Hybrid Anticipatory Control Mechanisms
(This text is an abridged form of an application for research funding)

1. General Information

1.1. Applicant

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1.2. Research Theme
Real-time hybrid anticipatory control system

1.3. Key word
Anticipation

1.4. Field and Specialty
Applied Informatics/Computational Design

1.5. Probable Duration of Research
Five years
To begin in the summer of 2003

1.6. Probable Duration of Grant Support
36 months

1.7. Preferred Starting Date of Grant Support
1 June 2002

1.8. Summary of Research Plan
This application for a grant is to cover research in a real-time hybrid anticipatory control system. If is based on both anticipatory computing and soft computing. Anticipatory computing is a new form of computation developed within the framework of the research financed by the DFG (cf. NA 196/5-1 and NA 196/5-2).

An anticipatory system is defined as a system whose current state depends on a future state, and can be formulated as

$$x(t) = f[x(t), x(t+1),p]$$

Soft computing is a term that covers several perspectives—fuzzy sets, fuzzy neurosystems, perception-based computing, etc.—that have been proven effective in the digital processing of non-clear-cut formations pertinent to complex phenomena.

Consequently, the emphasis of this Proposal resides in the implementation of anticipatory computing as related to possibilistic models. This should make possible the management of complex systems that can be controlled by a computer system as well as by a human user.

The project is focused on real-time control, i.e., adjustment. The solution sought must correspond to the time expectations of control systems, which must function with great precision, but which must also be capable of adjustments to circumstances. The research must lead to a solution that facilitates applications to various machines (automobiles, airplanes, boats and ships, and other control systems).

2. Current State of the Research – Work Already Done

2.1. Current State of the Research

a) So-called hybrid control mechanisms represent a relatively new area of research. User-independent control mechanisms facilitate the automation of certain production procedures. In a hybrid context, autonomous control should complement user control. In addition, the control mechanism should support the user in his/her control decisions. These mechanisms are usually reactive: something happens and the control mechanism reacts to this (to a disturbance, for example). In an anticipatory system, anticipatory procedures will be facilitated in such a way that knowledge related to the controlled process is integrated in the decision process.

The major research in this direction has been done in the area of intelligent agents, fuzzy modeling, autonomous control, etc. (See among others: Y. M. Park *et al:* Self-organizing Fuzzy Controller for Dynamic Systems, 1995.; V.M. Popov: The Solution of a New Stability Problem for Control Systems, 1973; D. Nanck and R. Kruse: Fuzzy Control Rules, 1993; A. Isidori: Non-linear Control Systems, 1995; F. Klawonn et al: Fuzzy-Regelung, 2002; T. Kohonen: Self-organized Formation of Topological Correct Feature Maps, 1982; A. Nürnberger *et al:* Neuro-Fuzzy control based on the Nefcon-Model, 1999; H. J. Zimmermann: Fuzzy Technologien, 1995; L. A. Zadeh: A Rational for Fuzzy-Control, 1972.)

In the Proposal itself (cf. 3.II.5.2 and 3.II.5.3) I refer specifically to two researchers (Davidsson and Tsoukalas), who base their work on anticipation. Allow me to state that such works almost always relate to the results of my own research in anticipation.

b) The current state of research in relation to what I have called anticipatory computing can be highlighted by the following information:

1. Anticipation as a theoretical foundation was brought into scientific discourse through the work of Robert Rosen (cf. The Mathematical Foundations of Biology, 1985) and Mihai Nadin (1991, I.1: cognitive sciences)
2. The work of D. Dubois made further contributions (III, 14)
3. The international conferences on Computing Anticipatory Systems (CASYS), held yearly since 1997 and presented by the Society for Research in Dynamic Systems (SSDS), have made a significant impact. The results of three conferences have been published in Proceedings (See Bibliography, 6).

My own work, to which I shall return in 2.2, belongs to these foundational texts through which new directions for research were first established. It is difficult to refer to one's own work impartially, and moreover, to critically evaluate its significance. I have presented my own perspective and the current state of the discussion in an encompassing summary, which is attached. Please consider this text as an integral and detailed part of this Proposal, as set forth in 2.1 and 2.2.

2.2. My Own Preliminary Research

This Proposal builds on research already carried out, and which has three dimensions

a) Work in the foundation of anticipation studies

As already mentioned, at the end of the 1980's and the beginning of the 1990's, I carried out research in anticipation in the framework of Cognitive Science, that is, in relation to the functioning of minds (human cognitive functioning). A summary of my work was published in a bi-lingual book, *Mind—Anticipation and Chaos* (1991, Bibliography nr. 1) in the book series "Milestones in Thinking and Research." In 1996, a copy of the book was sent to the DFG.

b) Work supported by the DFG resulted in the following published works

Anticipation: The end is where we start from, a DVD on the aspects of anticipation, 2002.

Anticipation – The End Is Where We Start From (English-German-French text). Baden, Switzerland: Lars Müller Publishers, 2003, 150 pp.

Anticipation: A Spooky Computation, in *CASYS, International Journal of Computing Anticipatory Systems* (D. Dubois, Ed.), Partial Proceedings of CASYS 99, Liege: CHAOS , Vol. 6, pp. 3-47.

Not Everything We Know We Learned, in *Adaptive Behavior in Anticipatory Learning Systems.* Heidelberg/New York: BertelsmanSpringer, 2003.

Anticipation - Breaking Away from our Deterministic Conditioning, in Identity≡Foundation (www.identityfoundation.de)

Trust: das Prinzip Vertrauen. (M. Nadin, editor, assisted by L. Becker and T. Eicher). Proceedings of the international colloquium: Trust. The 21st Century and Beyond. Heidelberg: Synchron WVA, 2001. 378 pp.

c) Results of Research

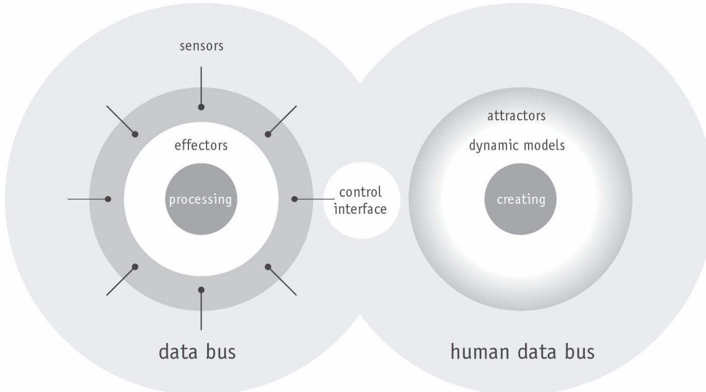
A prototype with anticipatory characteristics was constructed and tested. Real-time data was made available through the research in the form of bond auctions (Prof. Lehman) and VRLI (Prof. Tomb). The prototype was also tested as a Web application.

The anticipatory model contained in this prototype is based on the evaluation of possibility spaces. Concretely, the mathematical description of a transaction (e.g., an auction or a visualization) was first simulated through a pre-computation, which contained full possible values, in order to determine to what extent these influence the transaction researched. It was demonstrated that the possibility of optimizing very complex processes could be achieved through these faster-than-real-time pre-computations.

3. Goals and Research Outline

3.1. Goals

An increasing number of control and automation mechanisms emerges as hybrid digital implementations. A data bus serves as a unified conduit for relevant information regarding the processes subject to computer-assisted control or automation. The data accumulated with the help of an array of various sensors can be used for communication purposes (information made available locally or at remote locations) and to optimize the functioning of the system in question. The data can also be fed into integrated automation programs of various degrees of intelligence, which in turn can be networked. In order for an integrated hybrid control mechanism to function, the data pertinent to human actions is subject to a second bus—the living bus. And the two—data bus and living bus—are integrated.



In short, the goals are:

- Design and implementation of a hybrid anticipatory monitoring and control system
- Design and implementation of a mechanism for the integration of machine-based and human-based anticipatory control mechanisms
- Design and implementation of a real-time control mechanism with anticipatory characteristics.

In order to achieve these goals, the research will address

- architecture for a hybrid control system
- the complementarity of reaction-based control and anticipation-based control
- human-machine interaction
- real-time soft-control mechanisms
- Overall, perception-based computing applied to hybrid control mechanisms is the long-range (five years) goal

3.2. Research outline

I. Defining the Task at Hand

The most optimistic technological view is that eventually, no matter how complex a task or operation is, it can be fully entrusted to a control mechanism programmed to ensure optimal functioning of the system. An intelligent control mechanism would make the system autonomous (self-controlled). The least optimistic view ascertains that for a broad range of applications, the expectation of intelligent self-control is justified. However, for some control systems, of high complexity or of a dynamics scientists still do not fully understand, self-control is unattainable. The following sentence is often quoted: “Automation can take care of 99% of the application; what remains is the high-risk difference” (cf. Bradley, 2002, p. 53).

Using knowledge describing the system controlled, and performing abductive reasoning, we could assess the likelihood of previously minimized events. To this category of events belongs the operation of a system outside its assigned function. (A car serves mobility purposes, not ramming through a wall as in a terrorist attack. The same holds true for an airplane, intended to transport people and products quickly over long distances, but not to crash into buildings.) Anticipation can provide an answer to these kinds of possible events even if they are highly improbable (possibility vs. probability).

I.1. Hybrid control mechanisms

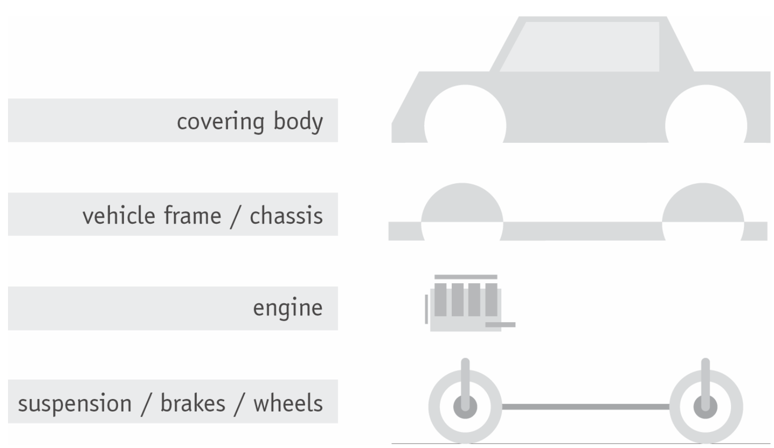
Indeed, as various scientists have reported, there are some activities for which the only solution is a hybrid, i.e., a combination of digital control mechanisms complemented by human control, even though this human involvement is increasingly supported by encompassing digital mechanisms: sensor-based data collection, data evaluation, digitally driven controls through effectors, for example. In other cases, the human being is the beneficiary: cars to be driven, boats to be steered, airplanes to be piloted. Among the examples often given in respect to desired human involvement are driving (e.g., cars, trucks); flying (the complexities above and beyond the automatic pilot procedures); navigation (in various situations such as difficult terrain and taxing weather conditions). The interface to the human operator (driver, pilot, engineer, etc.) should adapt itself to the needs of the operator as these change when the context changes (reduced visibility during a storm or darkness, or blinding sun reflection all to be compensated by the dynamic interface). Anticipation can support "form-fitting" interfaces and thus improve the control mechanisms of the system in question. Obviously, in fully automated production lines, or in dedicated robotic implementations, the issue of a complementary human control capability is eliminated. However, in certain kinds of production situations—those that cannot be standardized given the nature of the production process and the many variables involved—complementary human control, supporting enhanced human performance, remains the last option. Despite the fact that progress has been made in representing the intelligence appropriate to complex control mechanism and expressing it in artificial intelligence (AI) procedures of all kinds—from the expert systems of the past to the neural networks and genetic programs of our days—human control is in some cases the solution of last resort.

I.2. Intelligence and anticipation

Indeed, it seems that an important component of what defines human intelligence remains outside our descriptions (algorithmic or non-algorithmic). For quite some time (cf. Nadin, 1988, 1991, 1999), I have maintained that this component is the anticipatory characteristic of the living, in particular of the human mind. In the meanwhile, quite a number of researchers have joined me in ascertaining this, even though our views are far from being equivalent (cf. CASYS). Previous research, resulting in a first anticipatory computing model (Deutsche Forschungs Gemeinschaft/German National Science Foundation, and Stanford University, 1999), allowed for testing on data processing in which anticipation plays an important role: bond issuance (the issuing agency's anticipation of market reaction; low acceptance of a new issue, which can be costly); visualization of complex phenomena (which from among the data is essential, which data can be ignored without affecting the outcome; in this case, the efficiency of data accumulation processing is at stake). The implementation I proposed is basically a pre-computation, during which range of data and significance, expressed in degree of importance (weight attached to data), are tested. Consequently, real data is subjected to a pre-evaluation before being processed. Data of low relevance to the outcome (already tested using data samples) is either discarded or marginally accounted for.

I.3. An example: automobile control

Based on experience acquired to date, I have been able to advance the notion of anticipatory computing as part of improved control mechanisms for extremely complex situations (research project advanced at DC RTNA, Palo Alto, CA, May 2002; see http://anticipation.g3wo.com or http://grafcosf.com/users/mihai/). Let's take the automobile as an example.



The digital data bus (implemented in various ways by different manufacturers) makes possible a level of control never before possible. It provides real-time information and supports efficient control mechanisms.

I.3.1. Basically, every component of the complex machine called a car can be monitored in real time. What results is a digital map of this machine's functioning. From this digital map, the user/driver or the maintenance program can infer to the condition of the machine and even prevent malfunctioning or breakdown. As a result, cars endowed with a digital bus and the appropriate mechanisms for control reach, among other thing:

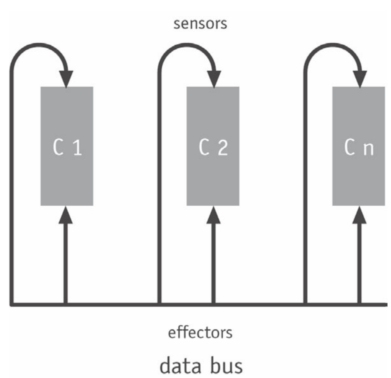
- higher security levels (for the driver and traffic participants)
- lower energy consumption
- lower emission levels
- higher performance
- lower cost per mile/kilometer
- lower maintenance costs.

I.3.2. In fact, a digital bus and the appropriate control mechanisms are the means for reactive and proactive control procedures that are used for

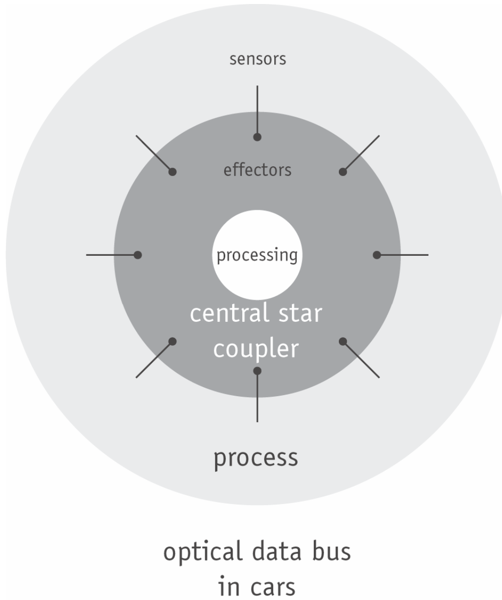
- accumulating data from the various components
- facilitating control of individual components or combinations thereof
- facilitating integration, and automation
- facilitating generation of a performance map
- facilitating interface to the outside world (GPS, telemetry, etc.)
- facilitating effective control mechanisms.

In the economic equation of mobility, the research and development (R&D) costs for such systems, production costs, and maintenance still exceed the immediate benefits to the driver. The secondary benefits (e.g., lower pollution, less dependency on oil, increased security) are usually difficult to assess.

I.4. A generalized problem: definition
Similar to the car, any other machine can be considered. It consists of interrelated components, integrated functions, and it provides a quantifiable output.



Any machine (car, airplane, production line, etc.) can be subject to the reactive model of control. Sensors provide data from components. Data are transmitted to the digital bus and eventually made available through some interface with the environment in which the machine operates. In other words, the *physics* of the automobile (and of any machine) is reflected in the digital model; and the control mechanism is focused on the high number of various cause-and-effect sequences describing the deterministic properties of the integrated system making up the machine (in particular, the car).



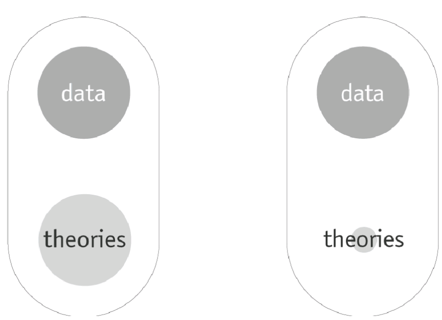
II. Prolegomena to anticipation

II.1. Anticipation is a characteristic of the living that is usually associated with the mind. It makes possible the performance of actions for which scientists do not have a good deterministic (i.e., cause-and-effect sequence) description. Davidsson *et al* [1994] provide several examples:

> A tennis player has to anticipate the trajectory of the ball in order to make a good hit. A stockbroker makes forecasts of stock prices in order to make a good deal. In short, they use knowledge of future states to guide their current behavior. To do this they make use of an internal model of the particular phenomenon. The experienced tennis player's use of his model is probably on an unconscious level and has been learned through tedious sensorimotor training. A novice, on the other hand, has to use his model of the ball's trajectory in a more conscious manner. Similarly, the stockbroker's model is probably on a conscious level, learned through theoretical studies and experience of previous stock prices. (p. 1427)

Such examples were documented by other authors as well (cf. Wolpert, 1998; Dubois, 1999).

In respect to the subject of the research herewith proposed, it is important to notice that in driving, navigation-related activities, orientation, control of extremely complex machinery, etc. anticipatory instances have also been recorded in a wide variety of quantitative assessments. This justifies the characterization of anticipation as a field rich in data but still very poor in a theoretic foundation.



This observation should explain why, despite the applied nature of this proposal, a limited amount of foundational research, necessary for providing the methodology for implementation, will have to be funded.
Davidsson *et al* continue their assessment by confirming the evaluation of the situation that I described above:

> ...anticipatory reasoning has not been sufficiently studied and, as a consequence, is not well understood within the field of intelligent autonomous systems. This is probably due to the strong influence from the more traditional sciences, e.g., physics, that have essentially been limited to the study of causal systems which, in contrast to anticipatory systems, do not take knowledge of future states into account. We believe that autonomous systems with the ability to anticipate as described above would exhibit novel, interesting and possibly unexpected properties that might enhance the capacity of autonomous systems. (p. 1428)

With all this in mind, I will proceed in providing a framework for the understanding of the project, insisting on the above-defined elements. Let me point out, that recently, under the influence of the research in anticipation carried out through my group, many new attempts became known in the area of integrating an anticipatory perspective in decision and control applications, as well as in the understanding of human-machine interaction. Noteworthy in this vein are multimodal interfaces, the so-called affective computing, human-centered engineering, and organic computing inspired by genetics and by models based on evolution theory. In the German IT development plan, extending to 2006 (cf. BMBF IT Research 2006 of the, i.e., the detailed guidelines document of the Bundesministerium fuer Bildung und Forschung/Federal Ministry for Education and Research), all these themes are highly ranked. They are also subject to funding as priority objectives.

II.2. A frame of reference for anticipation and agent control technology
II.2.1. Traditional agents
Growing interest among computer scientists in the field of autonomous agents is probably due to the emergence of a promising model for digitally supported interaction, quite different from the traditional models practiced so far. I refer here to *agents* technology*,* which follow an anthropomorphic view of the world, that is, the world seen through the eyes of the human being. Agents are often referred to as reactive, or behavior-based programs endowed with capabilities pertinent to a certain activity or to an array of activities. Early work in agents development [Nilson, 1969]) advanced an approach based on two main components:

- the world model, i.e. a description of the agent's environment;
- a planner of a sort.

The functioning of this early generation of agents (also known as *traditional* agents) can be described through the sequence

Sensory acquisition of data—world model—planner based outline of actions—action cycle

From sensors ("sense the environment and produce sensor-data," cf. work on *Shakey,* a mobile automaton [Nilson, 1969]), information is derived to update the world model. In turn, this is "used" (i.e., accessed) by the planner in order to "decide" (e.g., decision tree procedures) which actions to take; that is, which output will drive what kind of choice from among those made available in the program. These decisions serve as input to the effectors that actually carry out the actions (i.e., are activated). Here I have attempted to translate the anthropomorphic language used by agents researchers because there is always the risk of suggesting that some things "happen" by themselves, and not as a result of the elaborate programming effort behind each agent. Once we focus on anticipation, it will become even clearer why terminology needs to be precise.

II.2.1.1. Deliberation and action

Writing or automatically generating the software that is expressed in these kinds of agents prompted computer scientists and AI professionals to observe that even if they were able to perform some relatively advanced cognitive tasks, such as planning and problem solving, agents had problems with more elementary tasks, such as routine reaction—something happened that was not predicted in regard to the agent. (The cat that jumps in front of a car can be accounted for through the planner, but a "dead pixel" on a scene analyzer might appear as an undecidable bit of information that will confuse the system [cf. DaimlerChrysler Report, 1994]). These occurrences sometimes require fast action but no extensive deliberation. One of Stanislav Lem's stories illustrates the situation quite tellingly. Think about a traffic situation, or a flight control episode (near-collision situation) in order to realize that after a perfect performance, the agent can fail due to a trivial occurrence. The limits of this approach are reflected the in the pursuant reactive model embodied in new agents (cf. Gershonson [2001], a good survey of work in the field).

II.2.2. Behavior-based agents

As a premise for the new concept stands the idea, derived from cognitive studies, that most of our daily activities consist of routine actions rather than being the result of abstract reasoning. In some ways, the behavioral premise was reactivated and tested in a variety of new situations. Instead of ambitious world modeling and difficult planning capabilities—all with high computational cost—the agents were endowed with a finite collection of simple action-reaction cycles, i.e., behaviors. Changes in the environment result accordingly in a stimulus-response fashion (almost Pavlovian in nature [1904]). In retrospect, we know that some of the most influential solutions in the form of such agents are Brooks' robots, based on a subsumption architecture. They belong to the "intelligence without representation" paradigm. Noteworthy are also the so-called Pengi implementations (cf. Agre and Chapman [1987]) —based on activity theory—and situated automata, with an epistemological substratum (cf. Rosenschein and Kaelbling [1987]).
In defining this stage in the development of agent technology, we can join the many authors who make the following observation:

> Probably the most controversial element of this new approach concerns the representation of knowledge. Brooks, in particular, argues that explicit representations of the world are not only unnecessary but also get in the way when implementing actual agents. Instead the agent should use the world as its own model, continuously referring to its sensors rather than to an internal world model. [Davidsson *et al,* p. 1439]

Behavior-based agents have been shown to perform better in situations in which the first-generation agents fail: accomplish a limited number of simple tasks in real-world domains. However, in addition to not being particularly versatile, they have problems with handling tasks that require knowledge about the world that must be obtained by reasoning or from memory, rather than perception—a notion to which I shall return. According to Kirsh [1991], some possible candidates for such tasks are activities which require

- response to events beyond the agents current sensory limits;
- some amount of problem solving;
- understanding a situation from an objective perspective, or prediction of other agents' behavior.

II.3.Synergy of inputs/Multimodal processing architecture

From the perspective of biologically inspired computation, in particular evolutionary models, the main objective to the behavioral reaction is that the living can be described, from the viewpoint of information processing architecture, as a multimodal system. No reaction is reducible to one specific sensory channel. Rather, a combination (prompting the notion of synergy) of inputs, through a number of different channels, explains both precision and richness of human action. This (multimodal) combination allows us to understand that agents reduced to the behavioral model cannot reach a similar precision and richness [cf. Sjölander, 1994]. The human being is capable of generalization and abstraction, due to a sort of "central representations" that other species, superceded by human beings in evolution, do not have. As computer scientists working on evolutionary models know very well, evolutionary advantages are relative; they need to be understood in the context of the actions which we try to emulate through agents or other intelligent programs, including programs with learning capabilities. To go from monosensorially governed constructions of several internal representations to a centralized intermodal representation is probably one of the most important aspects in the evolution of mind [cf. Nadin, 1991].

II.4. High-level reasoning/low-level reactive capabilities

The suggestion is that as things stand now, agents based on the reactive paradigm will not reach human-level performance except for locally defined tasks. Ferguson [1992], Hendler [1990], Kuokka [1991], Lewis [1991], Mitchell [1990], and especially Zadeh [1996] have convincingly shown that an intelligent agent must have both high-level reasoning and low-level reactive capabilities. What this means needs to be further explored. Partially, this is a task related to anticipation and anticipatory characteristics supported by digital processes.

The rationale behind this hybrid approach—machine and the living—is to integrate the reaction ability of agents (quite appropriate for routine tasks) with the human faculty of planning, as this proved to be an essential ingredient in approaching advanced tasks (driving in a city situation, navigation under less than standard conditions, integration of tasks, etc.). In line with this model, several attempts have been made to integrate anticipation in such systems (Tsoukalas *et al* [1989], Davidsson *et al,* [1994], Nadin [1991, 1999], etc.). It should be pointed out here that solutions based on soft computing [cf**.** Zadeh, 1996] have a different premise: The human being operates on the basis of incomplete, imprecise, and limited information. Still, performance is higher than that of systems designed to reach spectacular levels of precision and that operate on huge amounts of data. Again, my suggestion is that the trade-off between the two computational solutions is due to anticipation. This suggestion is the core of the implementation that makes up the subject of this research proposal.

II.5. Implementation aspects: two perspectives

In what follows, I would like to present in parallel two implementations based on the notions spelled out above. I do so in order to point out what can be continued, and *what has to be fundamentally changed* if we want to achieve a control performance optimized through anticipatory characteristics. As the exposé of this research project application evolves, one could easily find out that there is a fundamentally different perspective in what I am proposing, although I also integrate the experience of the authors I will quote from.

II.5.1. Autonomous agents

(Davidsson, Astor, Ekdahl [1994])

According to Rosen [1985], an anticipatory system is "... a system containing a predictive model of itself and/or of its environment, which allows it to change state at an instant in accord with the model's predictions pertaining to a latter instant" (p. 339). Thus, such a system uses the knowledge concerning future states to decide which actions to take in the present.

In more formal terms, the next state of an anticipatory system would be a function of past and future states:

$s_{n+1} = f(s_1, s_{2\,\ldots}, s_n, s_{n+1}, \ldots, s_k), k > n$

whereas a causal system only depends on past states:

$s_{n+1} = f(s_1, s_{2\,\ldots}, s_n)$.

However, since an agent cannot normally have true knowledge of future states, it is, of course, not possible to implement an anticipatory system in this strict sense. The best we can do is to approximate such a system by using *predictions* of future states. Thus, we have:

$s_{n+1} = f(s_1, s_{2\,\ldots}, s_n, \hat{s}_{n,1}, \ldots, \hat{s}_{n,k-n}), k > n$

II.5.2. Procedural programming

(Tsoukalas, Lee, and Ragheb [1989]

The synthesis of such system is demonstrated using a model of a nuclear reactor. The model of the reactor is constructed using procedural programming methods and is coupled to a symbolic program which assumes the overall control function.

An Anticipatory System is a system containing a predictive model of itself and/or its environment, which allows it to change state at an instant in accordance with the model's predictions pertaining to a latter instant.

Although the impetus for the development of a theory for Anticipatory Systems has come from the field of theoretical biology in an attempt to explain the behavior of organisms [Rosen, Nadin], the present research suggests that it can provide a useful metaphor for the monitoring and control of engineering systems as well [Trakhtenbrot, 1973; Ragheb, 1986].

The basic premise of anticipatory control is that both current and anticipated (future) performance are the basis of diagnostic/control decisions, i.e., they are incorporated in the control strategy. Constructing a Model-Based System or an Expert System in a process environment with monitoring and control functions in the context of the anticipatory paradigm requires that it performs two main functions at any time t. *First,* it must where $\hat{S}_{n,i}$ is the predicted value of $\hat{S}_{n+i}$.

II.2.5.1.1. Computational Framework

In the suggested framework, an anticipatory agent consists mainly of three entities: an object system *S*, a meta-level component *M*, and a world model *W*. *S* is an ordinary (non-anticipatory) dynamic system, *W* is a description of the environment *including* *S*, but excluding *M*. *M* should be able to make predictions using *W* and to use these predictions to change the dynamic properties of *S*. Although the different parts of an anticipatory agent certainly are causal systems, the agent taken as a whole will nevertheless behave in an anticipatory fashion.

To get this approach working, it is essential that the sequence of states of *W* are parameterized by a time variable that goes faster than real time. That is, if *W* adequately describes the environment (and *S*) at some time t_0, then after an arbitrary time interval Δt, *W*'s sequence of states will have proceeded $t_0 + \Delta t$.

II.2.5.1.2. Implementational Issues

When implementing an anticipatory system, what should the different components (*S*, *M*, and *W*) correspond to, and what demands should be made upon these components? To begin with, it seems natural that *S* should correspond to some kind of reactive system similar to the ones described above. It must be a fast system in the sense that it should be able to handle routine tasks instinctively and, moreover, it should have an architecture that is both easy to model and to change. *M* would then correspond to a more deliberative meta-level component that is able to “run” the world model faster than real time. When doing this it must be able to reason about the current situation compared to the predicted situations and its goals in order to, among other things, detect undesirable situations that cannot be handled by the reactive component. If such a situation is detected it should decide whether (and how) to change the reactive component or to issue commands directly to the effectors. There is a large body of work concerning different aspects of meta-levels, but none of this work seems readily applicable to the outlined approach. The closest is perhaps the studies on reflective architectures and some works on meta-reasoning architectures in the context of autonomous agents.

Since a world model is based on a representation, it can only approximately describe any given subset of the real world. Thus, since world models are abstractions of reality, we must decide on which level of abstraction is the most appropriate for the world model. Gat **[**1993] argues that the debate concerning traditional agents versus reactive agents is really an argument about the proper use of a world model (i.e., internal state information). He writes that “... internal state should be maintained at a high level of abstraction and that it should be used to guide a robot’s action but not to control these actions directly.” Thus, local sensor information is necessary for the immediate control. He provides an example to show that this is probably also the way humans work. We are able to find our house and belongings because we have a world model at a high calculate current performance levels. This is done after it has obtained: (a) information from the external world, in the form of sensor readings, and their associated probability distributions, and (b) a set of criteria about how things ought to be, which are embodied quantitatively in a set of membership functions. These comprise the biggest part of its Knowledge Base, in the form of rules, constraints, heuristics, etc. *Second,* it must estimate the performance in the near future, that is, some time Δt later. To achieve this goal, it requires: (a) an estimate of current performance, (b) membership functions for the anticipated values of the state variables -- obtained through the employment of a predictive model -- and, (c) a memory of its past experience, concerning the effectiveness of earlier predictions. The methodology presented here allows for estimating present as well as future performance on the basis of probabilistic and possibilistic information and is demonstrated with the simulation of an anticipatory model-based system in a process environment.

II.2.5.3.1. Combining Probabilistic and Possibilistic Information in Anticipatory Systems

The basis for the calculation of the current and anticipated performance of a system are the notions of the probability of a fuzzy event and the fuzzified Bayes formula.

Let X = $\{x_l, x_2, ..., x_n\}$ and Y = $\{y_1, y_2, ..., y_m\}$ be sets of basic events with probabilities $p(x_i)$ and $p(x_j)$ respectively. Let $p(x_i, y_j)$ be the joint probability of x_i and y_j. A fuzzy event A on X is characterized by a membership function μ_A: X→[0,1], and similarly a fuzzy event A' on Y is characterized by a membership function μ_A: Y→[0,1]. The probability of the fuzzy events A and A' are given by:

$$P(A) = \sum_{i=1}^{m} \mu_A(x_i)p(x_i), \text{ and}$$

$$P(A') = \sum_{j=1}^{m} \mu_{A'}(y_j)p(y_j), \text{ and}$$

The conditional probability of the fuzzy event A' given the occurrence of A is[l]:

$$P(A'|A) = \frac{\sum_i \sum_j \mu_A(x_i)\, \mu_{A'}(y_j)\, p(y_j|x_i)\, p(x_i)}{\sum_i \mu_A(x_i)\, p(x_i)}$$

where $p(y_j|x_i)$ is the conditional probability of the basic event y_i conditional on the occurrence of the event x_i. The second equation is a fuzzified version of Bayes formula. For the logical operators AND, OR, and NOT, there exist equivalent expressions in probability and possibility theory. In the fuzzy set (or possibility) theory, AND corresponds to a MAX and OR to a MIN operator respectively.

level of abstraction. We do not know the exact location of our house or our belongings, but we use sensor data to fill in the details that the world model does not provide. We thus suggest that *W* should be on a rather high level of abstraction. Moreover, there is certainly a trade-off between how detailed the world model is and the accuracy of the predictions made using it; the higher the level of abstraction, the more accurate (i.e., probable) are the predictions.

In examining the two perspectives, one realizes three things:

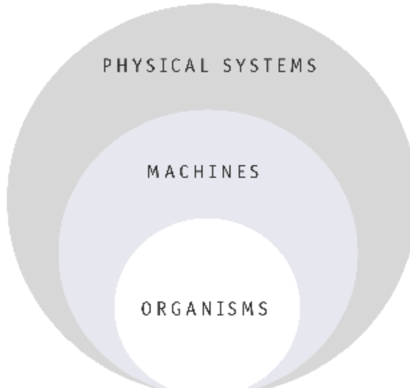
- the focus is on Rosen's definition
- the understanding that not anticipation as such, but rather simili can be expected
- the need to overcome the limitations of the two approaches. (I am aware that more work was carried out be the authors after publication of the respective articles, which are not by any means the most recent.) In particular, the situation under consideration is systems for which real-time performance is necessary. More will follow that will address this aspect.

II.6. Endowing agents with anticipatory characteristics
The system to be designed and implemented is based on an anticipatory computational model that complements the reactive model (and goes beyond the known attempts documented under IV.2.4 and VI.2.5). An anticipatory model in a hybrid implementation of a control mechanism should make possible performance above and beyond that afforded by control mechanisms based only on a reactive model of the process /machine/ system subject to automation. The extent of the increase in performance will depend on many factors and cannot be predicted by using ay of the currently known predictive methods. That an increase in performance can be expected is based on research reported at DARPATech 2002 (Anaheim, California, July 2002), by the ISPI (International Society for Performance Improvement) and by the preliminary reports submitted for Human Performance 2003 (a NASA Advanced Technology Integration conference). Especially relevant to the present application is the emphasis on Non-Invasive Measuring and Monitoring of individual performance.

III. The "Modelling Relation"

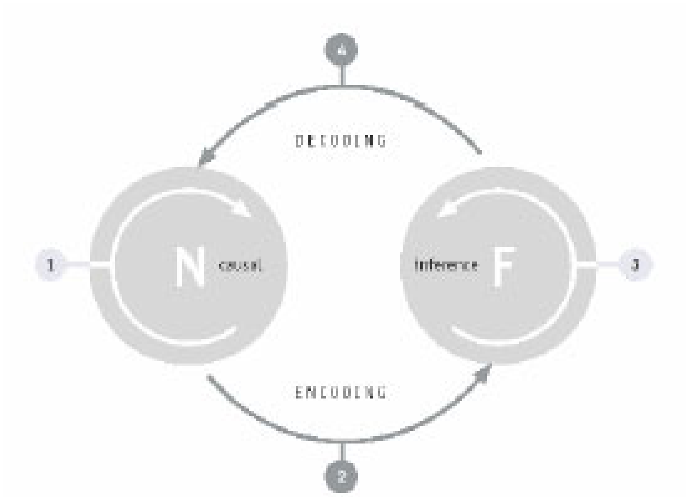
The research will be guided by knowledge pertinent to anticipation and to the task of a hybrid control system. Therefore, after examining what has been accomplished so far, together with the limitations of this work, this application will focus on

III.1.1. a different foundation
III.1.2. the "Modelling Relation"
III.1.3. an alternative architecture
III.1.3.1. an implementation that takes alternative models into account
III.1.3.2. competition among models and reward mechanisms.
III.1. Foundational premise of the project
III.1.1. The works of Robert Rosen [1985] and of Mihai Nadin [1991, 1999] make the distinction between physical systems and living systems/organisms. Rosen is very particular in his representation of the world. (Elsasser [1987] would probably have agreed with this representation.)



Without entering into detail—a discussion of this view cannot be properly pursued in the framework of a research grant application—I shall make two observations.
a) A hybrid system combines the physics of the machine and the characteristics of the living (physics, in the diagram, and life). It needs to be clearly stated that the organic is the embodiment o the physical *reality* (everything living is made up of physical elements, such as molecules) and characteristics not reducible to this reality, in particular, anticipation. (For more details, see Elsasser [1987].)
b) Furthermore, in order to efficiently deal with the living in computational terms, we need to understand the processes characteristic of the living. In this respect, the notion of causation needs to be refined.

3.1.2. Rosen introduced the so-called "Modelling Relation"



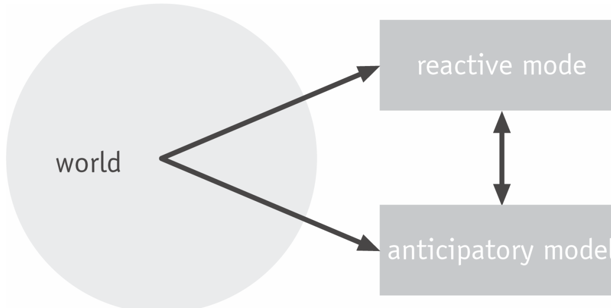
The description of the natural can be made in words, measurements (quantitative observations), mathematical descriptions, logical representations, and programs, which we can manipulate. This is how, from equations describing the motion of a solid body, we derive algorithms and eventually write programs simulating such motion. The encoding of a process in a program is an example:

Process (parameters) = (algorithmic descriptions) → programming language → program(s).

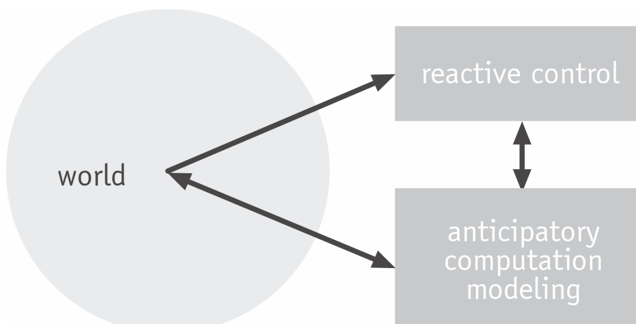
Once we have produced such a description—let's say in the form of a scientific hypothesis or in a mathematical form in a program, we apply further rational arguments to the description. This is how, for instance, we derive theorems from an axiom. Within a program, parameters can be subject to variations. Real-time data from the natural world drive the program and results in output:

Control (parameters) = Function (of parameters and data) = output.

This output can be optimized in respect to a certain goal (e.g., collision avoidance) or set of goals (e.g., best aerodynamic characteristics). If we add here that the living operates in a world from which it receives information through the senses, but also generates, through its own thinking, information pertinent to the action it is involved in, we have a complementary image: a reactive mode and an anticipatory model.



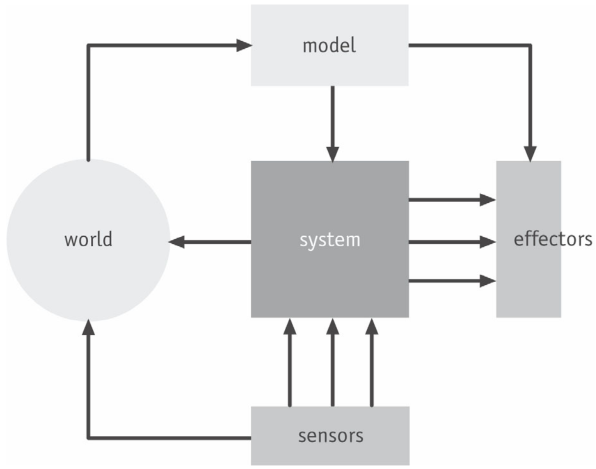
Based on the above, the following model will be defined, described, modeled, and tested:



The architecture for a control process integrating these two components has already been tested in several applications (e.g., monitoring and control pertinent to a nuclear reactor, robotics, in particular the Robocup [Veleso et al, 1998], in which a game of soccer endowed with anticipatory characteristics was played).

III.1.3. An alternative architecture
The system subject to control**:**

- S
- a context model W (sometimes called “world”)
- a model of the system operating in faster than M (real time)
- Sensors
- Effectors



Of special interest here is the Module M, because through this model, predictions are turned into actions. The model affects the system. Its predictions change the dynamic characteristic of S. The model can also control the Effectors and thus trigger some actions. Here we actually have two concurrent processes:

- a reactive process at the object level (system controlled)
- a predictive—anticipatory process—at the meta-level, i.e., the level pertaining to the model of the controlled system.

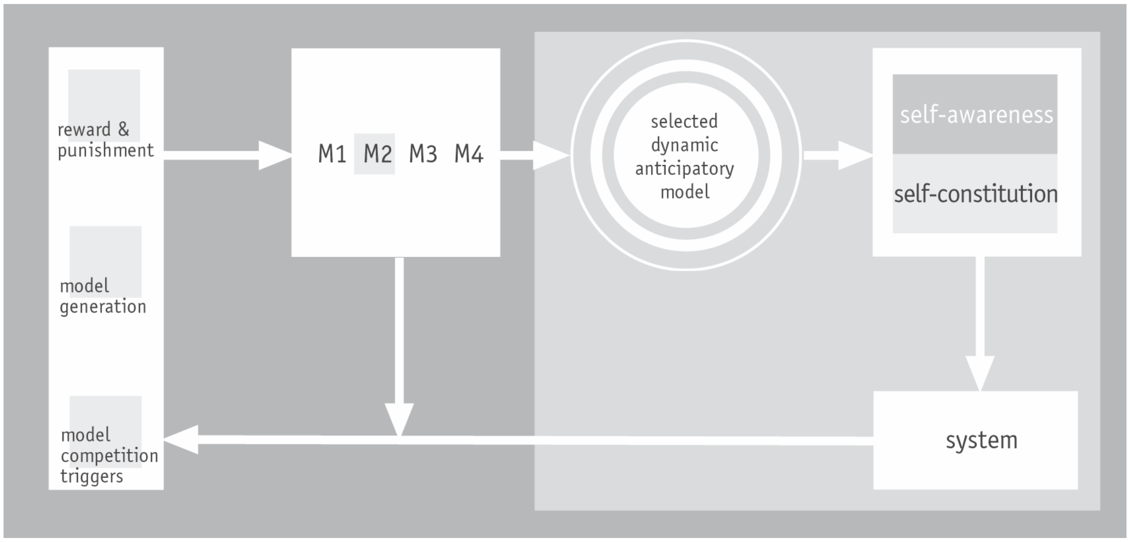
Their integration is by no means computationally trivial.

III.1.3.1. An implementation that takes alternative models into account
If instead of conceiving a module M—which is only a model S unfolding in faster than real time (such as a simulation, or flight control program)—we implement an architecture of choices, the complexity increases, but so does the ability to avoid a control system than is rather rigid. Indeed, M in the architecture under 3.1.3 is only appropriate if we know that the system has a limited degree of freedom. But if the functioning of a system is by its nature subject to more parameters and to many control paths (driving a car involves the coordination of engine performance, brakes, navigation, etc.)—in other words, if we deal with a non-linear modus operandi (many possibilities), we need an alternative model.

III.1.3.2. Competition among models and reward mechanisms
Moreover, if alternative predictions/anticipations are generated, we reach yet another level: Among the various possibilities generated “on the fly,” for each new situation, there will be competition. We can thus implement an architecture that makes the following available:

- a space of possibilities (in Zadeh’s sense [2003])
- conflicting possibilities—for each situation, a certain possibility is relatively better than the rest
- a selection and reward mechanism, much like in cognitive processes of anticipation—computational resources are allocated to the “winning” mechanism.

The following diagram suggests an alternative architecture:



At this moment, the description of processes with anticipatory characteristics is relatively rudimentary:

Control = function of (past state, current state, future state) of system.

In this case, knowledge of future states is a matter of possibilistic distributions. One of the main aspects of this research is to work on such distributions. But at the same time, we can reach pseudo-anticipatory characteristics by using *predictions* of the future state: Instead of "future state," write "predicted state."

As already pointed out, if the system were a closed system and we were able to have a complete description of it, we would be able to predict future states since we would have access to knowledge describing such states. But this idealized case pertains neither to cars and drivers, nor to other mechanisms that we would like to monitor and control.

III.2. Implementation aspects

A trade-off between how detailed the model M of S and the model of he world and the accuracy of predictions made using these models is anticipated. From all we know about such computations, it is clear that the higher the level of abstraction (in the description on which the models are based), the better the expected predictions (within the decidable aspect of the task).

More specifically: The model of the machine as such and the model of the world in which the machine in question operates are conceptually quite different. One is a state-machine of a sort (still to be defined), probably expressed in an autopoietic (self-generating) map. The other involves the description of the world in which the machine operates. From the driving simulators in operation today (Berlin, Detroit, Toulouse, and others), we know that this world must have sufficient detail, but still be reduced to a level of generality that makes it simulatable. Situation-dependent knowledge will serve as input to feedforward mechanisms. ("If driving up a hill, higher engine performance expected" is a limited example.) Feedforward mechanisms are also efficient in dealing with disturbances.

III.3. Performance measure

Tsoukalas *et al* [1989, p. 281] introduced the so-called "anticipated performance." I shall not go into the details of their presentation. What interest us in this respect is the following:
Sensors bring information regarding a hill; the system should anticipate the performance of the car based on the current condition (state of the engine, fuel supply, driver's condition, car load, weather, transmission condition, tire condition, brake condition, etc.). If the state of component C_n is defined as $State_{current}C_n$, this definition is a good measure of the performance of that component. Furthermore, if we know that Performance = function of State C_n, we can say that given another situation, during which

$State_{current}C_n$ becomes $State_{future}C_n$, a new $Performance_{future}$ = function of $State_{future}C_n$

is definable.

Regardless of whether we can describe it more precisely, or even compute it, there is a relation between the two performances. The question to be addressed is to what extent we can calculate $Performance_{future}$ based on $Performance_{current}$. In terms of soft computing, we can work on membership functions and focus on "will-be-adequate" or not, leaving the control mechanism to operate on fuzzy descriptions.

III.5. The issue of relevance

This subject is relevant for the following reasons:

III.5.1. Real-time aspects.

Components 1, 2, ...n can be further distinguished as functionally time independent and time sensitive. The functioning of components over time is adequately described by conditional probabilities: $p(y_j|x_i)$. They form a symmetric matrix [1987, p. 281], capturing experience and variation (as measured by sensors). If a component performs adequately at time t, it does not automatically mean that at $t = t+\Delta t$ it will also perform adequately. But *adequate* itself is hard to define in the performance of complex systems. This is why an idealized model and a state variable distribution will be developed in order to serve as a reference.

III.5.2. Learning

Functioning under continuously changing conditions means that control mechanisms will have to reflect this dynamic situation. I mention learning here, but I do not see how, within the effort already spelled out, a learning component can be developed. If the project advances the way I defined it so far, it will become possible to continue work by implementing a learning module.

IV. The Human Bus – Customizing Control

The notion of profiling is gaining fast acceptance in the IT community. Numerous applications of profiling (user profiles as participants in e-commerce, e-banking, e-learning, etc.) are made available commercially. Such profiles are a digital portrait of the individual: patterns of behavior (mainly decision-making) are extracted from information resulting from transactions performed on-line and off-line. Profiling received much attention after the world became aware of the dangers of identity theft, and even more after terrorist acts and threats.

In view of all what has been mentioned up to this point**,** the purpose of creating a human control-data bus (complementing the digital) of a control profile of the individual who drives a car, pilots an airplane, steers a boat, controls a production system, etc. is almost reducible to the purpose of generating a profile of the person involved in the action for which anticipatory control and commands is developed. This profile reflects the individual's characteristics as they change over time (including ageing).

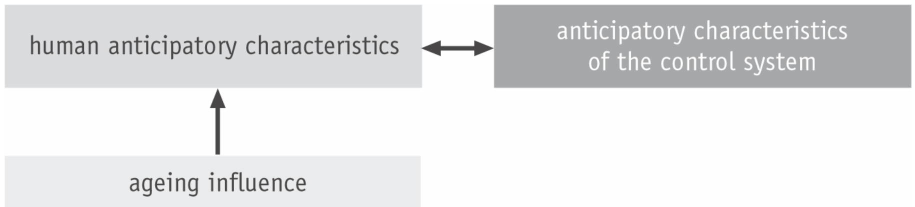
VI.1. Influences on human performance

Human performance is subject to many influencing factors: health, psychological state, environment, interaction elements (other people, interfaces of all kind, etc.), weather, time, season, ageing, and many others. No list can be as detailed as to capture all the aspects involved. Human performance is affected by awareness of being observed, whether the observation is obtrusive or non-obtrusive. Over the time of interaction with a machine, human performance changes. The interesting thing is that machines are conceived as ageless—they should maintain their performance—while ageing of the human is almost never accounted o in the design and manufacture of machines, although it affects the performance of control and monitoring.

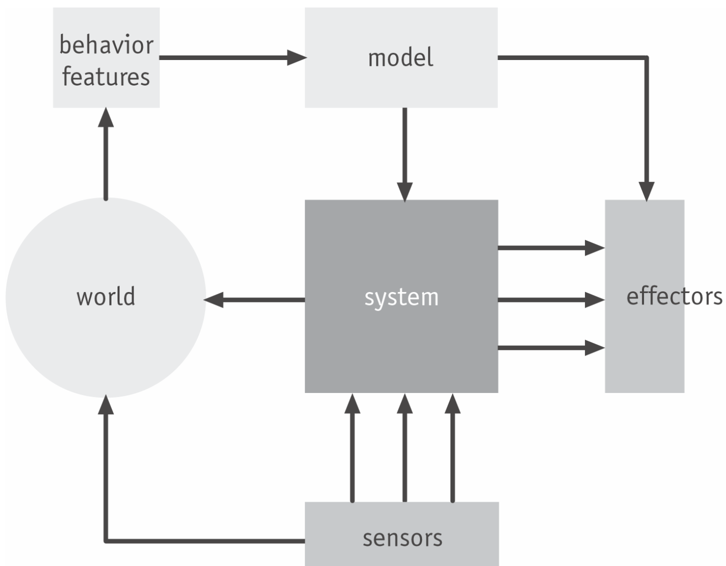
IV.2. Profiles

With all these aspects in mind, the project speaks for the *digital portrait/profile* of the user. The way to generate such a profile—probably through neural network digital methods—is to accumulate human performance data and subject it to data-mining procedures. Depending upon the nature of human performance—different in driving a car from piloting an airplane or using a production system—a profile will capture behavior features. Let's take as an example patterns of braking at a red light.

IV.2.1. These patterns depend on the time (day, night, twilight), traffic conditions, weather, parallel activities (talking to a passenger, listening to music or a report, consulting a navigation system for directions, etc.). Behavior features are indexed to such parameters (sensors report all the aspects mentioned) and to time. What results is a new situation:



As these are checked against each other, a new architecture becomes possible:



In this new architecture, the patterns of human control constitute a new module. These patterns continue to be influenced by the dynamic properties of the context in which the action subjected to monitoring and control takes place.

IV.3. Architecture of a real-time anticipatory control system..

Severe restrictions corresponding to the fact that a certain sub-domain of the machine subject to monitoring and control is time-sensitive speaks in favor of the need to address the characteristics of real-time systems. Let me detail some of these characteristics as they apply to the research.

IV.3.1. Characteristics of real-time processes

IV.3.1.1. Real-time processes are non-deterministic. This means that the next state of W, i.e., context of action, cannot be determined by the current state and the selected operation to be carried out (driving up a hill, acceleration requested, but the bridge over which the drive must go collapsed for some reason). As a consequence, in the computation of module W in the anticipatory architecture, we would need to integrate a possibilistic representation: all that can imaginably take place in the context. This representation is open-ended; more possibilities might arise. Therefore, such representations are subject to continuous refreshing.

IV.3.1. 2. *Real time* means to account for the fact that while a system is processing, the context changes. This characteristic of dynamic changes parallel to the digital process has the practical consequence of requiring that distinctions be made between

- the appropriateness of computation: corresponds or not—in clear-cut terms or in fuzzy terms—to the control function. In the example already given: Does combustion increase as required by the task, such as climbing a hill?
- the timing for action. If the task has a deadline (e.g., increase performance before the engine chokes), appropriateness of computation and deadline need to be coupled.

IV.4. Real time and anticipatory control
As a real-time system, anticipatory control is especially focused on the time intervals critical for a certain operation. Collision avoidance is a very good example: One cannot waste time on system locations while an accident might happen.
Within the anticipatory control system, we further distinguish
IV. 4.1. periodic behaviors (corresponding to stop-and-go situations). Periodicity determines actions through effectors, and thus we have an activation frequency that is part of the “wired-in” intelligence of the controlled system.
IV.4.2. aperiodic temporal expectations. Within this category we deal with non-deterministic events affecting the controlled entity. Internal and external sporadic events (driver’s loss of attention, a bridge collapses) cannot be predicted, or necessarily anticipated. The best we can do is to use a possibility schedule of extreme events. This will allow us to avoid dealing with such events in detail—a computationally impossible task—but rather get a general image of extreme occurrences and associate it to a frequency distribution.

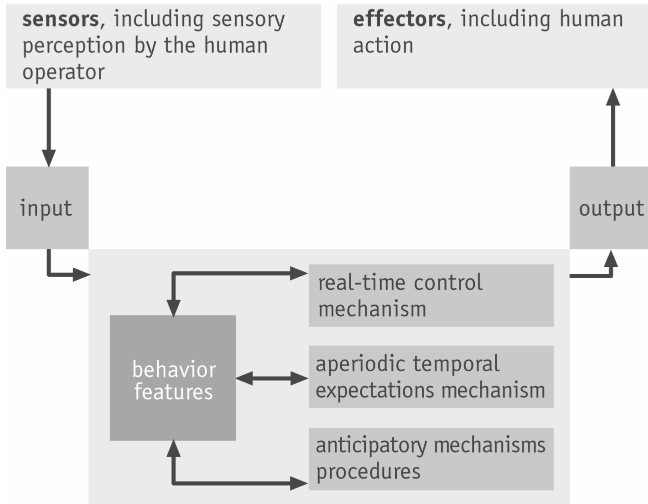
IV.5. Execution timing
We face a situation in which we can have

- execution after the deadline = low value, but still acceptable
- execution after the deadline = no value
- execution after the deadline = unacceptable (grave consequences).

The effort has to go into the direction of effecting change in the machine to be controlled (i.e., in the design and production of the car, airplane, train, boat, etc.) in order to allow for soft real-time anticipatory control.
In a soft real-time system, execution after the deadline is no longer a 0 or 1 situation (has no value/has value), but rather the value of the delayed execution of a controlled task decreases corresponding to the delay.

IV.6. Architecture of a combined and anticipatory system
This system should integrate the digital control bus and the human data bus (as expressed through the map of behavior features):

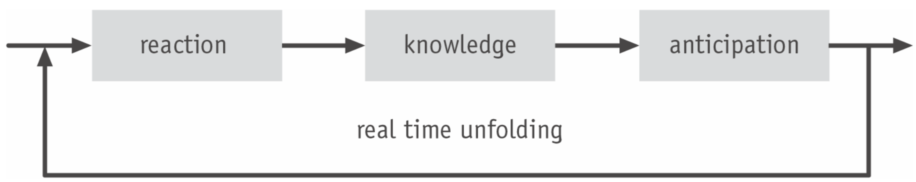
VI.6.1. Diagram



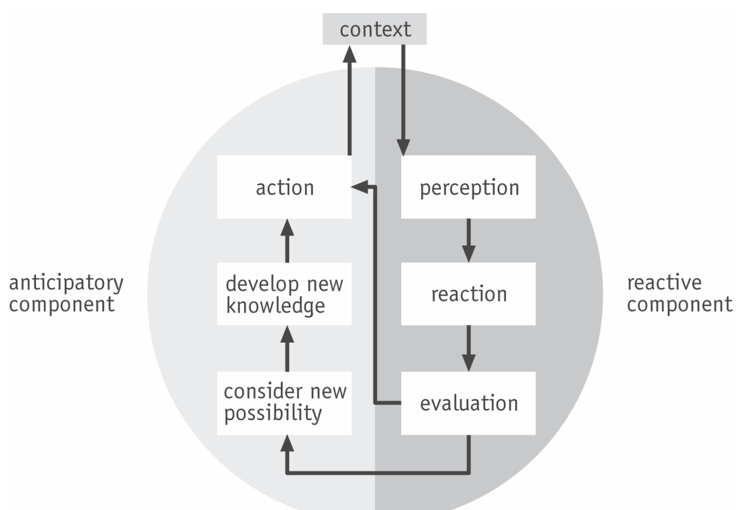
IV.6.2. Formalization

Control = Aggregate(Internal proactive agency, Selection mechanisms, Experience)

IV.6.3. What we have here, after all, is the following cybernetic control dynamics:



IV.6.4. In a more detailed manner, this appears to us as a phase sequence:



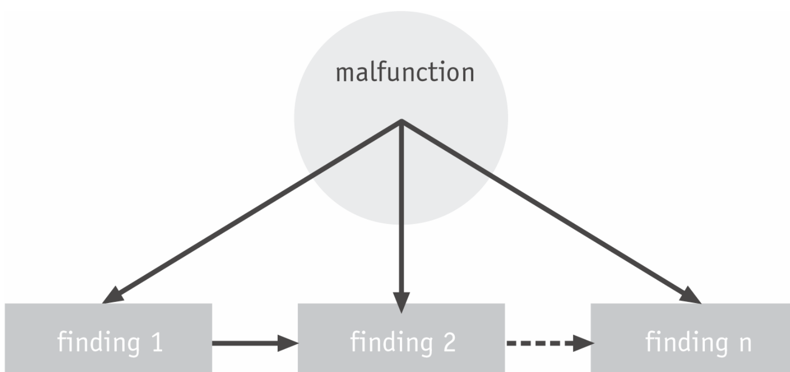
IV.6.5. The algorithm corresponding to this phase sequence can be formulated as follows:

Read incoming data values (perceptions) from the context (Read function), add values to the knowledge base maintaining their time identification (when), select appropriate action (reaction or anticipation, i.e., pre-computed prediction of future state). If not enough time is available for the computation, trigger reaction.

perception	←	context **t**
knowledge	←	knowledge **U** perception (t)
(knowledge, reaction)	←	selection_R (knowledge, possible reaction)
(knowledge, anticipatory action)	←	selection_A (knowledge, possible knowledge, reaction)
if (anticipatory action)	=	not completed
		then carry out (reaction)
		else carry out (anticipatory control)

4.7. Implementation of the anticipatory control system

The actual control will be performed over simulated processes. It is too early to select which such processes are more adequate for evaluating performance. In fact, we shall allow for the interaction between a digital data driven anticipatory mechanism and a control profile of the human operator.



The simple network structure or diagnosing a system is sufficient for pointing out the complexities of the implementation, but not the specific ways in which one or the other mechanism needs to be designed or an effective computational implementation.

V. Computing with perceptions

In his Foreword to the book, *Anticipation—The End Is Where We Start From,* Lotfi A. Zadeh [2003] made the following remark:

> Returning to the point I made earlier, my suggested modification of Professor Nadin's definition of Anticipation leads to the concept of what may be called perception-based anticipation. The marriage of anticipation and perception has important implications. First, it highlights that all living organisms, including humans, employ perception-based anticipative control to guide decision-making on goal-oriented stage decision processes. More specifically, if at a stage of a decision process I have n alternatives, $a_1, \ldots, a_n$, to choose from, then using a perception-based model of the underlying system, I form a

> perception of the next state and next output, and choose that a_i that brings me closer to the goal. As a simple example, this is what we do when we drive a car or balance a pile.
>
> More generally, perception-based anticipation is what makes it possible for humans to perform a wide variety of physical and mental tasks without any measurements and any computations. It is this remarkable capability that machines do not have.
>
> In my recent writings, I mentioned a theory, referred to as the computational theory of perceptions (CTP). In this theory, perceptions are dealt with through their descriptions in a natural language, e.g., traffic is heavy, Robert is very honest, speed is high, etc. The use of CTP opens the door to adding to machines the capability to operate on perception-based information expressed in a natural language. In particular, it makes it possible to train a neural network to produce perceptions in response to measurements. Such networks may be said to be neuroperceptive. Neuroperceptive networks may find important applications in automation of processes in which the output is a human assessment of, say, food or, more generally, of sensory perceptions [p. 3].

This is a promising avenue. If nothing else, this might become the continuation of the research proposal being submitted here. This will imply that the goals spelled out so far have been adequately reached, since they become the premise for perception-based computational implementation.

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