances in qualitative modeling techniques (dynamic cognitive maps) with a privileged source of real-time information on the behavior of skippers taken onboard during fishing trips. When connected to existing models of the population dynamics of different fish stocks, the model will provide a framework to test the effectiveness of different management measures, such as catch restrictions, marine closed areas, seasonal fishing bans, etc.

## II. Dynamic Cognitive Maps

The term Dynamic Cognitive Maps has been recently used to describe techniques that allow simulating the evolution of cognitive maps through time. Axelrod [1] work on cognitive maps (CM) introduced a way to represent real-world qualitative systems that could be analyzed using several methods and tools. However, those tools only provided a way to identify the most important structural elements of the CM. Complete, efficient and practical mechanisms to analyze and predict the evolution of data in CM were not available for years due to several reasons. System Dynamics tools like those developed by J.W.Forrester [16] could have provided the solution, but since in CM numerical data may be uncertain or hard to come by, and the formulation of a mathematical model may be difficult, costly or even impossible, then efforts to introduce knowledge on these systems should rely on natural language arguments in the absence of formal models. Fuzzy Cognitive Maps (FCM), as introduced by Kosko [20][21][22], were developed as a qualitative alternative approach to system dynamics. However, although very efficient and simple to use, FCM are causal maps (a subset of cognitive maps that only allow basic symmetric and monotonic causal relations between concepts)[10], and, in most applications, a FCM is indeed a man-trained Neural Network that is not fuzzy in a traditional sense and does not exploit usual fuzzy capabilities. They do not share the properties of other fuzzy systems and the causal maps end up being quantitative matrixes without any qualitative knowledge. Rule Based Fuzzy Cognitive Maps (RB-FCM) were introduced in [4][5][6][7][8][9][10][11] and were developed as a tool that models and simulates real world qualitative system dynamics while trying to avoid the limitations of those approaches. The following sub sections resume some features of RB-FCM that are useful to the comprehension of this paper.

### A. *Rule Based Fuzzy Cognitive Maps*

RB-FCM allow a representation of the dynamics of complex real-world qualitative systems with feedback, and the simulation of events and their influence in the system. They can be represented as fuzzy directed graphs with feedback, and are composed of fuzzy nodes (Concepts), and fuzzy links (Relations). RB-FCM are true cognitive maps since are not limited to the representation of causal relations. Concepts are fuzzy variables described by linguistic terms, and Relations are defined with fuzzy rule bases.

RB-FCM are essentially iterative fuzzy rule based systems where we added fuzzy mechanisms to deal with feedback, introduced timing mechanisms and new ways to deal with uncertainty propagation, and were we defined several kinds

Manuscript received December 14, 2007. This work was supported in part by the FCT - Portuguese Foundation for Science and Technology under project PTDC/MAR/66231/2006.

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of Concept relations (Causal, Inference, Alternatives, Probabilistic, Opposition, Conjunction, etc.) to cope with the complexity and diversity of the dynamic qualitative systems we are trying to model. Among new contributions brought by RB-FCM, there is a new fuzzy operation – the Fuzzy Carry Accumulation -, which is essential to model the mechanisms of qualitative causal relations (FCR – Fuzzy Causal Relations) while maintaining the simplicity and versatility of FCM.

### *B. Expressing Time in Dynamic Cognitive Maps*

Time is probably the most essential factor when modeling a dynamic system. However, most DCM approaches seem to ignore this fact. In order to maintain consistency in the process of modeling the dynamics of a qualitative system, it is necessary to develop and introduce timing control mechanisms. To allow the representation of time flow, delays, and the inhibition of certain relations when they have no influence on a given instant, changes were made to the engine of RB-FCM. The following sub sections give a brief summary of those mechanisms. More details can be found in [9]

#### *1) Implicit Time*

Time in RB-FCM must inevitably be represented implicitly in every relation; therefore, the responsibility of maintaining temporal coherence in the process of modeling a system relies heavily in the modeler. He or she must not only be responsible to find the nature and characteristics of the relation, but must also ensure that the magnitude of the relation is adequate to the time interval that it represents.

#### *2) Base Time (B-Time)*

Due to the iterative nature of the RB-FCM simulation process, each system iteration must represent the flow of a given amount of time. In RB-FCM this period is called Base Time (B-Time). It represents the "resolution" of the simulation, i.e., the highest level of temporal detail that a simulation can provide in the modeled system.

B-Time must always be implicit while defining each rule in each rule base, especially in the case of causal relations, since Variations are always involved in those relations. The linguistic variable indicating the highest possible amount of change in each Variation represents the largest amount of change that the physical entity modeled by the Variation is expected to suffer during the period of time that B-Time models.

#### *3) B-Time Selection*

The choice of B-Time is highly dependent on the Real-world system being modeled. It could be one hour, one day, two days, one week, one year, one century or any other time period. It depends on the desired or advisable level of detail, complexity and intended long-term analysis of the system. Shorter B-Times usually need more detailed and complex rule bases and imply a much more careful approach to the precision and validity of the rules. Longer B-Times should provide more valid long-term simulations, but short-term detail, precision and validity will possibly be sacrificed.

The intrinsic nature of the system is also an important factor for B-Time selection. Chaotic or pseudo-chaotic systems obviously need shorter B-Times (1 hour, 1 day), since small deviations in the first steps of the simulation will cause huge errors in later steps. On the other hand, stable systems that tend to converge to a single state or single cycle of states usually handle very well long B-Times (1 month, 1 year), which should be fully utilized to allow the implementation of less detailed rule bases and provide faster simulations.

#### *4) Other possible time intervals*

Since some relations only make sense at intervals larger than B-Time, in RB-FCM it is possible to include time intervals other than B-Time. Each concept and relation in RB-FCM can be associated with a time interval that indicates at which iterations should resolve the involved relations. To allow different time intervals, relations are inhibited when indicated. It is important to notice that relations, not concepts, are inhibited.

A different timing situation appears when B-Time is adequate for most of the system, but the effect of some relations is too small to provide a discernible effect for the selected B-Time. These situations can be prevented maintaining B-Time, modeling the critical relations as if its period is a B-time multiple (allowing a more detailed description of the effects of the relation), and inhibiting those relations during the simulation for the specified multiple of B-Time iterations.

RB-FCM also allows asynchronous timing of different relations.

#### *5) Delays*

Delays are the most obvious timing issue, and the only one that has been addressed on FCM on some occasions. Sometimes the effect of a relation is not immediate (or at least cannot be felt during B-Time), and the delay must somehow be modeled on the RB-FCM. A common example of this kind of timing events is the effect of oil-price variations on the cost of fuel or electricity: due to the fact that most countries have long term reserves, and the process of oil transport and refining is slow, then the people only feels those effects after a few weeks or even months.

On RB-FCM, delays on the effect of a relation are modeled recurring to a FIFO buffer with size Bufsize=delay/B-Time on the consequent of such relation. The value of the consequent Concept is computed with the first element of the buffer, creating an effective delay of Bufsize iterations. Obviously the precision of the delay depends on B-Time.

### *C. Fuzzy Subsystems (FSS)*

RB-FCM allow the inclusion of standard rule based fuzzy systems on a DCM. This fuzzy subsystems (FSS – introduced in [11] as FISS) are used to model the process of (more or less immediate) decision making by system entities: on a regular DCM each step of a chain decision process (involving several sequentially related concepts) suffers a delay corresponding to a single iteration (B-time);

on a FSS such delay does not exist, all steps of the decision making process are resolved in a single iteration.

## III. Approaches to Modelling Fishing Fleet Skippers Behavior

The concept of management of marine resources corresponds in fact to controlling the human predatory action over marine ecosystems. Man is the top predator in the marine ecosystems, being responsible for the over-exploitation of several animal species and by the destruction of marine habitats. One would believe that the human behavior, regarding fishing activities, would be much easier to model and predict than the behavior of other top predators in the ecosystem. However, the published scientific literature still puts in evidence many methodological and knowledge gaps in this subject. In none of the published work have the reasoning and decisions of the skippers been really modeled in an individual basis, being instead just inferred from observation of indirectly related data, such as the placement of fishing effort. In some works, direct interviews were formally made to fishermen, but most of the interviewed persons were retired from work (which may give a biased view of the fishing decisions at present) and those qualitative data were not further included in any model. In this work we aim to fill in some of these gaps in the modeling methodology and knowledge on the dynamics of fishing fleets having as a starting point the reasoning and individual decisions of the skippers. The model was developed by analyzing data collected from the purse-seiners fishing fleets in the Portuguese coast. Qualitative information like on which variables do the skippers base their decisions, and which decision do they take for different levels of those variables, was collected onboard through informal conversations with the skipper during navigation time and in between fishing operations and biological sampling work. This information gathering was carried out during a four year period by a biologist team that, along the years, gained a great experience of direct onboard contact with fishermen from different fleets. At the same time, it was also collected quantitative information on meteorological, oceanographical, economical and other variables that are likely to be taken into account by skippers.

A realistic model of the fishermen decision process would be a valuable tool to predict the options that the fishermen would take as a response to certain factors, such as management measures (catch or gear restrictions, marine protected areas, etc.), fluctuations in fish price, changes in fish abundance, etc. Several attempts to make such models have been made in the past in different parts of the world; however most of those models showed several kinds of shortcomings, such as data limitations, over-simplistic formulation, unrealistic assumptions or inadequate modeling methodologies. Many variables have been shown to influence the decisions taken by fishermen in their activity, such as the catch obtained per unit of effort [1][15][24][27], the size composition [3], fish price and vessel characteristics [17][18], economic profit [23], and fish abundance [23][24][26]. These variables, taken from different sources, such as logbooks [1][3][15][18][24][27], official statistics [17][18][23], and interviews with fishermen [19][25], have been modeled and analysed with many different statistical and mathematical methodologies, such as analysis of variance [18], Bayesian belief networks [24], Markov decision processes [13], Kalman filters [14], and neural networks [15]. Given that, for a realistic modelling of the behaviour of a fishing fleet, one has to model the behaviour of each individual skipper, by taking note of their decisions in response to a wide range of situations, none of the studies referred above has fully accomplished this goal. Most of those works make conclusions from indirect observations, from official data or logbooks, which are prone to severe misreporting, or from interviews with retired fishermen, which may give an outdated view of the fishermen behaviour. Moreover, the hypotheses tested and the models formulated are usually over-simplistic and cover single-species fisheries or fisheries limited in time or space. Finally, the methodologies adopted do not correspond, in most cases, to a framework that can be used in other situations (e.g. involving other variables) than the one described, and fail to represent well the decision process of fishermen. Even methodologies that may seem well adapted to this objective, such as Bayesian belief networks, are not able to account for an important feature of this kind of system, which is the existence of feed-back loops. Since Dynamic Cognitive Maps are a methodology that is particularly well adequate to dynamically treat qualitative and quantitative information and to represent the human reasoning and decision process, all above drawbacks could be overcome if the dynamic cognitive maps constructed were built based on information collected in real-time from skippers during fishing trips.

## IV. Purse-seine Fishing

Purse-seine fishing on the Portuguese coast is done on small ships with a cargo capacity of less than 20000 Kg. The primary catch is sardine, although 3 other species are common: anchovy, shub mackerel and horse mackerel. On purse-seine fishing, skippers look for fish using an echo-sounder while the ship is on the move. After fish is located, a purse net is dropped and used to capture the fish. The net dimension is around 1000m long by 120 m tall. A fishing operation takes around 2 hours to complete. Skippers act independently from other skippers in the fleet, although cooperation (information exchange regarding fisheries) is possible and common. Several fishing operations can be made in one day. A fishing day starts after 5PM, and usually ends early in the morning, although end time can vary a lot due to several factors.

## V. Model Design

The modelling design initially followed a standard (static) cognitive map approach. First, a team of biologist experts were gathered and asked to provide an initial list of all concepts considered relevant to model the problem. This step obviously took several iterations until the experts agreed on a stable set of concepts. The concepts were graphically displayed on a white sheet, and the next step consisted on establishing direct relations between those concepts. These relations started as simple directed links. During this process new concepts were found necessary, others were removed, and some were somehow combined or divided into several concepts. These concept rearrangements were often repeated until the final version of the DCM, presented in this paper, was obtained. The next step consisted in trying to indicate major causal effects and positive or negative influences in the proposed relations. During this step it was found that the simple mechanisms proposed by standard FCM to represent relations between concepts would not be sufficient to model the involved knowledge. Since the experts could express the knowledge using linguistic rules, and linguistic rules were deemed sufficient at the time, the option to move to RB-FCM was definitely taken. This also initiated the process of thinking in terms of designing a dynamic cognitive map instead of a static one.

As we have seen in section II.A, one of the more important issues when modelling the dynamics of a real world CM is timing. In our model, the problems started when a decision regarding the duration of each iteration of the simulation (b-time) had to be taken. The problem was in the fact that the system simulations should cover from several months to a few years (one can not see the effects of fishing politics in less time), but skipper decisions are taken on an hourly basis. If one opted to model the system on a daily basis one would not be able to model skipper behaviour during fishing trips and one would have flaws as those presented in section III. On the other hand, if one opted to model the system on an hourly basis, it would mean runs consisting of a few thousand to tens of thousands of iterations. On a regular DCM, the high number of feedback links would mean that, with such a high number of iterations, results would be highly unreliable (in the same sense that it is unreliable to make long term weather predictions) [7]. The solution found to solve this problem was to use a hierarchical approach: a “fishing” day would consist of several DCM, each being simulated on an hourly basis.

This led to the definition and implementation of what one called Meta states. A simpler version of this approach had been introduced in [12]. Each Meta state is a DCM that is simulated only when its Meta state is active. Transitions between Meta states occur when, during simulation, the DCM reaches certain conditions. Although each Meta state is active in different timing instants, a concept from a given Meta state can still get its inputs from concepts in other Meta states (the value it gets is the one assumed by the concept in the last active iteration of its Meta state.) Meta states can be represented using state diagrams. Fig. 1 shows the five Meta states and Meta state transitions that are used to model a fishing day (further details are given in the next section.) Note that when a Meta state is inactive, its concepts maintain their last computed value. A collateral advantage of using Meta states was the fact that it really does not make sense to update all concepts in every iteration. For example, in the proposed model it makes not sense to update the concept that calculates the best departure time when the ship is already at sea…

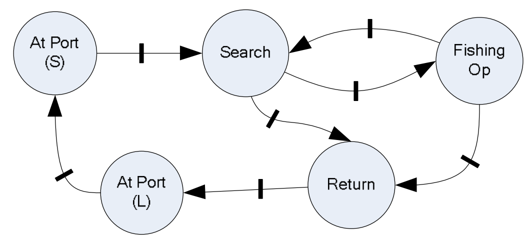


Fig. 1- System Meta-states: Each meta-state contains a DCM that is simulated when its meta-state is active. Only one Meta state is active on a given instant. Transitions between Meta states occur when the active DCM reaches certain conditions.

Another issue involving timing simulation was noted by the experts: several skipper decisions had to be made without delay (in a short time, less than 1 hour), although the decision process involved several chained related concepts. This was however easily solved using the FSS mechanisms proposed in RB-FCM [4][11](section IIC).

During the modelling process several kinds of concepts and relations were deemed necessary. The model needed to operate quantitative, qualitative, probabilistic and stochastic data indiscriminately, which led to the creation of some new mechanisms to implement those relations. These mechanisms are concretized in the next section.

The overall modelling process was obviously not instantaneous; it took several months until a version deemed satisfactory by all involved parts was completed.

## VI. Purse-seine Fishing Skippers Behavior Model Overview

This section gives an overall description of the proposed Dynamic Cognitive Map of Purse-seine Fishing Skippers Behavior. A detailed description, which is not possible here due to lack of space, will be done on a dedicated longer paper.

The model considers b-time as 1 hour, i.e., each iteration represents 1 hour. Although b-time is rather short, the model is intended to be used for medium to long term simulations (few months to several years), which means runs consisting of a few thousand to tens of thousands of iterations. In this model it is viable to perform such a high number of iterations because one fishing day was divided into several Meta states.

Fig. 2 shows all concepts of the DCM and the connections (relations) among them. It also shows the five meta-states – a solid rectangle surrounding several concepts –, and the fuzzy subsystems (FSS) – a dashed rectangle surrounding several concepts. Remember that the effects of relations within a FSS have an almost immediate effect in the consequent concept (within the same iteration), while the effects of relations outside a FSS have a 1 hour delay (corresponding to a single iteration of the CM). Note that the representation of the relations among concepts are very simplified and expressed by a single directed arrow.

Four different kinds of concepts can be identified:

- Levels – fuzzy variables represented by rectangles;
- Variations – fuzzy variables represented by an ovals;
- Crisps – crisp level variables represented by rounded corner rectangles;
- Inputs – crisp or fuzzy external inputs represented by hexagons.

All Level, Variation and Input concepts are associated with several fuzzy membership functions that represent their linguistic terms.

Relations are not explicitly represented in the figure due to lack of space. It is however possible to differentiate relations expressed by fuzzy causal rule bases (FCR) from fuzzy and crisp rule bases (FRB, CR) – the latter are represented by black dots. Other relations (represented by different symbols) will be explained in the relevant Meta state.

The current model contains nearly 40 concepts, over 20 different membership function sets representing linguistic terms and 16 fuzzy rule bases (FRB) containing approximately 930 fuzzy rules.

### *A. Meta States*

There are 5 different Meta states that simulate one fishing day (Fig. 1). Each fishing day starts with the system in the *At Port (Start)* state, where decisions whether to start a fishing trip and when to leave port must be made. After leaving port, the skipper heads on a given direction and starts looking for fish using the echo sounder (*Search*). While searching, and according to the echo sounder results, a decision must be made on whether to start a fishing operation, continue searching or return to port. During the fishing operation (*Fishing Op*), fish is captured using a purse-net. At the end of a fishing operation, the skipper must decide on keep searching or return to port. The return Meta state (*Return*) is used to simulate the duration of the return trip. At the end of the fishing day, the ship arrives to port *(At Port Landing)* where we have the landing operation (the catch is unloaded and sold at the auction market), and the skipper makes a balance of the fishing day.

The following subsections describe the most important issues in modeling each meta state DCM.

### *B. At Port (Start)*

The *At Port (Start)* DCM consists of a single FSS where the skipper decides whether to leave or not to leave on a fishing trip, and, in affirmative case, what is the best departure time. All involved knowledge is expressed using fuzzy rule bases. The decision to leave is based on the predicted profit (which is itself based on the latest fish observations), and on the existence of external restrictions, like for example, ship damage or seasonal fishing bans. Departure time is influenced by the season of the year (sunset time influences the behavior of the target species), predicted profit and last profit. FCR are used to calculate the variation of departure hour since last day. Some of these FCR are non-linear and non-symmetric [10]; therefore a common FCM could not be used to express the relations among the involved concepts.

### *C. Searching*

After leaving port, the skipper spends most of its time observing the info given by the echo sounder. Echo sounder markings are usually not conclusive, and can at best be described qualitatively. The skipper usually qualifies the markings using linguistic terms Good, Average or Bad (in the system there is also the membership function Null, to represent marking absence), and also tries to determine the fish species. Based on these data and on the fish sell price, the skipper has an idea of how good is the potential catch (Echo Sounder Info). The above reasoning is implemented in the model by a FSS that uses FIRs. When combined with the current hour and last day catch, the FSS result is used to determine if the search should continue, the trip should end, or a fishing operation should start. A FIR is used to model this decision. The system also takes into account how far the ship is from port in order to use this information on the return trip.

### *D. Fishing Operation*

In order to model the fishing operation, one had to mix crisp, fuzzy and probabilistic random data. This resulted on the following FSS:

- The catch values are computed based on the echo sounder markings using a table of probability distributions per species. The table was built based on observations gathered through a 4 year period, and relates real world skipper predictions (based on their qualitative interpretation of the echo sounder markings), with the catch from the respective fishing operation. Note that the catch is often far different from the skipper prediction (in both quantity and composition);
- As a result of the fishing operation, the model returns a quantitative amount of fish – ranging from a couple of hundreds of Kg to more than 15000Kg – depending on the involved species (CatchQ *species*). This quantitative value is then evaluated qualitatively (also depending on the captured species), and is accumulated with eventual previous catches to obtain the qualitative value “Total Catch *species*”. Due to

political seasonal restrictions on the catch maximum quantity, some of the captured fish may have to be thrown back to the water (slipping). The qualitative result of the current day fishing operation (LndCatch) is obtained using FIR that combines the qualitative values of each species total catch.

- The model will use the qualitative evaluation of the day catch and the current time to simulate skipper decision on returning to the port to land the catch or to continue searching. This is done using a FIR that basically relates the skipper satisfaction degree with its appreciation of "how good was the day" using rules like:

  "If LndCatch is Very Good then I am Satisfied"

  "If LndCatch is Ok and it's Late then I'm Satisfied"

  "If LndCatch is Ok and it's Early then I'm Not Satisfied"

The total Fishing Operation lasts roughly 2 hours (which means that is completed in 2 iterations).

### E. *Returning*

After a decision is made to return, the model must simulate the returning trip. This consists on a given number of iterations where basically only the current hour is changed. The arrival time is computed based on time and distance from port when the decision to return was made.

### F. *At Port (Landing)*

At the end of the trip, a very simple qualitative economic model is used to compute the day's profit/loss. The model only takes into account variable costs:

- Trip duration and cost of fuel per hour is used to calculate the expense using a FIR;
- The qualitative sell price and the qualitative catch landing are used to calculate revenue using a FIR;
- A qualitative Profit indication is calculated using a FIR.

The indicative qualitative profit value is used by the model (and the skipper) as a factor in next day operation.

## VII. Results

The presented system is very close to its final version, although further changes and/or developments are obviously still possible (namely in the optimization of the fuzzy rule bases.) In order to validate the model, the Fishing Operation Meta state was altered the following way: instead of using the table probability distributions to generate a random catch based on the echo sounder observation, we used real world data obtained on fishing trips during a one year period (not all outings were recorded, though); the data was taken from the echo sounder and the catches obtained on those fishing trips. Real world data was used for the following concepts: *Echo Sounder Markings*; *Predicted Species*; *Distance*; *CatchQ (for each of the 4 species)*; *Price; Sunset; External Restrictions.*

By using this approach, we were able to compare the model of the skipper behavior with the real world skipper's behavior when faced with similar data. Analysis of the results show that, using the current model, the total number of fishing trips and the total number of fishing operations after 8640 iterations (1 year) was the same, which means that all major decisions (when to leave port and when to start a fishing operation) were modeled correctly. In what concerns the decision on when to return to port (which influences the trip total duration), there were often important differences. However, those differences could be explained by the fact that we lacked a complete record of the necessary echo sounder data: we had access to the data of all fishing operations, but the data records corresponding to the situations where the echo sounder shows some fish but the skipper decides not to start a fishing operation was not complete. Therefore it was possible that the real world trips continued because fish markings appeared on the echo sounder (although not good enough to start a fishing op), while the model decides to return because it had no data records indicating fish presence at all.

On a side note, profit analysis shown that, given the high price of fuel during the simulated period and the recorded fish availability, the fishing trips results barely covered the operation costs. This is consistent with the state of mind of the real world skippers when interviewed regarding the state of their business (precise financial records are confidential, therefore there is no data to make a more proper analysis).

While using the model in its regular operation mode, no strange behaviours have been noticed, although no extensive simulations of complex cases have been seriously analyzed yet. Therefore we can conclude that, for now, the model behaves as intended, and can be used to simulate "what-if scenarios".

## VIII. Conclusion and Future Developments

This paper presents a Dynamic Cognitive Map model of Purse-seine Fishing Skippers Behavior, focusing on some relevant issues regarding modelling real world qualitative dynamic systems. In order to solve those issues, the presented model had to evolve from a standard DCM, and adopt features that bring it closer to a state machine. However it still keeps the essential elements that characterize a DCM, namely a set of cyclic interrelated concepts describing real world entities whose evolution through time is simulated using an iterative model. The biggest difference lies essentially in the fact that not all relations are active simultaneously.

Although the model is close to its final form, an important future development lies in its connection to existing (or new) models of the population dynamics of different fish stocks, which currently are generated from external inputs. In fact, an important factor influencing, and at the same time being influenced by the fleet dynamics is the abundance of the different resources. A possible approach to expand the model could be to estimate abundance of relevant resource by using surplus biomass dynamics fisheries assessment models, based on the logistic or in the Lotka-Volterra equations. A different (and more challenging) approach could be the use of DCM to model abundance.

The presented model exhibits a sound behaviour and has been validated using real world data. Therefore, when integrated with the above mentioned models of the population dynamics of different fish stocks, it can start to be used to test the effectiveness of different management measures, such as catch restrictions, marine closed areas, seasonal fishing bans, etc.

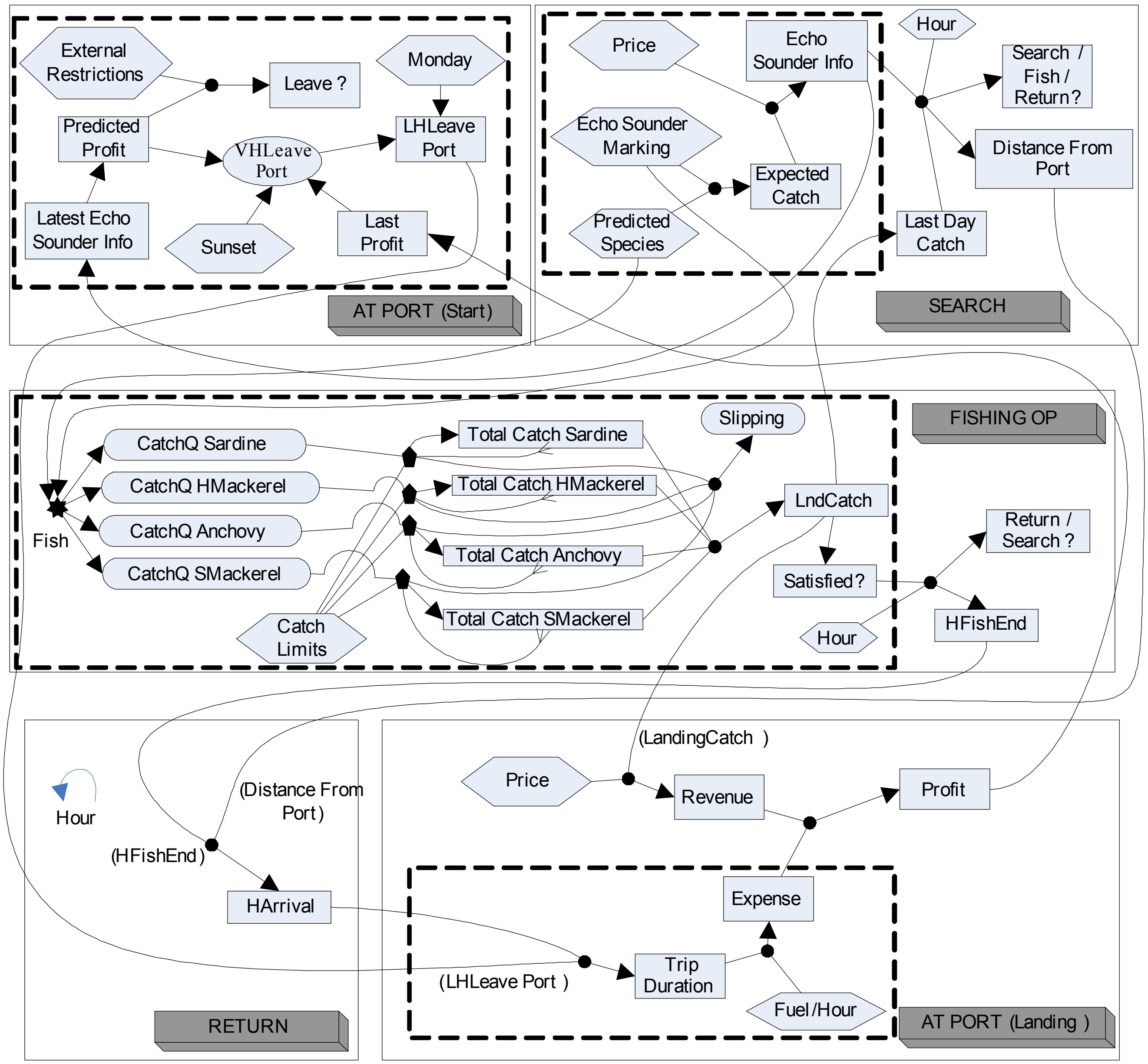


Fig. 2 Purse-seine Fishing Skipper Behavior Dynamic Cognitive Map

## REFERENCES


[1] Allen, P.M., McGlade, J.M. 1986. Dynamics of discovery and exploitation: the case of the Scotian shelf groundfish fisheries. Canadian Journal of Fisheries and Aquatic Sciences, 43: 1187-1200.

[2] Axelrod, R., “The Structure of Decision: Cognitive Maps of Political Elites”, Princeton University Press, 1976

[3] Béné, C. 1996. Effects of market constraints, the remuneration system, and resource dynamics on the spatial distribution of fishing effort. Canadian Journal of Fisheries and Aquatic Sciences, 53: 563-571.

[4] Carvalho, J.P., “Mapas Cognitivos Baseados em Regras Difusas: Modelação e Simulação da Dinâmica de Sistemas Qualitativos”, PhD thesis, Instituto Superior Técnico, Universidade Técnica de Lisboa, Portugal , 2002

[5] Carvalho, J.P., Tomé, J.A., ”Rule Based Fuzzy Cognitive Maps - Fuzzy Causal Relations”, Computational Intelligence for Modelling, Control and Automation, Edited by M. Mohammadian, 1999

[6] Carvalho, J.P., Tomé, J.A., ”Rule Based Fuzzy Cognitive Maps – Qualitative Systems Dynamics”, Proceedings of the 19th International Conference of the North American Fuzzy Information Processing Society, NAFIPS2000, Atlanta, 2000

[7] Carvalho, J.P., Tomé, J.A.,"Issues on the Stability of Fuzzy Cognitive Maps and Rule-Based Fuzzy Cognitive Maps", Proceedings of the 21st International Conference of the North American Fuzzy Information Processing Society, NAFIPS2002, New Orleans, 2002

[8] Carvalho, J.P., Tomé,J.A., “Fuzzy Mechanisms For Causal Relations”, Proceedings of the Eighth International Fuzzy Systems Association World Congress, IFSA'99, Taiwan, 1999

[9] Carvalho, J.P., Tomé,J.A.,"Rule Based Fuzzy Cognitive Maps - Expressing Time in Qualitative System Dynamics ", Proceedings of the 2001 FUZZ-IEEE, Melbourne, Australia, 2001

[10] Carvalho ,J.P., Tomé, J.A., “Rule Based Fuzzy Cognitive Maps and Fuzzy Cognitive Maps - A Comparative Study” , Proceedings of the 18th International Conference of the North American Fuzzy Information Processing Society, NAFIPS99, New York, 1999

[11] Carvalho, J.P., Tomé, J.A., “Qualitative Modelling of an Economic System Using Rule Based Fuzzy Cognitive Maps” , Proceedings of FUZZ-IEEE 2004, IEEE International Conference on Fuzzy Systems, Budapest, Hungary, 2004

[12] Carvalho, J.P., Carola, M., Tomé, J.A., “Using Rule Based Fuzzy Cognitive Maps to Model Dynamic Cell Behaviour in Voronoi Based Cellular Automata”, IEEE World Congress on Computational Intelligence, WCCI 2006, 2006

[13] Dorn, M.W., “Fine-scale fishing strategies of factory trawlers in a midwater trawl fishery for Pacific hake (Merluccius productus)”, Canadian Journal of Fisheries and Aquatic Sciences, 55: 180-198, 1998

[14] Dorn, M.W., “Fishing behavior of factory trawlers: a hierarchical model of information processing and decision-making”, ICES Journal of Marine Science, 58: 238-252, 2001

[15] Dreyfus-León, M.J., “Individual-based modelling of fishermen search behaviour with neural networks and reinforcement learning. Ecological Modelling”, 120: 287-297, 2001

[16] Forrester, J.W., several papers available online at http://sysdyn.mit.edu/sd-intro/home.html

[17] Herrero, I., “Risk and strategy of fishers alternatively exploiting sea bream and tuna in the Gibraltar strait from an efficiency perspective”, ICES Journal of Marine Science, 61: 211-217, 2004

[18] Hilborn, R., Ledbetter, M., “Analysis of the British Columbia salmon purse-seine fleet: dynamics of movement”, Journal of the Fisheries Research Board of Canada, 36: 384-391, 1979

[19] Holland, D.S., Sutinen, J.G., „An empirical model of fleet dynamics in New England trawl fisheries” Canadian Journal of Fisheries and Aquatic Sciences, 56: 253-264, 1999

[20] Kosko, B., “Fuzzy Cognitive Maps”, International Journal of Man-Machine Studies, 1986

[21] Kosko, B., “Fuzzy Engineering”, Prentice-Hall International Editions, 1997

[22] Kosko, B., “Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence”, Prentice-Hall International Editions, 1992

[23] Laloë, F., Pech, N., Sabatier, R., Samba, A., “Model identification for flexible multifleet-multispecies fisheries: a simulation study”, Fisheries Research, 37: 193-202, 1998

[24] Little, L.R., Kuikka, S., Punt, A.E., Pantus, F., Davies, C.R., Mapstone, B.D., “Information flow among fishing vessels modelled using a Bayesian network”, Environmental Modelling & Software, 19: 27-34, 2004

[25] Neis, B., Schneider, D.C., Felt, L., Haedrich, R.L., Fischer, J., Hutchings, J.A., „Fisheries assessment: what can be learned from intervieweing resource users?” Canadian Journal of Fisheries and Aquatic Sciences, 56: 1949-1963, 1999

[26] Pech, N., Samba, A., Drapeau, L., Sabatier, R., Laloë, F., “Fitting a model of flexible multifleet-multispecies fisheries to Senegalese artisanal fishery data”, Aquatic Living Resources, 14: 81-98, 2001

[27] Rijnsdorp, A.D., Dol, W., Hoyer, M., Pastoors, M.A., “Effects of fishing power and competitive interactions among vessels on the effort allocation on the trip level of the Dutch beam trawl fleet”, ICES Journal of Marine Science, 57: 927-937, 2000

[28] Zadeh, L., “Fuzzy Sets and Applications: Selected Papers, Wiley-Interscience”, 1987