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Applying Fuzzy based Inductive Reasoning to Analyze Qualitatively the Dynamic Behavior of An Ecological System

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Abstract

In the last decade a variety of methodologies for representing and evaluating knowledge qualitatively has been developed, particularly within the field of Artificial Intelligence. Qualitative reasoning methodologies represent an alternative to quantitative modeling approaches, if the knowledge about the system of interest is imprecise or incomplete, as it is often the case when dealing with ecological systems. As most of the methodologies have not outgrown toy examples, it re-

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mains challenging to apply those methodologies to real world applications. In Biosphere 2, a closed ecological system, the level of O_2 has dropped and the CO_2 level has risen continuously during its closure between 1991 and 1993. The mechanisms of carbon cycles have been subject to multiple research efforts, and are therefore formulated as general rules in principle. However, the specific situation within Biosphere 2, a closed ecosystem, might influence the validity of these rules. Thus, the structure of the carbon cycle in Biosphere 2 is not well known, yet abundant data exist on some of the important fluxes and pools. Whereas deductive, quantitative as well as qualitative, methodologies need knowledge about the structure of the system to derive the behavior of the system, the fuzzy-based inductive reasoning methodology FIR derives inductively the behavior model by analyzing time series. The derived behavior model comprises cases and information how to retrieve prototypical cases that can be adapted to the given situation. Thus, FIR combines one-shot inductive and incremental case-based reasoning techniques in analyzing and forecasting dynamic systems.

Introduction

In the last few years a variety of artificial intelligence methods have been applied to meet the challenge of modeling and simulation in ecology (Loehle 1987, Schmoldt et al. 1994, Uhrmacher 1995). Besides object-oriented methodologies, especially methodologies dealing with qualitative and incomplete knowledge have attracted the interest of the ecologists. They incorporate qualitative, i.e. not numerically scaled, knowledge, addressing the continuing criticisms due to the constraints of quantification and accuracy (Fryer 1987). Although qualitative modeling is neither less expensive than quantitative modeling nor does it obviate the need for a profound understanding of the application domain, it does offer a different and alternative view of the problem which is one reason to examine the possibilities and limitations of qualitative methodologies in real world applications more closely (Shugart and Urban 1988).

The methodology "Fuzzy-Based Inductive Reasoning" (FIR) is a qualitative inductive methodology for modeling and simulation (Klir 1985). As a qualitative methodology the method is based on nominal or ordinal scaled variables. Unlike other qualitative modeling and simulation approaches, summarized under the name of qualitative or naive physics (De Kleer and Brown 1984, Kuipers 1986), FIR does not start with the knowledge about some general qualitative rules of behavior, but with a set of data. It proceeds inductively, learning the behavior of a system by observing. The system is considered as a black box, whose structure is only poorly known. The knowledge about the system is restricted to some input- and output variables and their histories. It is the task of FIR to discover the causal structures of the system. As an inductive methodology it uses the rule of concomitant behavior: if one phenomenon varies regularly in some manner whenever another phenomenon varies in some particular way, it is supposed that the first is connected with the second through some chain of causation. Thus, contrary to deductive qualitative modeling and simulation methodologies, FIR can operate on systems, whose structure is not completely known. In addition, it does not share the difficulties of deductive qualitative modeling techniques with tightly coupled and complex systems. Due to the qualitative character of the constraints and variables, qualitative deductive simulations tend to explode into branching paths including intractable behavior especially when applied to extensive examples. FIR is therefore well suited for certain ecological applications, particularly if the structure of the system is not known, but expected to be tightly coupled, and data and some hypotheses about dependencies are available. Thus, FIR stands in the tradition of other inductive reasoning methods, like statistical, inductive (Quinlan 1986) and case-based learning methodologies (Kolodner 1993). Yet unlike the former it works on fuzzy data and does not require any special distribution of the data. Unlike the latter it is conceptualized to address particularly dynamic systems. Many relations to case-based reasoning systems exist which shall be addressed throughout the paper.

In the experiments we used the tool SAPS-II which implements the fuzzy-based reasoning methodology (FIR) as a CTRL-C library. In the meantime, another implementation of SAPS-II became available as a Matlab toolbox.

The essential features in SAPS-II will be outlined; for more detailed information we refer to the literature (Cellier et al., 1996; Mugica and Cellier 1993).

The carbon cycle of Biosphere 2

Biosphere 2 is a closed ecological system that was designed to study processes and the dynamics of an ecological system analogous to the global biosphere. For this, the 1.28 ha of Biosphere 2 include different biomes, a wilderness consisting of desert, ocean, freshwater and saltwater marsh, Savannah and rain forest, and an intensive agriculture biome. The latter supports food for 8 humans who lived in Biosphere 2 for two years. Biosphere 2 is materially closed, but open to energy flow (sunlight, electricity, heat transfer) as well as information flow. 1800 Sensors are measuring the key variables on the average once every 15 min, to document and assist in controlling the atmosphere and the different ecological systems constituting Biosphere 2 (Nelson et al 1993).

As contrasted with current knowledge about carbon cycles on earth's biosphere where the general structure of the model is known but data on the pools and fluxes between pools are poorly documented, the structure of the carbon cycle in Biosphere 2 is not well understood, but abundant data exist on some of the important fluxes and pools. Efforts have been made throughout the history of the development of Biosphere 2 to develop predictive models of the carbon cycle inside Biosphere 2. Modeling and simulation however have been subject to available resources of time and knowledge. The lack of comparable knowledge from the modeling of carbon cycles in earth's biosphere has also hampered model development. The modeling effort though has led to some understanding of the specifics of carbon flows inside Biosphere 2, which will help in developing the inductive model.

Fuzzy-based Inductive Reasoning

The fuzzy-based inductive reasoning methodology has been developed in the context of a general framework that supports the specification of different levels of system-analytical problems (Klir 1985). These epistemological levels are hierarchically arranged depending on the type of knowledge that is available. Starting at level zero the amount of knowledge increases as we ascend the epistemological hierarchy. Each level includes the knowledge of the levels below. The lowest level is called the source model, the set of variables we are interested in. The level above is the data model, where the temporal development of each variable is known as a sequence of episodes, its history. The behavior model, located at the next higher hierarchical level, includes, aside from the knowledge about variables and their histories, knowledge about the relationships that exist among them. One level up are located structural systems with knowledge about the subsystems of a system and its coupling structure. On the meta level the knowledge how those structural systems are interrelated is located. Other meta levels may follow (Klir 1985).

Depending on the quality of the data, possibilistic and probabilistic models of data, behavior and structure are distinguished. Based on fuzzified variables, we shall ascend the epistemological hierarchy up to the level of possibilistic behavior models by applying fuzzy based inductive reasoning to the carbon cycle within Biosphere 2. We shall cover the epistemological levels of source model, data model and behavior model, and shall apply the derived behavior model to forecast the CO_2 value in Biosphere 2.

The source model

The identification of the model starts with the selection of the variables of interest. This set of variables represents the lowest epistemological level of the hierarchy, the source model. Each inductive modeling necessarily starts with some kind of deductive hypothetical knowledge. As general hypotheses about the carbon cycle and the variables that might be of interest are known, they can be used to identify the model, even if those rules do not match exactly the situation of Biosphere 2.

Photosynthesis and respiration, including the oxidation of soil organic matter, play a key role in the carbon cycle. Thus, variables such as temperature, photosynthetic photon flux, soil moisture, and the leaf area and biomass of above ground vegetation could be included into the source model. Other influences are less well analyzed, e.g. the influences of soil microbial biomass. The vegetation in Biosphere 2 is affected by a number of anthropogenic influences, such as the watering, harvesting, and the pruning of the different biomes in Biosphere 2. These are planned interventions by the Biospherians and may have an impact on the short and longer term carbon dynamics in a manner analogous to the effect of land use changes on earth's biosphere. Other variables are specific for the situation in Biosphere 2. Well understood influences on Biosphere 2 carbon cycle are the carbon dioxide scrubber, loss through atmosphere leakage and the effect of the supplemental atmosphere that has been injected into Biosphere 2 three times during the two years of its first mission. With the discovery of the unaccounted for 'loss' of a large fraction of the oxygen within Biosphere 2, the geochemical uptake of carbon dioxide, as so called carbonation, by concrete within Biosphere 2 has been identified as a major factor within the carbon cycle (Severinghaus et al. 1993). Other factors impacting carbon flow within Biosphere 2 are the poorly quantified effects of the ocean biome and potential sedimentation with the fresh and salt water marshes. Table 1 shows our first experimental source model, which we selected, with temperature, harvesting etc. as input variables and CO_2 as the only output variable.

variable	quantitative?	experiment?
temperature	yes	A / B
photon flux	yes	A / B
harvesting	no	-
cropping	no	-
watering	no	-
pruning rain forest	no	-
scrubber activity	no	A / B
compost	no	-
air-injection	yes	-
CO_2	yes	A / B
O_2	yes	B

Table 1: The experimental source model of carbon cycle within Biosphere 2

The source model that was actually used in ascending the epistemological ladder makes use of a subset of the above listed variables only. At the time of evaluation in December 1993 a lot of data had not been made available for scientific research. Data that were not measured by sensors and consequently were not stored in the database system could not be included in the evaluation. The restricted availability of data affects the validity of the deduced behavior model, as the results of the experiment will show.

Other variables proved to be of no relevance for our purpose. The injection happened too rarely to identify a causal pattern for a qualitative and inductive reasoner. The compost was hardly turned on throughout the time span of consideration, as the Biospherians tried to keep the CO_2 level as low as possible.

The data model

The methodology of FIR is based on pattern matching between possible inputs and outputs of the system of interest. To learn these patterns FIR needs a so called training set or sample, i.e. a set of data that document representatively the behavior of the system in form of time histories. To determine the data model, we take into consideration the amount of available data and its nature. Two different time periods will be considered within the evaluation. Experiment A will include six months starting September 26, 1991 when Biosphere 2 was closed, experiment B covers 1 year from October, 1992 until the end of September 1993. Most of the variables are measured in a quantitative scale continuously (every 15 minutes) throughout the year. The time step used in experiment A is two hours, whereas in experiment B the data are taken every 4 hours, i.e. only a subset of the actually measured data are used in the data models. Most of the variables in Biosphere 2 describe quasi continuously the development of variables. Other variables, e.g. watering, cropping, and harvesting, indicate special seasonal activities that may possibly influence the short term dynamics of carbon cycle. These include also specific and periodical events such as the injection of atmosphere into Biosphere 2 or the turning "on" and "off" of the scrubber. Due to the lack of availability of data we had to restrict the variables mainly to those that are measured continuously by the sensors (Tab. 1).

The quantitative values have to be recoded, i.e. discretized, into qualitative values, so that the data represent a gap-free history of the variables. Each history is a sequence of non-overlapping episodes, where each episode is a tuple consisting of a qualitative value and a time interval. To convert the quantitative information into a qualitative scale the number of possible values for each variable has to be determined. Two qualitative values describe the activity of the CO_2 scrubber, namely "on" and "off" whereas five possible qualitative values characterize the history of the other variables. The discretization into five different qualitative values has proven to maintain sufficiently the information stored in the quantitative data. Experiments showed that a finer grained scaling implies higher computational cost without increasing the quality of the results accordingly. Landmarks that separate neighboring regions are selected to map quantitative into qualitative values. The selection takes place in such a way that the data are nearly equally distributed among the qualitative values, and such that the qualitative data reflect crucial aspects of the quantitative time series (Table 2).

	very low	low	normal	high	very high	
Oxygen [%]	13.91	15.27	17.33	18.14	18.79	21.26
Carbon dioxide [ppm]	1530.4	2378.2	2958.4	3643.2	3974.6	4801.2
Photon [uE/m^2/Sec]	0.0	0.01	211.3	782.5	1257.6	2144.9

Table 2: Landmarks of oxygen, carbon dioxide and photon (experiment B)

How ever carefully the landmarks are chosen, compared to the quantitative information, the new qualitative values seem to be rather coarse. To take into consideration the possible inexactness of the data and to smooth the crispness of the qualitative values, the variables are discretized into fuzzy variables (Zadeh 1975). SAPS-II uses bell-shaped membership functions that carry a value of 0.5 at the landmark between two neighboring classes, and a value of 1.0 at the arithmetic mean between two neighboring landmarks.

Each *fuzzy value* is a triple, consisting of a *qualitative (class) value* , the *fuzzy membership value* , and the *side value.* The side value indicates whether the original quantitative value is to the left or to the right of the maximum of the bell-shaped memberhsip function associated with the class in which the quantitativ value is discretized.

The behavior model

We ascend the next level of the epistemological hierarchy, the behavior model, with the selected data model. Experiment A includes three input variables: temperature, photon-flux, and the activity of the scrubber, whereas experiment B takes into consideration the oxygen contents of the air as an additonal input variable. To obtain an idea about the relevant time span, an autocorrelation function is applied. The results showed that a time span covering three time steps should be sufficient in both experiments, e.g. carbon dioxide and photon showed high covariance at lags 3, 6 etc. Therefore, a time window is moved with depth 3 over the time series, and transforms the time series into a virtual set of cases which can be analyzed independently. The reasoning process considers eleven (experiment A) and fourteen (experiment B) possible input variables respectively, instead of the original three and four possible basic inputs variables. Experiment B includes as potential input variables: temperature, oxygen, photon flux, and scrubber activity at the current, the past, and the "pre-past" time steps, and carbon dioxide at the past and "pre-past" time steps.

By transforming the time series into a set of cases that are analyzed independently, the reasoning process resembles now other inductive or case-based reasoning techniques, which are conceptualized for the classification of static cases rather than for the forecasting of dynamic behavior.

Case-based reasoning systems rely on distinguishing relevant from irrelevant information when indexing and retrieving prototypical cases. Therefore, they employ deductive models or, as does FIR, inductive techniques (Kolodner 1993).

The mechanism of SAPS-II determines the relevant input variables out of the set of possible inputs by exhaustively searching through all possible combinations of variables. Thereby, a complexity number limits the search space. It determines the maximal number of inputs that are selected out of the set of generally possible inputs.

To assess the quality of the selected input variables, FIR calculates a matrix by compressing the information of the data model. In probabilistic models, each cell of the matrix shows the observation frequency: the probability with which we assume to observe a certain output to be observed for any given input. In possibilistic models, the matrix elements denote the certainty or confidence with which we can expect a certain input/output combination. Therefore, each input/output combination is associated with a confidence value that is calculated as the minimum of the membership values of its variables. If different cases with the same input/output combination exist, the maximum among their individual confidence values determines the final confidence that relates a qualitative input combination with the occurrence of a specific output (Klir 1993).

To measure the information content of a specific matrix, the Shannon Entropy is applied in SAPS-II. Since the Shannon Entropy favors matrices with numerous inputs, the final quality measure is determined as the product of a normalized Shannon entropy and an observation ratio, which guarantees that each state has been observed sufficiently often, in our case five times (Cellier 1991). The Shannon Entropy as a quality measure strives for specialization, whereas the observation ratio strives for generalization.

The derived behavior models of the two experiments (A) and (B) are quite similar. In both cases, the system favors a solution that relates the CO_2 level to the CO_2 and photon levels of the prior time step. Since the time step is 2 respectively 4 hours, the true time dependence between the old CO_2, photon flux, and the new CO_2 lies somewhere between zero and two hours. Based on experiment B, FIR suggests an alternative set of possible input variables. Here, the output CO_2 is explained by the current and past temperature, the scrubber activity two time steps earlier and the past CO_2 value. This is not unusual, since SAPS-II typically returns more than one result. As values of the observation ratio and the normalized Shannon entropy are given for each solution, the user can select the one that is optimal for his or her purpose by weighing the observation ratio and Shannon entropy differently. However, all solutions contain CO_2 at the prior time step as an input, which indicates a high autocorrelation between the current and the past (two to four hours old) CO_2 values.

In the probabilistic behavior model, the matrix is interpreted as a set of rules that can be applied to answer the question of interest, e.g.:

if the past value of photon flux is low and
the past value of CO_2 level is normal
then the value of CO_2 will be high with a probability of 0.72

A probabilistic behavior model assumes the possibility to derive general rules of behavior, i.e. a general transition matrix, that answers the question of interest sufficiently well. After the inductive process of abstraction has been completed there is no need to consult the cases again. This is not the case in case-based systems in general or the possibilistic behavior model in particular (Kolodner 1987).

Time Series & Prototypical Cases

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16.70	0	2725.2	1638.4
16.72	0	2378.4	751.1
16.71	0	$\boxed{2552.0}$	$\boxed{0.0}$
16.71	0	$\boxed{2694.4}$	0.0
16.69	0	2854.2	0.0
16.67	0	2941.6	659.4
16.65	0	2614.8	1619.5

...

...

2725.2	1638.4	2378.4
2378.4	751.1	2552.0
2552.0	0.0	2694.4
2694.4	0.0	2854.2
2854.2	0.0	2941.6

...

Figure 1: Transforming Time Series into Prototypical Cases (Behavior model I). The columns of the time series describe from left to right oxygen[%], scrubber activity, CO_2 [ppm] and photon flux [uE/m^2/Sec] before recoding (Experiment B).

Whereas in probabilistic models the behavior model is given by the matrix, in possibilistic models the behavior of a system is encoded as a set of cases, i.e. time series, that are filtered and flattened corresponding to the set of input variables that are found to be optimal. The matrix itself is only employed to find the relevant inputs, i.e. to construct prototypical cases (Fig.1). These prototypical cases are used to answer the question of interest, i.e., to predict the CO_2 value, given the values of the input variables. In the following we want to consider two alternative behavior models, which have been identified by

SAPS-II based on the data model of experiment B. Whereas the first behavior model (I) expresses a causal relationship between the past photon flux and the past carbon dioxide and the current carbon dioxide, the second behavior model (II) explains the current carbon dioxide by the current and past temperature, the "pre-past" scrubber activity, and the past carbon dioxide. Thus, the prototypical cases are structured according to the following rule "schemes".

(I)	**IF**	CO_2 (t-1) = ?x **and** photon(t-1) = ?z
	THEN	CO_2(t) = ?y
(II)	**IF**	CO_2 (t-1) = ?x **and** temperature (t)= ?z **and** temperature(t-1) = ?u **and** scrubber(t-2) = ?v
	THEN	CO_2(t) = ?y

The possibilistic behavior model comprises a set of cases and the information about the relevant input/output combinations. Similar to other case-based reasoning methods, FIR keeps the cases as an integral part of the derived model.

Forecasting

The application of this model can best be explained referring to case-based learning systems, as well. We are interested in forecasting the CO_2 value, given a certain constellation of input values.

First, those cases are retrieved that match best the given qualitative inputs. To adapt those cases to the situation of interest, the membership and side values of the current input are compared with those of the selected cases. The selected cases are ordered according to their similarity with the current input.

The definition of similarity plays a crucial role in case-based reasoning systems. Often domain models help in deciding which case is the most similar (Goel 1991, Koton 1989) or other cases are employed to answer this question (Seitz and Uhrmacher 1996). However, in most cases similarity is defined in terms of distance measures, particularly if the influence of variables is not context dependent, and metrical information is available (Duda and Hart 1973).

In FIR, similarity is defined as a Euclidean distance. The case that has the most similar membership and side value is identified. The qualitative class value and side value of its corresponding output are selected to forecast the qualitative and side values of the new output. The membership value of the new output is determined differently. Here, a distance-weighted average of membership values of the five-nearest input neighbors is computed to form the membership value of the new output (Mugica and Cellier 1993).

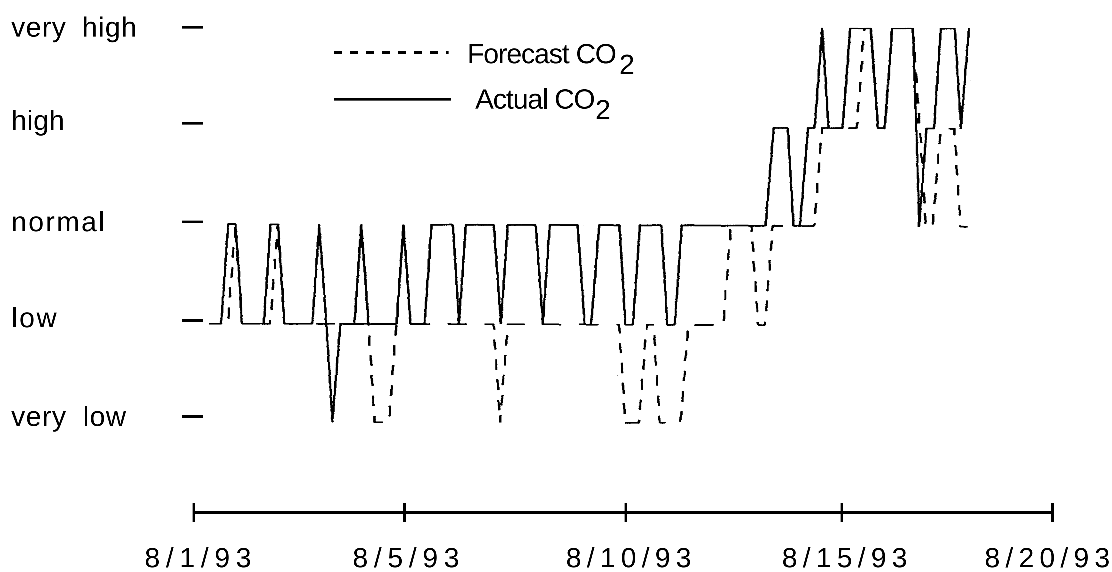

Figure 2: Qualitative Development of Carbon Dioxide (Behavior model I)

Similar to most case-based learning approaches the case base is extended incrementally, whereas a relearning of the relevant inputs requires to start from scratch, because the set of relevant inputs is constructed inductively by "one-shot" learning. To predict a longer period of time, FIR adds the new case to the case base automatically, and uses this information when determining the CO_2 value of the next time step. As new cases are added to the case base without the interaction of an expert, errors might accumulate over time.

Results of simulation

As only part of the available data were used as the training set, the remainder of the data, which cover the last two months of the experiment's time period, can be used to validate the behavior model. In experiment B, the histories over the last two months of the variables photon flux, temperature, scrubber activity and O_2 contents are taken as inputs to determine their outputs.

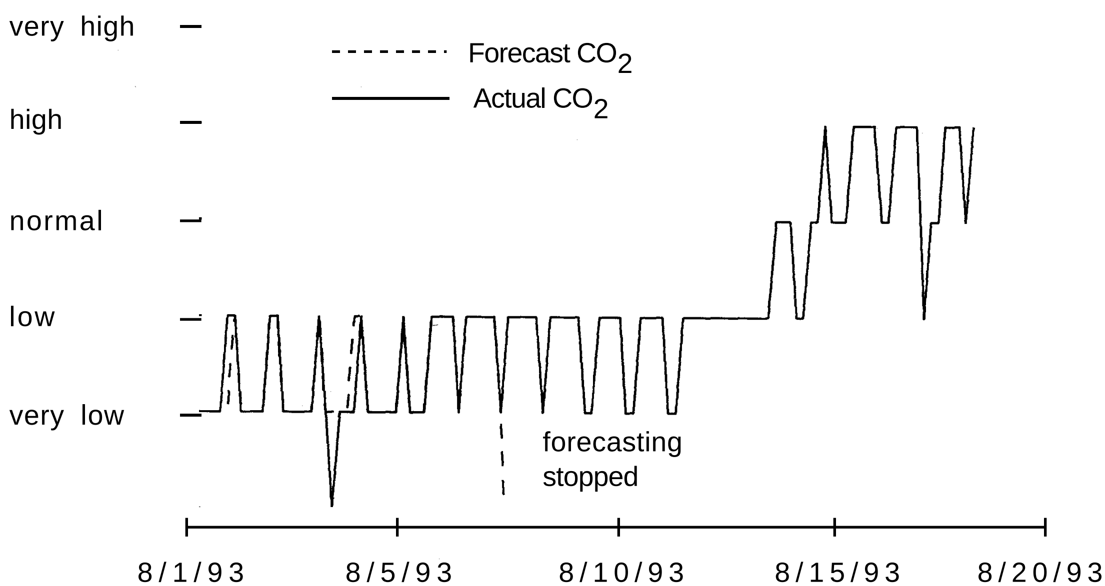

Figure 3: Qualitative Development of Carbon Dioxide (Behavior model II)

Figures 2 and 3 show the results of the forecasting. The solid line represents the actual development of CO_2 during August 1993 whereas the dashed line is forecast by FIR. Based on only two input variables, namely the past CO_2 and the past photon flux, the entire time span is predicted, thereby the accuracy varies. Whereas the prediction shows in the first and last part of the predicted period only small errors, between August 4 and August 15 a qualitative deviation between forecast and measured data can be observed. The forecasting which takes the scrubber activity, the temperature and the past CO_2 as inputs is more accurate but stops after a few days of forecasting, as FIR is confronted with a state it has never observed before. No prototypical case that matches the current one can be found. This observation corresponds to our first postulate that the more inputs we consider the more accurate the results will be but the more likely a situation will occur where FIR cannot predict anything. The results can be improved by combining both strategies, i.e., whenever a case occurs that stops the forecasting based on the more accurate and specific behavior model, the output can be calculated using to more general and less accurate behavior model.

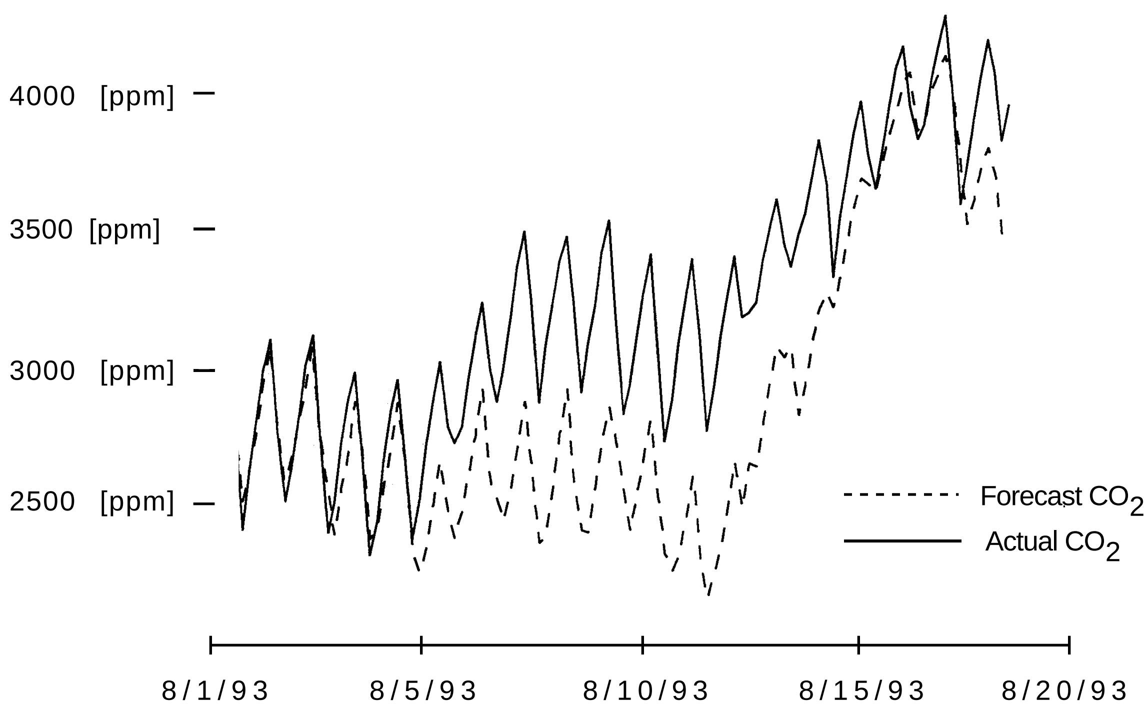

Figure 4: Quantitative Development of Carbon Dioxide (Behavior model I)

Figure 4 finally shows the results of Figure 2 after defuzzification, transforming the fuzzy triple into quantitative data. The quantitative representation shows that the daily variation of the CO_2 level is described in a rather exact way, however the forecasting of the CO_2 level lies one qualitative value below the observed CO_2 development about one third of the predicted time period. Intuitively, the photon flux and the carbon dioxide of four hours before are sufficient to cover the daily dynamic of the carbon dioxide. Yet other factors, which have not been considered in the source and data model, e.g. an intensive harvesting, which took place during August, might have caused the difference between the observed and forecast behaviors in the long term dynamics.

Conclusion

Based on fuzzified data, FIR realizes a strategy that combines incremental case-based and one-shot inductive reasoning techniques to predict the dynamic behavior of the system. After defining the source and data models, the behavior model is derived inductively. Thereby, the time series that constitute the data model are transformed into sets of cases that are analyzed independently. The behavior model comprises cases and information about the relevant inputs to determine the output. Most calculation effort is put into the identification of the relevant inputs which guide the retrieval of prototypical cases. Based on the homogenous structure of the retrieved cases, the forecasting, i.e. the calculation of similarity and adaptation, employs simple distance-based methods.

The detour over the fuzzification of variables, such as photon flux and carbon dioxide, which had originally been quantitatively scaled, led to a quantitative prediction, which demonstrated FIR, and its implementation SAPS-II to be a reliable method in predicting and analyzing the behavior of ecological systems, whose structure is not well known. The simulation results have shown that exogenous and climatic variables, e.g. temperature photon flux, alone are not able to explain the behavior of the CO_2 dynamics in Biosphere 2 completely. To support concrete decisions in managing Biosphere 2 it is necessary to include also anthropogenic factors, such as watering, pruning, and cropping.

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