QUALITATIVE REASONING AND DECISION TECHNOLOGIES
N. Piera Carreté and M.G. Singh (Eds.)

QUALITATIVE SIMULATION APPLIED TO REASON INDUCTIVELY ABOUT THE BEHAVIOUR OF A QUANTITATIVELY SIMULATED AIRCRAFT MODEL

Alvaro de Albornoz
Dept. Ing. de Sist. y Automática,
Universidad Politécnica de Cataluña,
Av. Diagonal 647, 2ª planta,
08028 Barcelona,
SPAIN

François E. Cellier
Dept. of Elec. and Computer Eng.,
University of Arizona,
Tucson, AZ, 85721,
U.S.A.

ABSTRACT

In this paper, qualitative simulation based on fuzzy measures is applied to reason inductively about the behaviour of a quantitatively simulated B-747 aircraft model, to determine when a structural malfunction occurs, to hypothesize about the nature of this malfunction, and to decide upon a global strategy that allows to operate the quantitative aircraft model under the modified flying conditions.

In an earlier paper [12], a crisp inductive reasoner had been employed for the same purpose. The new paper demonstrates the enhanced discriminatory power and the improved forecasting capability of the fuzzy inductive reasoner in comparison with the crisp inductive reasoner when applied to this problem. Also, the fuzzy inductive reasoner allows to predict a quasi-continuous response spectrum, whereas the crisp inductive reasoner is able to predict discrete (class) values only.

1 INTRODUCTION

So-called intelligent systems operate in a discrete way and with a symbolic knowledge representation, that is, as qualitative systems. In many cases, intelligent systems must interact with the real physical world that is based on continuous time and space, or cooperate with lower-level controllers that are realized by means of more classical quantitative signal and system representations. The interaction between these two types of systems calls for a new mixed qualitative/quantitative modeling paradigm that may well be able to compensate for the shortcomings inherent in each of the two types of knowledge representation schemes and may help to solve problems that are beyond the capabilities of either of these two methodologies alone.

Over the past few years, several different methodologies for qualitative descriptions of continuous-time processes have emerged. Some of these methodologies are knowledge-based, such as the Naive Physics approach [4], and others are pattern-based, such as the Inductive Reasoning paradigm [5] and the Neural Network methodology.

A major objective of our own research is the development of a methodology to combine the quantitative simulation of a continuous process with the qualitative simulation of an automated supervisory control system. In this paper, qualitative simulation is applied to inductively reason about the behaviour of a quantitative simulation model representing a B-747 airplane in high-altitude horizontal flight.

The quantitative simulation model of the aircraft offers the possibility to simulate various types of malfunctions in the airplane behaviour without destroying any real equipment and, even more importantly, without endangering a human crew. The qualitative model can be trained to determine when a malfunction occurs in the quantitative model, it can be made to hypothesize about the nature of this malfunction, and may eventually be brought to suggest a global control strategy that would allow to safely operate the quantitative aircraft model under the modified flying conditions. It is hoped that the qualitatively operating, intelligent, supervisory control unit can ultimately be made sufficiently robust so that it would still be able to function properly when embedded in the control of a real aircraft.

Such an algorithm could eventually be implemented as a "watchdog autopilot," i.e., as an addition to a conventional autopilot that would allow the autopilot to remain operational after a malfunction has taken place. On a shorter-term basis, such a system could be used by a human pilot as an on-line automated advisor, i.e., a diagnostic aid and a consultation system, that alerts the pilot to perceived problems, and offers advise as to how to deal with them.

A previous research effort at the University of Arizona resulted in a crisp inductive reasoner that was able to recognize, within a few seconds after a simulated malfunction had taken place, that the aircraft had qualitatively changed its behaviour, which then triggered a diagnostic engine that enabled the reasoner to distiguish between 10 different types of malfunctions after stimulating the aircraft by adding a small amount of binary noise to the input signals and examining the aircraft's reaction. The results of this study were reported in [12].

The current research effort extends the previous investigation by incorporating fuzzy measures into the inductive reasoning process, and by modifying the algorithm for the evaluation of the quality factor of the qualitative (structural) relationships found by the inductive reasoner. In this paper, the enhancement of the discriminatory power of a fuzzy inductive reasoner over a crisp inductive reasoner will be demonstrated. While the previously used reasoner had sometimes difficulties to discriminate between different types of malfunctions, the fuzzy inductive reasoner is able to discriminate clearly and unambiguously between different types of malfunctions that make the aircraft react in similar ways. Also, the fuzzy inductive reasoner is often able to identify malfunctions in a shorter span of simulated time of the quantitative model than its crisp counterpart.

2 DESCRIPTION OF THE APPLICATION

A number of publications on inductive reasoning have previously been published by the same research group. The earliest paper describing the method can be found in [1]. Details on the numerical aircraft model and the application of the crisp inductive reasoner to it can be found in [11]. A compressed version of [11] was published in [12]. The fuzzy extension of the inductive reasoning methodology was first discussed in [6], and was elaborated upon in [2]. Finally, the combination of quantitative and qualitative simulations involving a differential equation model for the quantitative subsystem and a fuzzy inductive reasoner for the qualitative subsystem was first presented in [3]. In the interest of saving space, the results that were presented in the aforementioned earlier publications will not be repeated

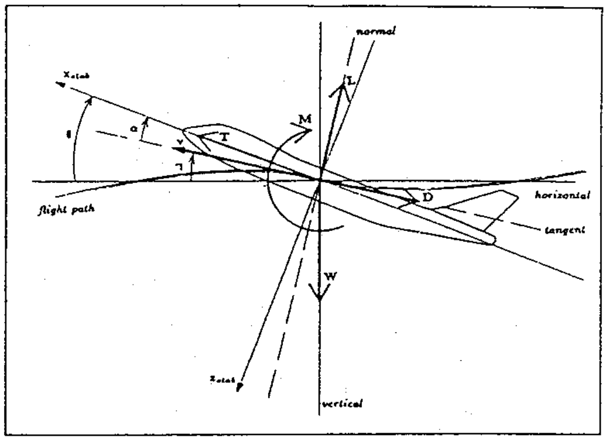

Figure 1: Axes, angles, forces, and moments of the aircraft.

here. The interested reader is friendly invited to consult the earlier publications to familiarize him or herself with the details of the methodology. The authors will be delighted to send free reprints of the papers upon request.

In this section, a brief description of the quantitative and qualitative models will be given, emphasizing the differences between the crisp and the fuzzy inductive reasoners, as well as the importance of the chosen application.

2.1 The Quantitative Model.

A brief explanation of the mathematical aircraft model is needed to introduce the variables that will be used in the qualitative model. The mathematical aircraft model used in this study reflects an essentially longitudinal flight restricted to longitudinal deviations from a trimmed reference flight condition, which is characterized by the requirement that the resultant force and moment acting on the aircraft center of mass are zero.

The model uses the typical equations for the angle of atack α, the flight path angle γ, and the pitch angle θ. The relationship between the different variables is depicted in figure 1.

The quantities affecting the airplane in flight are its weight W, the thrust T developed by the engines, the aerodynamic forces Lift L and Drag D, and the aerodynamic pitching moment M. The weight of the aircraft will be considered constant. The thrust will be considered as being a function of the flight velocity and of its own control variable δ_T, the throttle opening. The aerodynamic forces L and D compose the force response of the aircraft to the motion. The Lift is assumed as being the normal component of the aerodynamic force with respect to the flight path, and the Drag is its tangential component. The model uses the standard way of expressing the aerodynamic forces L and D, and the aerodynamic momentum M, that is, through their non-dimensional aerodynamic coefficients C_D, C_L, and C_M.

Two control laws are implemented in the model, one for the elevator deflection with feedback on the pitch angle, the other for the thrust with feedback on the velocity:

$$\delta_e = \delta_{e_{trim}} + K_\theta(\theta - \theta_{trim}) \tag{1}$$

$$T = T_{trim} + K_u(u - u_{trim}) \tag{2}$$

where δ_e is the elevators deflection, T the thrust of the engines, and u the velocity in the x-axis direction.

The parameters used in the model are those of a Boeing 747 aircraft in a cruise flight at high altitude.

The numerical aircraft model has been coded in the continuous system simulation language ACSL [8]. Some transients/accidents were built into the aircraft model in order to alter its normal structural behaviour. These structural changes in the longitudinal flight are simulated by modifying the original airplane parameters in a discrete event section of the program that is executed at a randomly selected time instant. Once the event has been activated, another random number is drawn to determine which of the accidents is supposed to occur. The simulated emergencies are not necessarily realistic in terms of what might happen to the real aircraft, but this is not essential to our goal. It is, however, important to realize that the qualitative model is kept in the dark with respect to when the accident takes place, and which of the accidents has been selected.

2.2 The Qualitative Model.

The practicality of combining qualitative and quantitative simulation models of continuous-time processes using fuzzy inductive reasoning techniques has been demonstrated in [3]. The construction of the qualitative model itself is also described in detail in the same reference. In this section, only a brief description will be given in order to show the differences between the crisp and the fuzzy inductive reasoner, since these differences will be elaborated upon later in the paper.

The data extracted from the numerical ACSL simulation constitute the "measurement data" of the qualitative model. The execution of the quantitative model, and the extraction of the measurement data matrix were done under the control of MATLAB [7]. The measurement data matrix is a real-valued matrix in which each column represents one recorded variable, and each row represents one complete data record collected at one time instant.

These data must then be discretized to enable the qualitative reasoning process. In the language of inductive reasoning, the discretization of data is referred to as "recoding" [5]. The recoding module converts continuous signals into multivalued discrete signals. In the fuzzy case, a fuzzy membership value is appended to the recoded (class) value. In the fuzzy systems literature, the process of discretization is usually referred to as "fuzzification" [9].

The inductive reasoner operates exclusively on the qualitative class values and reasons about qualitative spatial and temporal relationships without proposing a single quantitative relationship and, in fact, without even knowing that they exist. The discretized variables are used to find the most plausible qualitative relationship among theml, which is called the optimal mask. This optimal mask will in turn be used to qualitatively forecast the behaviour

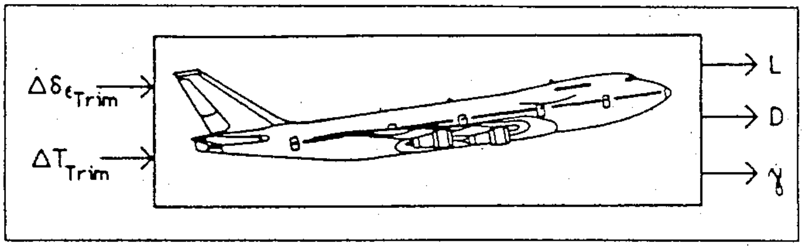

Figure 2: Qualitative input and output variables

of other variables. This process is called qualitative simulation through inductive reasoning. The forecasting can be viewed as a temporal inference engine.

From the resulting qualitative variables, continuous signals can then be "regenerated" that can subsequently be used as inputs to other quantitative or qualitative submodels. In the context of fuzzy systems, the regeneration process is known as "defuzzification," and represents the inverse process of recoding. The fuzzifiers/defuzzifiers act as interfaces between the qualitative and the quantitative submodels.

To build the qualitative model of the aircraft, not all of the variables that were obtained by the numerical simulation were used, but only a subset of five variables that capture the main characteristics of the aircraft during high altitude longitudinal cruise flight.

Figure 2 depicts the two input and three output variables included in the optimal mask analysis, namely the differential elevator deflection δ_e, the differential thrust δ_T, the lift L, the drag D, and the flight path angle γ.

The process to build the qualitative model is the following:

- The numerical model is randomly excited. In this way, the recorded data are rich in information about the reaction of the system to input stimulation at all frequencies. This mode of operating the aircraft is called the "shaken flight."
- The numerical model is excited once more, this time with harmonic functions of fairly long periods. In this way, a more realistic but still dynamic flight simulation results. This step is used to determine the limits that the variables can realistically assume.
- The optimal masks obtained from the first excitation and the landmarks obtained from the second are used to forecast the future behaviour of the plane under any flight condition, prodided that these flight conditions have previously been observed by the qualitative model.
- A threshold error alarm is incorporated to decide when a structural change has taken place.

2.3 Differences Between a Crisp and a Fuzzy Inductive Reasoner

There exist two main differences between the previously reported crisp inductive reasoning methodology and the currently employed fuzzy inductive reasoning apprach. The first lies

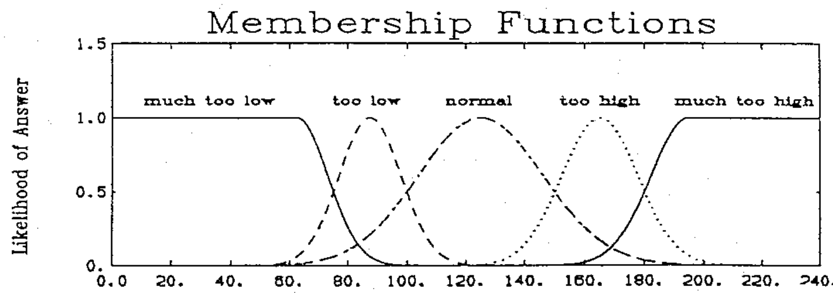

Figure 3: Typical membership functions used by SAPS

in the computation of the quality measure of the masks, and the second lies in the utilization of the available fuzzy measures in the forecasting process.

a) The Quality Factor.

The quality of a structural relationship, i.e., a mask, is primarily determined through the Shannon entropy of its state transition matrix, which determines its forecasting power over a single step. However, it is not practical to use the Shannon entropy exclusively in the performance index that evaluates the quality of a mask. The reason is that, with growing mask complexity, the number of discrete states the system can be in grows. Since the total number of observations remains constant, the observation frequencies of the observed states become smaller and smaller, until eventually every state that has ever been observed has been observed precisely once. Thus, all observed state transitions are totally deterministic, and the forecasting power over a single step is maximized. However, the predictiveness of the model over several steps will nevertheless be poor, since already the next predicted state will, in all likelihood, have never been observed before, which will bring the forecasting process to an immediate halt.

The previously employed methodologyy used the complexity of the mask, that is, the number of relationships among variables, in the performance index. However, the mask complexity is only an indirect measure of the number of legal states. The currently employed methodology uses the observation ratio, a quality measure that reduces the mask quality if there exist states that have been observed less often than five times. This leads to a better selection of the optimal mask.

b) Fuzzy Measures.

The crisp inductive reasoner worked with crisp landmarks in the recoding of the measurement data. These rigid landmarks were responsible for a loss of valuable information about the system that could no longer be exploited by the qualitative model, and this in turn led to a reduction in its forecasting capabilities, which diminishes the discriminatory power of the tool in the application at hand.

Fuzzy measures were introduced as a technique to deal with the uncertainty of landmarks. Instead of saying that a variable belongs to the class "normal" for values above a certain landmark, and to the class "low" for values below that landmark, a fuzzy measure allows to specify that, as we pass the landmark in the negative direction, the answer "normal" becomes less and less likely, whereas the answer "low" becomes more and more likely.

Figure 3 depicts the fuzzy membership functions used by SAPS-II, the inductive reasoner employed in this research. They are normal distributions with values 1.0 at the arithmetic mean of any two neighboring landmarks, and 0.5 at the landmarks themselves.

The fuzzy membership functions allow to recode each numerical value into a qualitative triple composed of the class value (as in the previous methodology), the fuzzy membership value, which is a measure of the likelihood of the class value, and the side value which indicates whether the quantitative value is to the left or to the right of the maximum of the fuzzy membership function. No information is lost in the recoding process. The original real-valued measurement data can be regenerated exactly from the qualitative triple. The forecasting process must now predict, for a given set of inputs, not only the class value of the output, but also its membership and side values. Thereby, the numerical information is indirectly preserved, which in turn makes it possible to regenerate real-valued output signals from the qualitative model with a surprisingly good accuracy.

The fuzzy membership functions allow to preserve more quantitative information in the reasoning process, whereas the class values can still be used to process the available information in a qualitative fashion. Thus, the qualitative analysis allows to generate quickly a rough qualitative response, while the fuzzy membership functions can then be used to smoothly interpolate between the qualitative class values to obtain a quasi-continuous response spectrum. In the application at hand, the fuzzy membership functions serve to enhance the discriminatory power of the event classifier.

3 THE CONTINUOUS MONITORING SYSTEM

Modern control technology makes it possible to build highly automated control systems for very complex processes such as jet cruisers, nuclear power plants, space stations, etc. However, no automatic control technique presently available is able to adapt itself to unpredicted structural changes in the system. Man-in-the-loop systems have been the answer to this problem until now. However, when the degree of system complexity increases, human operators are being overloaded by the amount of information they are provided with. To address this problem, monitoring systems are needed that mimic the human situation assessment process, that are able to identify specific events, learn how the system behaves, and come up with a new control strategy for the system once it has been structurally modified.

In other words, the inductive reasoning functions are used to qualitatively and inductively reason about the measurement data taken from the ACSL simulation run. The quantitative data will be used to build a qualitative model that represents the behaviour of the airplane in the vicinity of a steady-state trajectory. If a sudden structural change occurs, the qualitative model will receive inputs that have never been seen before, which means that it will no longer be able to predict the future behaviour of the system, which, in turn, trips off an alarm indicating that an accident has happened.

In a separate libary, other qualitative models are stored that represent a variety of structural changes of the aircraft. Once the original model is no longer able to predict the system behaviour, these models are consulted in order to identify the one that best predicts the new behaviour of the aircraft. As each of these models represents a particular type of accident, this information can then be used to conclude what type of accident has happened, i.e., to discriminate between different types of accidents. In the very moment when a library model has become capable of correctly predicting the behaviour of the structurally modified system, the continuous monitor is able to know what accident has taken place, and with this information, it can decide upon an appropriate corrective action to be taken

step\var	Real values L	Real values D	Real values γ	Forecast values L	Forecast values D	Forecast values γ	Error matrix $error_L$	Error matrix $error_D$	Error matrix $error_\gamma$
2501	3	3	3	3	3	3	0	0	0
2502	2	3	3	2	3	3	0	0	0
2503	2	2	3	2	3	3	0	1	0
2504	1	1	3	1	1	3	0	0	0
2505	1	1	3	1	1	3	0	0	0
2506	1	1	2	1	1	2	0	0	0
2507	1	1	1	1	1	1	0	0	0
2508	2	1	1	2	1	1	0	0	0
2509	2	2	1	2	1	1	0	−1	0
2510	1	2	1	1	3	1	0	1	0

step\var	L	D	γ	L	D	γ	$error_L$	$error_D$	$error_\gamma$
2501	3	3	3	3	3	3	0	0	0
2502	2	3	3	2	2	3	0	0	0
2503	2	2	3	2	3	3	0	0	0
2504	1	1	3	1	1	3	0	0	0
2505	1	1	3	1	1	3	0	0	0
2506	1	1	2	1	1	2	0	0	0
2507	1	1	1	1	1	1	0	0	0
2508	2	1	1	2	1	1	0	0	0
2509	2	2	1	2	2	1	0	0	0
2510	1	2	1	1	2	1	0	0	0

Figure 4: Differences between the same forecast points without and with fuzzy measures

3.1 Structural Changes of the Aircraft.

The original aerodynamic parameters of the Boeing 747 airplane at cruise flight were modified to obtain four different models with which a library was constructed. These models represent structural changes of the original plane, and were thought to be sufficiently representative to be considered as accidents.

The four models were obtained in the same way as the original one, following the sequence of steps presented in section 3.2. The main characteristics of these models are:

- **Model B4** is the original model that represents a Boeing 747 in cruise flight at high altitude. Its aerodynamic parameters are considered as reference values for the other models.
- **Model 747** represents a Boeing 747-300 in cruise flight. The values for the Lift L, Drag D, aerodynamic momentum M, and the pitch angle θ are changed in comparison with the B4 model.
- **Model B5** represents a change of the original B4 model, in which the aerodynamic parameters L and D are increased, whereas M and θ are decreased.
- **Model B13** represents another change of the B4 model. Here, L, D, and θ are increased, whereas M is decreased.
- **Model B14** is very similar to the B4 Model. The only difference is that M and θ are a little increased.

step\var	$error_L$	$error_D$	$error_T$	alarm
995	0	0	1	0
996	0	0	0	0
997	0	0	0	0
998	0	0	0	0
999	0	0	0	0
1000	0	0	0	0
1001	0	0	−1	0
1002	0	0	0	0
1003	0	0	0	0
1004	−2	3	−1	1
1005	−3	1	−1	1
1006	1	0	0	1
1007	0	0	0	1
1008	0	0	3	1
1009	−3	2	2	1
1010	−1	3	0	1

step\var	$error_L$	$error_D$	$error_T$	alarm
995	0	0	0	0
996	0	0	0	0
997	0	0	0	0
998	0	0	0	0
999	0	0	0	0
1000	0	0	0	0
1001	1	0	−2	0
1002	−3	−1	1	1
1003	0	−2	1	1
1004	−2	1	−1	1
1005	−1	2	0	1
1006	2	−1	1	1
1007	−1	1	0	1
1008	−3	0	−2	1
1009	−3	2	0	1
1010	0	3	0	1

Figure 5: Differences between crisp and fuzzy threshold error alarms for the detection of the accident

3.2 Detection of the Accident.

The detection of accidents proceeds as follows: the failure detector implemented in the qualitative model forecasts the future behaviour of the system and then compares this forecast with the actually measured data. As the forecast is based on past behaviour of the system, it is somewhat adaptive to slow changes in system parameters or a slow drift in the steady-state, but a sudden structural change is immediately detected since the behaviour of the system can no longer be forecast with the optimal masks that have been evaluated for the system under observation.

The failure detector works through a threshold error alarm that counts the incorrect forecasts within a given period of time, and trips the alarm whenever the accumulated number of incorrectly predicted future states surpasses a threshold that is built into the detector. At such time, the inductive reasoner initiates a search for another qualitative model that correctly represents the qualitative behaviour of the structurally modified system.

3.3 Recognition of the Type of Accident.

The recognition of the type of accident starts when the qualitative model initiates the search for another set of optimal masks that represent the behaviour of the new system. The process

$step \backslash var$	$error_L$	$error_D$	$error_\gamma$	$alarm$
201	0	−1	0	0
202	0	0	−2	0
203	0	0	−1	0
204	−1	0	−1	1
205	−1	0	0	0
206	0	0	0	0
207	1	0	−1	0
208	0	−1	0	0
209	−1	0	−1	1
210	0	0	0	0

$step \backslash var$	$error_L$	$error_D$	$error_\gamma$	$alarm$
201	0	0	0	0
202	0	0	−1	0
203	0	0	0	0
204	0	0	−1	0
205	0	0	0	0
206	0	0	0	0
207	0	0	0	0
208	0	0	0	0
209	2	0	−1	1
210	0	0	0	0

Figure 6: Differences between crisp and fuzzy threshold error alarm for the recognition of the type of accident

errors varies consistently between 3% and 12% when the correct qualitative model is being used. This permits a reduction in the threshold value used by the monitor. Furthermore, an incorrect forecast often led to an entire chain of consequence errors, which would immediately trip the alarm if the accumulation window was selected too narrowly. The new system doesn't exhibit this problem any longer. False alarms are no longer caused by error chains, is very similar to that of the failure detection. For each qualitative model (optimal mask) in the data base, the forecast values of this new qualitative model are compared with the true measured (and recoded) values of the quantitative model of the structurally modified plant. If the error surpasses the threshold, the currently investigated qualitative model does not represent the behaviour of the system, and another qualitative model must be chosen from the library. Exactly one qualitative model should pass the test, irrespective of when the error occurs during the simulation. If no qualitative model is able to pass the test, the threshold value has been chosen too stringently, whereas multiple models passing the test indicate poor failure discrimination. It is hoped that the range of acceptable threshold values is wide, i.e., the correct accident can be identified using a fairly small threshold value, whereas all other optimal masks will call for a considerably higher threshold value before they pass the test as well. Once the new model is identified, the monitoring system acts exactly as before the accident. Figure 6 depicts the differences in the threshold error alarm for the recognition of the accident with and without fuzzy measures.

4 CONCLUSIONS

The main advantage of the improved methodology is a significant reduction of the number of forecasting errors. The previously used system as described in [12] had between 25% and 33% errors in the forecasting points, while with the new system the percentage of and therefore, the accumulation window of the threshold error alarm can be made much shorter, which allows the structural change to be detected several points earlier than using the old system. With respect to the recognition of the accident itself, the B4 to B747 transition is identified seven sampling intervals earlier than before, and the B4 to B13 transition is identified three sampling intervals earlier.

The other main advantage is the unambiguous identification of the post-accident steady state, i.e., the new set of optimal masks that correctly describe the post-accident behaviour. Using the new algorithm, the former confusion between the B5 and B13 post-accident states [12] is completely avoided, in spite of them exhibiting very similar post-accident behaviours.

In this paper, it was shown that adding fuzzy measures to an inductive reasoner can significantly improve its qualitative simulation accuracy, and thereby its discrimination power.

References

1. [Cellier and Yandell, 1987] Celiier, F.E. and D.W. Yandell, "SAPS-II: A New Implementation of the Systems Approach Problem Solver," *International Journal of General Systems,* **13**(4), pp. 307-322, 1987.

2. [Cellier, 1991] Cellier, F.E., *Continuous System Modeling,* Springer-Verlag, N.Y.

3. [Cellier, et al, 1992] Cellier, F.E., A. Nebot, F. Mugica and A. Albornoz, "Combined Qualitative and Quantitative Simulation Models of Continuous-Time Processes Using Fuzzy Inductive Reasoning Techniques," in: Proceedings of the IFAC SICICA'92 Symposium, Malaga, Spain.

4. [Hayes, 1979] Hayes, P.J., "The Naive Physics Manifesto," in: Expert Systems in the Microelectronic Age. (D. Mitchie, ed.), Edinburgh University Press, U.K.

5. [Klir, 1985] Klir, G.J., *Architecture of System Problem Solving,* Plenum Press, N.Y.

6. [Li and Cellier, 1990] Li, D. and F.E. Cellier, "Fuzzy Measures in Inductive Reasoning," in: Proceedings of the 1990 Winter Simulation Conference, New Orleans, La.

7. [Mathworks, 1992] Mathworks, Inc., *The Student Edition of MATLAB for MS-DOS or Macintosh Computers,* Prentice-Hall, Englewood Cliffs, N.J., 1992.

8. [MGA, 1991] Mitchell & Gauthier Associates, Inc., *ACSL: Advanced Continuous Simulation Language — Reference Manual,* Edition 10.0, Concord, Mass., 1991.

9. [Mizumoto and Zimmermann, 1982] Mizumoto. M. and H. Zimmermann, "Comparison of Fuzzy Reasoning Methods," *Fuzzy Sets and Systems,* Vol. 8, pp. 253-283.

10. [Stevens and Lewis, 1992] Stevens, B.L. and F.L. Lewis, *Aircraft Control and Simulation,* John Wiley & Sons, USA, 1992.

11. [Vesanterä, 1988] Vesanterä, P.J., *Qualitative Simulation: A Tool for Global Decision Making,* MS Thesis, Dept. of Electrical & Computer Engineering, University of Arizona, 1988.

12. [Vesanterä and Cellier, 1989] Vesanterä, P.J. and F.E. Cellier, "Building Intelligence into an Autopilot Using Qualitative Simulation to Support Global Decision Making," *Simulation,* **52**(3), 1989.