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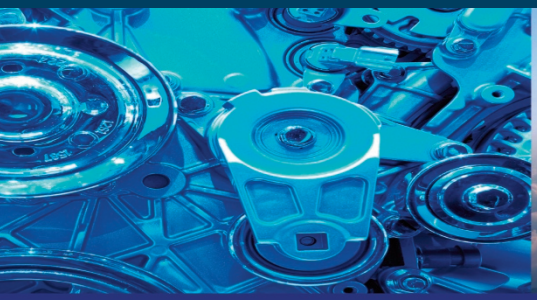

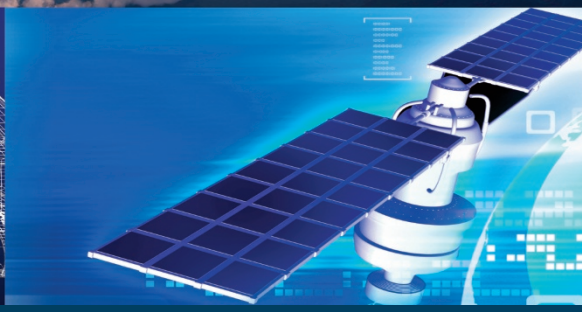

Volume 1

New Autonomous Systems

Alain Cardon and Mhamed Itmi

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Reliability of Multiphysical Systems Set

coordinated by
Abdelkhalak El Hami

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Introduction

In this book, we present the results of our research on the modeling and design of a software system allowing for systems with a very strong sense of autonomy with intentionality. We are operating in the context of systems built with a complex substratum, which have multiple electronic components deploying a variety of specific features. The scale of the development of these electronic systems is very important in the current technological climate, allowing the construction and use of technological components in all areas. These systems, however, still have an autonomy that is limited to the use of their functional capabilities, as is the case of automated robotic systems used in various industrial, economic and cultural fields. They require human operators to control them, as is the case for drones. The main problem involves providing these types of systems with a computing level which allows for an intentional autonomy that will drive their behaviors.

We present a complete model that gives these systems a very strong behavioral autonomy, providing them with the ability to make behavioral decisions based on desires, to have their own intentions and even to be aware of their autonomy. We will, therefore, be presenting how to give these systems the ability to intentionally generate artificial representations of things that they perceive and design, so that they behave in the way they want, of course within the limits of a common sociality. The idea is, indeed, to develop a proto-self.

We believe that a truly autonomous system, which has a substrate composed of many distributed mechanical and electronic components, can be unified by the development of a meta-software layer that would consider this substrate to be its corporeity. With this understanding of corporeity, the

system can generate its own internal representations of its situation: representations of its condition, its posture, allowing it to develop its actions intentionally. This meta-software layer must enable total self-regulation of the substrate of the system by itself, without any external control, and it would need to be reliable. It must continuously generate what we call representations, which are the complex generated constructs composed of a number of software agents activating and aggregating to create shapes and images expressing all the semantic aspects. These representations should indicate what the system apprehends in its environment, based on the knowledge it has acquired but also based on its tendencies and its desires, feeling these representations to deepen them. This software layer will allow the system to continuously manage its own action plans, evaluate them and memorize them in order to improve and evolve. Therefore, in this work, we describe a new model of the autonomy of artificial systems, an autonomy strongly inspired by higher living organisms.

We present the computable concepts for the perception of object situated in a system's environment, the notions of representation for something and the system's concerns that will lead it to be interested in one thing rather than another. For this, we will establish a specific definition of the computing architecture of the layer generating the representations, with all the necessary elements for the system to develop tendencies, desires and needs. For this, we will develop a new concept for control in massive multi-agent systems to meet, in real-time, the aggregations of agents with multiple semantic indications.

We also show that such systems inherently communicate with each other, such that they have the tendency to unite in order to form a very large meta-system. As these models are perfectly implementable today, it will be up to the scientific community to decide whether or not to create them and whether or not to put them at the disposal of the people for their use. We hope such developments will be applied in very ethical fields.

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1

Systems and their Design

1.1. Modeling systems

A system is designed to provide one or more services. It is made up of hardware, software and human resources, with the aim to satisfy a precise, well-defined need. Such systems abound in the history of science. Thanks to accumulating experience, technological progress and ever improving modeling approaches, methods to develop these are constantly gaining efficiency. The description of a system potentially involves various notions about its components, their aggregation and their interactions with each other and with the system's environment.

A system usually consists of a set of interdependent entities whose functions are fully specified. The system is completely characterized according to an equational or functional approach, in an iterative top-down or bottom-up process. The process is top-down in an analytical approach whereby each part can be broken down into smaller subparts that are complete sub-systems themselves. Conversely, when the approach consists of building a system up from the basis of simpler sub-systems, the iterative process is called bottom-up. The system's realization and potential evolution are predetermined in a strict, narrow field, and its functionalities can pertain to various applicative areas such as electricity, electronics, computer science, mechanics, etc.

Because of the advances being made in system design as well as in information and communication technologies, there is a tendency to design

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ever larger systems that involve an increasing number of strongly connected elements and which handle large volumes of data.

Systems can be categorized according to various typologies. Here, we will only focus on two classes: conventional systems and complex systems.

1.1.1. *Conventional systems*

Systems said to be individual or conventional have their inputs and outputs fully specified, in the sense that everything is already designed for them in the early stages of their conception. The vast majority of the systems we interact with belong to this class. Management applications, scientific computation programs and musical creation aids are all examples of conventional systems. The constitutive elements of such systems are defined and organized precisely to accomplish the tasks for which the system was formatted. They process inputs and produce actions or results that are the essential goals of the system, i.e. its "raison d'être". Even if it continues to evolve while it is operational, as soon as it starts to depend on a project manager the system belongs to the class of conventional systems, for whom everything is delimited by a tight framework. An automatic teller machine (ATM) is a good example of such a system. Every single use-case must have been clearly defined, modeled and tested so that the machine is able to perform its duties reliably and respond accurately to its users (the customers and the bank). Operating in a degraded mode or in the event of unforeseen circumstances must have also been considered.

Conventional systems benefit from the development of computer networks, which expand their access to resources and their ability to interact. They also tend to become more complex, but they remain essentially conventional systems. Let us consider the example of service-oriented architectures (SOA) with, for instance, the recent development of cloud computing services. The great variety of services offered entails an intricate organization of many different subsystems within one global cloud. The architecture nevertheless remains a conventional system as long as the services offered can be deduced from the sum of the services provided by its subsystems. Integrating new systems in order to add new services will create a larger system that remains conventional because of its functional description. In such systems, the management of malfunctions is usually also built in.

1.1.2. *Complex systems*

Among the many types of systems that are detailed in the literature, complex systems are particularly often focused upon because of their unpredictable behavior. Complex systems usually apply to subjects in which a multidisciplinary approach is an essential part of any understanding: economy, neuroscience, insect sociology, etc.

Authors globally agree to define a complex system as a system composed of a large number of interacting entities and whose global behavior cannot be inferred from the behaviors of its parts. Hence, the concept of emergence: a complex system has an emergent behavior, which cannot be inferred from any of its constitutive systems. Size is not what qualifies a system as complex: if its parts have been designed and arranged so that they interact in a known or predictable way, then it is not a complex system. However, a non-complex system becomes complex as soon as it integrates a human being as one of its constituents.

Many behavioral features of complex systems are subject to intense research and scrutiny: self-organization, emergence, non-determinism, etc. To study complex systems, researchers usually resort to simulations, which enable them to grasp an idea, if incomplete, of the behavior of a system. In fact, complex systems exhibit some behavioral autonomy, a notion that will be detailed further on, when we relate it to the concept of proactivity.

Any information system that includes functional elements while taking human decisions and actions into account as well as handling multiple perspectives is a complex system in which the components are set in various levels of a multi-scale organization.

1.1.3. *System of systems*

The concept of system of systems (SoS) [JAM 08] was introduced into the research community without being characterized by a clear, stable definition. Several approaches to refine the concept can be found in the literature. It primarily implies that several systems operate together [ZEI 13]. Architectures that ultimately fall back in the conventional system class, where a centralized mechanism fully regulates the behavior, like in families of systems, are not considered to be SoS. Examples of SoS can be found in super-systems based on independent complex components that cooperate

towards a common goal, or in large scale systems of distributed, competing systems.

The most common type of SoS [MAI 99] is that which is made of a number of systems that are all precisely specified and regulated so as to provide their own individual services but that do not necessarily report to the global system. To qualify as an SoS, the global system must also exhibit an emergent behavior, taking advantage of the activities of its subsystems to create its own. The number of subsystems can not only be large, but it can also change, as subsystems are able to quit or join the global system at any moment. This description highlights the absence of any predefined goal and underlines the essentially different mode of regulation of such an SoS. In other words, the general goal of an SoS need not be defined *a priori*.

The SoS can evolve constantly by integrating new systems, whether it be for financial reasons or because of technological breakthroughs. An SoS can thus gain or lose parts "live" [ABB 06]. This shows that an SoS cannot be engineered in a conventional manner, neither with a top-down nor with a bottom-up construction process.

This approach demands a specific architecture whose functioning implies some level of coordination/regulation as well as a "raison d'être", manifesting itself by a drive towards one or several goals. This raises several issues about autonomy, the reasons for such an organization in autonomous systems, behavioral consistency, orientation of activity and regulation of such systems.

To approximate the behavior of an SoS, one can use distributed simulations. These simulations are similar to peer-to-peer simulations except that additional tools are required to apprehend emergent behaviors (see Figure 1.1).

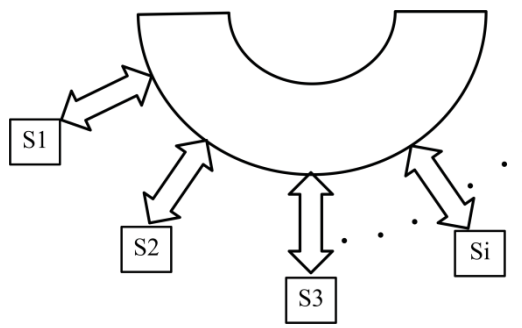

Figure 1.1. *Peer-to-peer organization around a network*

1.2. Autonomous systems

The concept of an autonomous system (within the field of robotics) implies a system able to act by itself in order to perform the necessary steps towards the achievement of predefined goals, taking into account stimuli that, in robotics for example, come from sensors. In the literature, the perspectives on the notion of autonomy are diverse because the capacity to act by oneself can have various aspects and defining features, depending on whether it is applied to, for example, an automaton, a living being, or even a system able to learn in order to improve its activity.

Implied by the notion of autonomous system, which goes beyond that of non-autonomous system, the notion of intelligent regulation goes beyond the notion of regulation. Intelligent regulation calls upon algorithmic notions as well as upon linguistics and mathematics applied to systems and processes [SAR 85]. The regulation of hierarchical systems is often described by three level models that are widely documented in the literature. The following briefly reminds the reader of the basics of this modeling approach, which can be studied in more detail in the original paper by Saridis [SAR 85]. The three levels are:

– the organizational level;

– the coordination level;

– the executive level.

The first level seeks to mimic human functions, with a tendency towards analytical approaches. The following remarks can be formulated about this approach:

– the proposed model is hierarchical (top-down) and therefore describes a machine submitted to the diktat of the organizational level (the question remains of how information is communicated upwards);

– the approach relies heavily on computation and ignores any work on knowledge representation. Therefore, processing is done in a “closed world”, which seems prone to prevent any adaptation to multidisciplinary;

– the detailed definitions of each of these levels worsen this separation: for example, the two first levels do not even take into account notions such as organization and emergence;

– integrating two systems seems impossible in Saridis’s approach. Since there is absolutely no notion of proactivity in that approach, integrating a

new proactive system is not plausible. Working on an *a priori* knowledge means that regulation is determined in advance, whereas a proactive element can't be strictly regulated;

– that the notion of perspective, or point of view, is lacking is another significant point, as it is essential to our approach. In fact, one of our fundamental assumptions is that knowledge depends on perspective, which makes it relative. In our approach, knowledge is, therefore, subjective and we do not assume any absolute truth.

In this work, we propose a biology-inspired model of autonomous systems. It differs from the model described above. Our approach will show that we do not address the same issues as these addressed by strictly analytical approaches.

In order for the system to behave like an autonomous organism, its architecture must be made of elements that are considered as artificial organs. More importantly, the most elementary levels of the system must be made of informational components that also have some level, even if minimal, of autonomy, that are sensitive to their environment and that alter themselves merely by activating themselves and operating.

1.3. Agents and multi-agent systems

The concept of agents is used in various areas. Definitions differ according to the area to which the notion of an agent is applied. In economy, for instance, agents are defined as selfish human entities, which is not pertinent for the computer science field. In the specific field this work focuses on, an agent is defined as [NEW 82]:

> *An active, autonomous entity who is able to accomplish specific tasks. This definition comes from A. Newell's rational agent, in which the knowledge level is set above the symbolic level. The knowledge represented by rational agents is not only made of what it knows, but also of its goals as well as its means of action and communication*.

More precisely, an agent is:

– an intelligent entity that acts rationally and intentionally towards a goal, according to the current state of its knowledge;

– a high-level entity, although slave to the global system, which acts continuously and autonomously in an environment where processes take place and where other agents exist.

Furthermore, in order to specify the bounds of the concept, M. Woolridge and N.R. Jennings introduced the strong and weak notions of agent [WOO 94].

1.3.1. *The weak notion of agent*

An agent pertaining to the weak notion of agent must exhibit the following features:

– it must be able to act without any intervention from any third party (human or agent) and it must be able to regulate its own actions as well as its internal state, using predefined rules;

– it must be endowed with some sociality, in other words, it must be able to interact with other (software or human) agents when the situation demands it, in order to accomplish its tasks or help other agents accomplish theirs;

– it must be proactive, in other words, it must exhibit an opportunistic behavior and an ability to make its own decisions.

1.3.2. *The strong notion of agent*

The two authors define agents pertaining to the strong notion as having, in addition to the abilities of weak agents, the following features:

– beliefs: what the agent knows and interprets of its environment;

– desires: the goals of the agent, defined according to its motives;

– intentions: in order to realize its desires, the agent performs actions that manifest its intentions.

This strong notion of agent qualifies them as truly autonomous complex systems rather than as the usual software agents that constitute a system that might be, on the whole, complex. The three features are non-trivial because they are inspired from human psychology, which Artificial Intelligence (AI) specialists can hardly make models from on the basis of classical

knowledge representation formalisms. In this work, we won't be using the strong notion; we will instead focus on systems based on architectures of numerous agents in the weak sense. We assume that beliefs, desires and intentions can only exist at the global level of the whole architecture, emerging as patterns from the coordinated, organized behavior of the agents.

1.3.3. *Cognitive agents and reactive agents*

Computer science initially saw agents in two different ways. The first one, called "cognitive", considers agents as intelligent entities that are able to solve problems by themselves. Any such agent can rely on a limited knowledge base, some strategies and some goals to plan and accomplish its tasks. These entities, that we can qualify as "intelligent", will necessarily have to cooperate and communicate with each other. In order to study this collaborative feature of cognitive agents, researchers rely on sociological work to address issues related to coordination of social agents.

The second perspective on agents is called "reactive". In this perspective, the intelligent behavior of the system is considered to emerge from the interactions of the various behaviors of its agents, behaviors that are much simpler than these of cognitive agents. In this framework, agents are designed with neither complex cognitive representations nor fine-grained reasoning mechanisms. They only have mechanisms that enable them to react in various manners to the events they perceive.

Nowadays, agents are widely considered to have cognitive abilities that, albeit limited, are effective because they are specified with rules and meta-rules that are implemented in the agent's structure as early as during the design stage. The central issue is thus how to make such agents relate to each other, interact and how some agents can establish themselves as hegemonic. These issues need to be addressed in order to understand how, on the basis of the set of active agents and according to the current situation, the most appropriate and efficient behavior can emerge in the global system. This approach will therefore not focus its reflection on the notion of individual agents but rather on notions such as agent organization. Such organizations will be constituted of very large numbers of agents whose interactions will have to be used and regulated. This leads us to the notion of multi-agent

systems, well-organized sets of agents that perform various actions that, when combined, constitute the system's behavior.

Let us nevertheless give a minimal definition of agents, in the constructionist perspective of systems modeling. Agents considered as conceptual entities should have, according to J. Ferber [FER 99], the following properties:

– ability to act in a planned manner, within its environment;

– skills and services to offer;

– resources owned by itself;

– ability to perceive its environment, although in a limited manner because it can only build a partial representation of that environment;

– ability to communicate directly with other agents through links called relations of acquaintance;

– willing to act in order to reach or optimize individual goals according to a satisfaction function, or even to a survival function;

– intentional behavior towards reaching its goals, taking into account its resources and skills as well as what it perceives and communications it receives.

1.3.4. *Multi-agent systems*

A multi-agent system (MAS) is made of many agents that constitute an organization, i.e. an identified system that reorganizes itself through its actions and through the relations between its elements. It configures and reconfigures itself in order to realize its action on the environment. Systems that are developed in AI simulate, in a specific domain, some human reasoning abilities on the basis of inference-based reasoning mechanisms that operate on knowledge representation structures. On the contrary, MAS are designed and implemented as sets of agents that interact in modes involving cooperation, concurrence or negotiation and continuously reconfigure themselves in order to always set up the most efficient organization.

An MAS is thus defined by the following features:

– each of its constitutive agent has limited information and problem solving abilities. Its knowledge and understanding are partial, local with respect to the general problem that the MAS must process and solve;

– there is no global, centralized control system in the MAS. This is essential;

– the data the systems relies upon is also distributed. Some interface agents gather data and manage its distribution as well as timing issues;

– the problem-solving computation that the MAS must perform each time it is solicited, its actual functioning, emerges from the asynchronous coordination of its constitutive agents. This emergence selects a limited number of agents who are in charge of realizing the problem's action/solution.

The MAS can also be seen as a set of agents that are situated in an environment made of other agents and objects, which are different from agents. Agents use the objects of the environment. These objects, in a strictly functional, computer science sense, are purely reactive entities that provide information and produce functional actions. Agents can interpret both the information that the objects' methods provide and the behavior of other agents, with the necessarily incurred delays. In other words, agents use objects and communicate with other agents in order to reach their goals. This model enables us to discriminate the information to be gathered accurately, which will be produced by objects systematically (this defines the role of objects) from its analyses and multi-level conceptual interpretations produced by the organization of agents (this defines the role of the organization of agents).

1.3.5. *Reactive agent-based MAS*

The agents that constitute these systems are considered to be merely reactive. A range of reflex methods are programmed so that the agents can react to any event that might occur. Actions are broken down into elementary behavioral actions that are distributed among agents. The efficient synchronization of the distributed actions then becomes the issue to address. Each agent is in charge of a so-called stimulus–action link that it must manage with accurate timing, taking the state of the environment into