A General Methodology for Designing Self-Organizing Systems

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Our technologies complexify our environments. Thus, new technologies need to deal with more and more complexity. Several efforts have been made to deal with this complexity using the concept of self-organization. However, in order to promote its use and understanding, we must first have a pragmatic understanding of complexity and self-organization. This paper presents a conceptual framework for speaking about self-organizing systems. The aim is to provide a methodology useful for designing and controlling systems developed to solve complex problems. First, practical notions of complexity and self-organization are given. Then, starting from the agent metaphor, a conceptual framework is presented. This provides formal ways of speaking about “satisfaction” of elements and systems. The main premise of the methodology claims that reducing the “friction” or “interference” of interactions between elements of a system will result in a higher “satisfaction” of the system, i.e. better performance. The methodology discusses different ways in which this can be achieved. A case study on self-organizing traffic lights illustrates the ideas presented in the paper.

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1. INTRODUCTION

Over the last half a century, much research in different areas has employed self-organizing systems to solve complex problems, e.g. [Ashby 1956; Beer 1966; Bonabeau et al. 1999; Di Marzo Serugendo et al. 2004; Zambonelli and Rana 2005]. Recently, particular methodologies using the concepts of self-organization have been proposed in different areas, such as software engineering [Wooldridge et al. 2000; Zambonelli et al. 2003], electrical engineering [Ramamoorthy et al. 1993], and collaborative support [Jones et al. 1994]. However, there is as yet no general framework for constructing self-organizing systems. Different vocabularies are used in different areas, and with different goals. In this paper, I present an attempt to develop a general methodology that will be useful for designing and controlling complex systems [Bar-Yam 1997]. The proposed methodology, as with any methodology, does not provide ready-made solutions to problems. Rather, it provides a conceptual framework, a language, to assist the solution of problems. Also, many current problem solutions can be described as proposed. I am not suggesting new solutions, but an alternative way of thinking about them.

As an example, many standardization efforts have been advanced in recent years.
such as ontologies required for the Semantic Web [Berners-Lee et al. 2001], or FIPA standards. I am not insinuating that standards are not necessary. Without them engineering would be chaos. But as they are now, they cannot predict future requirements. They are developed with a static frame of mind. They are not adaptive. What this work suggests is a way of introducing the expectation of change into the development process to be able to cope with the unexpected beforehand, in problem domains where this is desired.

The paper is organized as follows: in the next section, notions of complexity and self-organization are discussed. In Section 3, original concepts are presented. These will be used in the Methodology, exposed in Section 4. In Section 5, a case study concerning self-organizing traffic lights is used to illustrate the steps of the Methodology. Discussion and conclusions follow in Sections 6 and 7.

2. COMPLEXITY AND SELF-ORGANIZATION

There is no general definition of complexity, since the concept achieves different meanings in different contexts [Edmonds 1999]. Still, we can say that a system is complex if it consists of several interacting elements [Simon 1996], so that the behavior of the system will be difficult to deduce from the behavior of the parts. This occurs when there are many parts, and/or when there are many interactions between the parts. Typical examples of complex systems are a living cell, a society, an economy, an ecosystem, the Internet, the weather, a brain, and a city. These all consist of numerous elements whose interactions produce a global behavior that cannot be reduced to the behavior of their separate components [Gershenson and Heylighen 2005]. For example, a cell is considered a living system, but the elements that conform it are not alive. The properties of life arise from the complex dynamical interactions of the components. The properties of a system that are not present at the lower level (such as life), but are a product of the interactions of elements, are sometimes called emergent [Anderson 1972]. Another example can be seen with gold: it has properties, such as temperature, malleability, conductivity, and color, that emerge from the interactions of the gold atoms, since atoms do not have these properties.

Even when there is no general definition or measure of complexity, a relative notion of complexity can be useful:

**Notion 2.1.** The complexity of a system scales with the number of its elements, the number of interactions between them, the complexities of the elements, and the complexities of the interactions [Gershenson 2002]:

\[
C_{sys} \sim \#E \#I \sum_{j=0}^{#E} C_{e_j} \sum_{k=0}^{#I} C_{i_k}
\]

The complexity on an interaction \(C_i\) can be measured as the number of different possible interactions two elements can have.\(^1\)

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\(^1\)This can be confirmed mathematically in certain systems. As a general example, random Boolean networks [Kauffman 1969; 1993; Gershenson 2004b] show clearly that the complexity of the network increases with the number of elements and the number of interactions.

\(^2\)Certainly, the number of possible interactions for certain elements is impossible to enumerate or
The problem of a strict definition of complexity lies in the fact that there is no way of drawing a line between simple and complex systems independently of a context. For example, the dynamics of a system can be simple (ordered), complex, or chaotic, having a complex structure. Cellular automata and random Boolean networks are a clear example of this, where moreover, the interactions of their components are quite simple. On the other hand, a structurally simple system can have complex and chaotic dynamics. For this case, the damped pendulum is a common example. Nevertheless, for practical purposes, the above notion will suffice, since it allows the comparison of the complexity of one system with another under a common frame of reference. Notice that the notion is recursive, so a basic level needs to be set contextually for comparing two systems.

The term self-organization has been used in different areas with different meanings, as is cybernetics [von Foerster 1960; Ashby 1962], thermodynamics [Nicolis and Prigogine 1977], biology [Camazine et al. 2003], mathematics [Lendaris 1964], computing [Heylighen and Gershenson 2003], information theory [Shalizi 2001], synergetics [Haken 1981], and others [Skår and Coveney 2003] (for a general overview, see [Heylighen 2003b]). However, the use of the term is subtle, since any dynamical system can be said to be self-organizing or not, depending partly on the observer [Gershenson and Heylighen 2003; Ashby 1962]: If we decide to call a “preferred” state or set of states (i.e. attractor) of a system “organized”, then the dynamics will lead to a self-organization of the system.

It is not necessary to enter into a philosophical debate on the theoretical aspects of self-organization to work with it, so a practical notion will suffice:

**Notion 2.2.** A system described as self-organizing is one in which elements interact in order to achieve dynamically a global function or behavior.

This function or behavior is not imposed by one single or a few elements, nor determined hierarchically. It is achieved autonomously as the elements interact with one another. These interactions produce feedbacks that regulate the system. All the previously mentioned examples of complex systems fulfill the definition of self-organization. More precisely, the question can be formulated as follows: when is it useful to describe a system as self-organizing? This will be when the system or environment is very dynamic and/or unpredictable. If we want the system to solve a problem, it is useful to describe a complex system as self-organizing when the “solution” is not known beforehand and/or is changing constantly. Then, the solution is dynamically strived for by the elements of the system. In this way, systems can adapt quickly to unforeseen changes as elements interact locally. In theory, a centralized approach could also solve the problem, but in practice such an approach would require too much time to compute the solution and would not be able to keep the pace with the changes in the system and its environment.

In engineering, a self-organizing system would be one in which elements are designed in order to solve dynamically a problem or perform a function at the system level. Thus, the elements need to divide, but also integrate, the problem. For example, the parts of a car are designed to perform a function at the system level: to drive. However, the parts of a (normal) car do not change their behavior in time,
so it might be redundant to call a car self-organizing. On the other hand, a swarm of robots [Dorigo et al. 2004] will be conveniently described as self-organizing, since each element of the swarm can change its behavior depending on the current situation. It should be noted that all engineered self-organizing systems are to a certain degree autonomous, since part of their actual behavior will not be determined by a designer.

In order to understand self-organizing systems, two or more levels of abstraction [Gershenson 2002] should be considered: elements (lower level) organize in a system (higher level), which in turn organize with other systems to form a larger system (even higher level). The understanding of the system’s behavior will come from the relations observed between the descriptions at different levels. Note that the levels, and therefore also the terminology, can change according to the interests of the observer. For example, in some circumstances, it might be useful to refer to cells as elements (e.g. bacterial colonies); in others, as systems (e.g. genetic regulation); and in others still, as systems coordinating with other systems (e.g. morphogenesis).

A system can cope with an unpredictable environment autonomously using different but closely related approaches:

— **Adaptation** (learning, evolution) [Holland 1995]. The system changes its behavior to cope with the change.

— **Anticipation** (cognition) [Rosen 1985]. The system predicts a change to cope with, and adjusts its behavior accordingly. This is a special case of adaptation, where the system does not require to experience a situation before responding to it.

— **Robustness** [von Neumann 1956; Jen 2005]. A system is robust if it continues to function in the face of perturbations [Wagner 2005]. This can be achieved with modularity [Simon 1996; Watson 2002], degeneracy [Fernández and Solé 2004], distributed robustness [Wagner 2004], or redundancy [Gershenson et al. 2006].

Successful self-organizing systems will use combinations of the these approaches to maintain their integrity in a changing and unexpected environment. Adaptation will enable the system to modify itself to “fit” better within the environment. Robustness will allow the system to withstand changes without losing its function or purpose, and thus allowing it to adapt. Anticipation will prepare the system for changes before these occur, adapting the system without it being perturbed. We can see that all of them should be taken into account while engineering self-organizing systems.

In the following section, further concepts will be introduced that will be necessary to apply the methodology.

3. **THE CONCEPTUAL FRAMEWORK**

Elements of a complex system interact with each other. The actions of one element therefore affect other elements, directly or indirectly. For example, an animal can kill another animal directly, or indirectly cause its starvation by consuming its resources. These interactions can have negative, neutral, or positive effects on the system [Heylighen and Campbell 1995].

Now, intuitively thinking, it may be that the “smoothening” of local interactions,
i.e. the minimization of “interferences” or “friction” will lead to global improvement. But is this always the case? To answer this question, the terminology of multi-agent systems [Maes 1994; Wooldridge and Jennings 1995; Wooldridge 2002; Schweitzer 2003] can be used. We can say that:

**Notion 3.1.** An agent is a description of an entity that acts on its environment.

Examples of this can be a trader acting on a market, a school of fish acting on a coral reef, or a computer acting on a network. Thus, every element, and every system, can be seen as agents with goals and behaviors thriving to reach those goals. The behavior of agents can affect (positively, negatively, or neutrally) the fulfillment of the goals of other agents, thereby establishing a relation. The satisfaction or fulfillment of the goals of an agent can be represented using a variable $\sigma \in [0, 1]$. Relating this to the higher level, the satisfaction of a system $\sigma_{sys}$ can be recursively represented as a function $f : \mathbb{R} \to [0, 1]$ of the satisfaction of the $n$ elements conforming it:

$$\sigma_{sys} = f(\sigma_1, \sigma_2, ..., \sigma_n, w_0, w_1, w_2, ..., w_n)$$

where $w_0$ is a bias and the other weights determine the importance given to each $\sigma_i$. If the system is homogeneous, then $f$ will be the weighted sum of $\sigma_i$, $w_i = \frac{1}{n} \forall i \neq 0, w_0 = 0$. Note that this would be very similar to the activation function used in many artificial neural networks [Rojas 1996]. For heterogeneous systems, $f$ may be a nonlinear function. Nevertheless, the weights $w_i$’s are determined tautologically by the importance of the $\sigma$ of each element to the satisfaction of the system. Thus, it is a useful tautology to say that maximizing individual $\sigma$’s, adjusting individual behaviors (and thus relations), will maximize $\sigma_{sys}$. If several elements decrease $\sigma_{sys}$ as they increase their $\sigma$, we would not consider them as part of the system. It is important to note that this is independent of the potential nonlinearity of $f$. An example can be seen with the immune system. It categorizes molecules and micro-organisms as akin or alien [Vaz and Varela 1978]. If they are considered as alien, they are attacked. Auto-immune diseases arise when this categorization is erroneous, and the immune system attacks vital elements of the organism. On the other hand, if pathogens are considered as part of the body, they are not attacked. Another example is provided by cancer. Carcinogenic cells can be seen as “rebel”, and no longer part of the body, since their goals differ from the goal of the organism. Healthy cells are described easily as part of an organism. But when they turn carcinogenic, they can better be described as parasitic. The tautology is also useful because it gives a general mathematical representation for system satisfaction, which is independent of a particular system.

A reductionist approach would assume that maximizing the satisfaction of the elements of a system would also maximize the satisfaction of the system. However, this is not always the case, since some elements can “take advantage” of other elements. Thus, we need to concentrate also on the interactions of the elements.

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3In some cases, $\sigma$ could be seen as a “fitness” [Heylighen and Campbell 1995]. However, in most genetic algorithms [Mitchell 1996] a fitness function is imposed from the outside, whereas $\sigma$ is a property of the agents, that can change with time.
If the model of a system considers more than two levels, then the \( \sigma \) of higher levels will be recursively determined by the \( \sigma \)'s of lower levels. However, the \( f \)'s most probably will be very different on each level.

Certainly, an important question remains: how do we determine the function \( f \) and the weights \( w_i \)'s? To this question there is no complete answer. One option would be to approximate \( f \) numerically [De Wolf et al. 2005]. An explicit \( f \) may be difficult to find, but an approximation can be very useful. Another method consists of lesioning the system\(^4\): removing or altering elements of the system, and observing the effect on \( \sigma_{sys} \). Through analyzing the effects of different lesions, the function \( f \) can be reconstructed and the weights \( w_i \)'s obtained. If a small change \( \Delta \sigma_i \) in any \( \sigma_i \) produces a change \( \Delta \sigma_{sys} \geq \Delta \sigma_i \), the system can be said to be fragile.

What could then be done to maximize \( \sigma_{sys} \)? How can we relate the \( \sigma_i \)'s and avoid conflicts between elements? This is not an obvious task, for it implies bounding the agents’ behaviors that reduce other \( \sigma_i \)'s, while preserving their functionality. Not only should the interference or friction between elements be minimized, but the synergy [Haken 1981] or “positive interference” should also be promoted. Dealing with complex systems, it is not feasible to tell each element what to do or how to do it, but their behaviors need to be constrained or modified so that their goals will be reached, blocking the goals of other elements as little as possible. These constraints can be called mediators [Michod 2003; Heylighen 2003a]. They can be imposed from the top down, developed from the bottom up, be part of the environment, or be embedded as an aspect [Ten Haaf et al. 2002, Ch. 3] of the system. An example can be found in city traffic: traffic lights, signals and rules mediate among drivers, trying to minimize their conflicts, which result from the competition for limited resources, i.e. space to drive through. The role of a mediator is to arbitrate among the elements of a system, to minimize interferences and frictions and maximize synergy. Therefore, the efficiency of the mediator can be measured directly using \( \sigma_{sys} \). Individually, we can measure the “friction” \( \phi_i \in [-1,1] \) that agent \( i \) causes in the rest of the system, relating the change in satisfaction \( \Delta \sigma_i \) of element \( i \) and the change in satisfaction of the system \( \Delta \sigma_{sys} \):

\[
\phi_i = \frac{-\Delta \sigma_i - \Delta \sigma_{sys} (n - 1)}{n}.
\]

Friction occurs when the increase of satisfaction of one element causes a decrease in the satisfaction of some other elements that is greater than the increase. Note that \( \phi_i = 0 \) does imply that there is no conflict, since one agent can “get” the satisfaction proportionally to the “loss” of satisfaction of (an)other agent(s). Negative friction would imply synergy, e.g. when \( \Delta \sigma_i \geq 0 \) while other elements also increase their \( \sigma \). The role of a mediator would be to maximize \( \sigma_{sys} \) by minimizing \( \phi_i \)'s. With this approach, friction can be seen as a type of interaction between elements.

Thus, the problem can be put in a different way: how can we find/develop/evolve efficient mediators for a given system? One answer to this question is the methodology proposed in this paper. The answer will not be complete, since we cannot have precise knowledge of \( f \) for large evolving complex systems. This is because the

\(^4\)This method has been used widely to detect functions in complex systems such as genetic regulatory networks and nervous systems.

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evolution of the system will change its own $f$ [Kauffman 2000], and the relationships among different $\sigma_i$’s. Therefore, predictions cannot be complete. However, the methodology proposes to follow steps to increase the understanding (and consequently the control) of the system and the relations between its elements. The goal is to identify conflicts and diminish them without creating new ones. This will increase the $\sigma_i$’s and thus $\sigma_{sys}$. The precision of $f$ is not so relevant if this is achieved.

It should be noted that the timescale chosen for measuring $\Delta \sigma_i$ is very important, since at short timescales the satisfaction can decrease, while on the long run it will increase. In other words, there can be a short term “sacrifice” to harvest a long term “reward”. If the timescale is too small, a system might get stuck in a “local optimum”, since all possible actions would decrease its satisfaction on the short term. But in some cases the long term benefit should be considered for maximization. A way of measuring the slow change of $\sigma_i$ would be with its integral over time for a certain interval $\Delta t$:

$$\int_t^{t+\Delta t} \sigma_i \, dt. \quad (4)$$

Another way of dealing with the local optima is to use neutral changes to explore alternative solutions [Kimura 1983].

Before going into further detail, it is worth noting that this is not a reductionist approach. Smoothing out local interactions will not provide straightforward clues as to what will occur at the higher level. Therefore, the system should be observed at both levels: making local and global changes, observing local and global behaviors, and analyzing how one affects the other.

Concurrently, the dependence $\epsilon \in [-1, 1]$ of an element to the system can be measured by calculating the difference of the satisfaction $\sigma_i$ when the element interacts within the system and its satisfaction $\tilde{\sigma}_i$ when the element is isolated.

$$\epsilon = \sigma_i - \tilde{\sigma}_i. \quad (5)$$

In this way, full dependence is given when the satisfaction of the element within the system $\sigma_i$ is maximal and its satisfaction $\tilde{\sigma}_i$ is minimal when the element is isolated. A negative $\epsilon$ would imply that the element would be more satisfied on its own and is actually “enslaved” by the system. Now we can use the dependences of the elements to a system to measure the integration $\tau \in [-1, 1]$ of a system, which can be seen also as a gradual measure of a meta-system transition (MST) [Turchin 1977].

$$\tau = \frac{1}{n} \sum_{i=1}^{n} \epsilon_i. \quad (6)$$

A MST is a gradual process, but it will be complete when elements are not able to reach their goals on their own, i.e. $\tau \to 0$. Examples include cells in multi-cellular organisms and mitochondria in eukaryotes.

In an evolutionary process, natural (multilevel [Michod 1997; Lenaerts 2003]) selection will tend to increase $\tau$ because this implies higher satisfaction both for...
the system and its elements (systems with a negative $\tau$ are not viable). Relations and mediators that contribute to this process will be selected, since higher $\sigma$’s imply more chances of survival and reproduction. Human designers and engineers also select relations and mediators that increase the $\sigma$’s of elements and systems. Therefore, we can see that evolution will tend, in the long run, towards synergetic relationships [Corning 2003], even if resources are scarce.

In the next section, the steps suggested for developing a self-organizing system are presented, using the concepts described in this section.

4. THE METHODOLOGY

The proposed methodology meets the requirements of a system, i.e. what the system should do, and enables the designer to produce a system that fulfills the requirements. The methodology includes the following steps: Representation, Modeling, Simulation, Application, and Evaluation, which will be exposed in the following subsections. Figure 1 presents these steps. These steps should not necessarily be followed one by one, since the stages merge with each other. There is also back-tracking, when the designer needs to return to an earlier stage for reconsideration before finishing a cycle.

This methodology should not be seen as a recipe that provides ready-made solutions, but rather as a guideline to direct the search for them. The stages proposed are not new, and similar to those proposed by iterative and incremental development methodologies. Still, it should be noted that the active feedback between stages within each iteration can help in the design of systems ready to face uncertainties in complex problem domains. The novelty of the methodology lies in the vocabulary used to describe self-organizing systems.
4.1 Representation

The goal of this step is to develop a specification (which might be tentative) of the components of the system.

The designer should always remember the distinction between model and modeled. A model is an abstraction/description of a “real” system. Still, there can be several descriptions of the same system [Gershenson 2002; Gershenson and Heylighen 2005], and we cannot say that one is better than another independently of a context.

There are many possible representations of a system. According to the constraints and requirements, which may be incomplete, the designer should choose an appropriate vocabulary (metaphors to speak about the system), abstraction levels, granularity, variables, and interactions that need to be taken into account. Certainly, these will also depend on the experience of the designer. The choice between different approaches can depend more on the expertise of the designer than on the benefits of the approaches.

Even when there is a wide diversity of possible systems, a general approach for developing a Representation can be abstracted. The designer should try to divide a system into elements by identifying semi-independent modules, with internal goals and dynamics, and with few interactions with their environment. Since interactions in a model will increase the complexity of the model, we should group “clusters” of interacting variables into elements, and then study a minimal number of interactions between elements. The first constraints that help us are space and time. It is useful to group variables that are close to each other (i.e. interacting constantly) and consider them as elements that relate to other elements in occasional interactions. Multiscale analysis [Bar-Yam 2005] is a promising method for identifying levels and variables useful in a Representation. Since the proposed methodology considers elements as agents, another useful criterion for delimiting them is the identification of goals. These will be useful in the Modeling to measure the satisfaction $\sigma$ of the elements. We can look at genes as an example: groups of nucleotides co-occur and interact with other groups and with proteins. Genes are identified by observing nucleotides that keep close together and act together to perform a function. The fulfillment of this function can be seen as a goal of the gene. Dividing the system into modules also divides the problem it needs to solve, so a complex task will be able to be processed in parallel by different modules. Certainly, the integration of the “solutions” given by each module arises as a new problem. Nevertheless, modularity in a system also increases its robustness and adaptability [Simon 1996; Watson 2002; Fernández and Solé 2004].

The representation should consider at least two levels of abstraction, but if there are many variables and interactions in the system, more levels can be contemplated. Since elements and systems can be seen as agents, we can refer to all of them as $x$-agents, where $x$ denotes the level of abstraction relative to the simplest elements. For example, a three-layered abstraction would contemplate elements (0-agents) forming systems that are elements (subsystems, 1-agents) of a greater system (metasystem, 2-agents). If we are interested in modeling a research institute, 0-agents would be researchers, 1-agents would be research groups, and the research institute would be a 2-agent. Each of these have goals and satisfactions ($\sigma^x$) that can be
described and interrelated. For engineering purposes, the satisfaction of the highest level, i.e. the satisfaction of the system that is being designed, will be determined by the tasks expected from it. If these are fulfilled, then it can be said that the system is “satisfied”. Thus, the designer should concentrate on engineering elements that will strive to reach this satisfaction.

If there are few elements or interactions in the Representation, there will be low complexity, and therefore stable dynamics. The system might be better described using traditional approaches, since the current approach might prove redundant. A large variety of elements and/or interactions might imply a high complexity. Then, the Representation should be revised before entering the Modeling stage.

4.2 Modeling

In science, models should ideally be as simple as possible, and predict as much as possible [Shalizi 2001]. These models will provide a better understanding of a phenomenon than complicated models. Therefore, a good model requires a good Representation. The “elegance” of the model will depend very much on the metaphors we use to speak about the system. If the model turns out to be cumbersome, the Representation should be revised.

The Modeling should specify a Control mechanism that will ensure that the system does what it is required to do. Since we are interested in self-organizing systems, the Control will be internal and distributed. If the problem is too complex, it can be divided into different subproblems. The Modeling should also consider different trade-offs for the system.

4.2.1 Control mechanism. The Control mechanism can be seen as a mediator [Heylighen 2003a] ensuring the proper interaction of the elements of the system, and one that should produce the desired performance. However, one cannot have a strict control over a self-organizing system. Rather, the system should be steered [Wiener 1948]. In a sense, self-organizing systems are like teenagers: they cannot be tightly controlled since they have their own goals. We can only attempt to steer their actions, trying to keep their internal variables under certain boundaries, so that the systems/teenagers do not “break” (in Ashby’s sense [Ashby 1947]).

To develop a Control, the designer should find aspect systems, subsystems, or constraints that will prevent the negative interferences between elements (friction) and promote positive interferences (synergy). In other words, the designer should search for ways of minimizing frictions φi’s that will result in maximization of the global satisfaction σsys. The performance of different mediators can be measured using equation (2).

The Control mechanism should be adaptive. Since the system is dynamic and there are several interactions within the system and with its environment, the Control mechanism should be able to cope with the changes within and outside the system, in other words, robust. An adaptive Control will be efficient in more contexts than a static one. In other words, the Control should be active in the search of solutions. A static Control will not be able to cope with the complexity of the system. There are several methods for developing an adaptive Control, e.g. [Sastry and Bodson 1994]. But these should be applied in a distributed way, in an attempt to reduce friction and promote synergy.
Different methods for reducing friction in a system can be identified. In the following cases, an agent A negatively affected by the behavior of an agent B will be considered:

— **Tolerance.** This can be seen as the acceptance of others and their goals. A can tolerate B by modifying itself to reduce the friction caused by B, and therefore increase $\sigma_A$. This can be done by moving to another location, finding more resources, or making internal changes.

— **CourtesY.** This would be the opposite case to Tolerance. B should modify its behavior not to reduce $\sigma_A$.

— **Compromise.** A combination of CourtesY and Tolerance: both agents A and B should modify their behaviors to reduce the friction. This is a good alternative when both elements cause friction to each other. This will be common when A and B are similar, as in homogeneous systems.

— **Imposition.** This could be seen as forced CourtesY. The behavior of B could be changed by force. The Control could achieve this by constraining B or imposing internal changes.

— **Eradication.** As a special case of Imposition, B can be eradicated. This certainly would decrease $\sigma_B$, but can be an alternative when either $\sigma_B$ does not contribute much to $\sigma_{sys}$, or when the friction caused by B in the rest of the system is very high.

— **Apoptosis.** B can “commit suicide”. This would be a special case of CourtesY, where B would destroy itself for the sake of the system.

The difference between Compromise/Apoptosis and Imposition/Eradication is that in the former cases, change is triggered by the agent itself, whereas in the latter the change is imposed from the “outside” by a mediator. Tolerance and Compromise could be generated by an agent or by a mediator.

Different methods for reducing friction can be used for different problems. A good Control will select those in which other $\sigma$’s are not reduced more than the gain in $\sigma$’s. The choice of the method will also depend on the importance of different elements for the system. Since more important elements contribute more to $\sigma_{sys}$, these elements can be given preference by the Control in some cases.

Different methods for increasing synergy can also be identified. These will consist of taking measures to increase $\sigma_{sys}$, even if some $\sigma$’s are reduced:

— **Cooperation.** Two or more agents adapt their behavior for the benefit of the whole. This might or might not reduce some $\sigma$’s.

— **Individualism.** An agent can choose to increase its $\sigma$ if it increases $\sigma_{sys}$. A mediator should prevent increases in $\sigma$’s if these reduce $\sigma_{sys}$, i.e. friction.

— **Altruism.** An agent can choose to sacrifice an increase of its $\sigma$ or to reduce its $\sigma$ in order to increase $\sigma_{sys}$. This would make sense only if the relative increase of $\sigma_{sys}$ is greater than the decrease of the $\sigma$ of the altruistic agent. A mediator should prevent wasted altruism.

\(^5\)Even when equation 3 relates the satisfaction of an element to the satisfaction of the system, this can also be used for the relation between satisfactions of two elements, when $\Delta \sigma_{i} = 0$ for all other elements.
Exploitation. This would be forced Altruism: an agent is driven to reduce its $\sigma$ to increase $\sigma_{sys}$.

A common way of reducing friction is to enable agents to learn via reinforcement [Kaelbling et al. 1996]. With this method, agents tend to repeat actions that bring them satisfaction and avoid the ones that reduce it. Evolutionary approaches, such as genetic algorithms [Mitchell 1996], can also reduce friction and promote synergy. However, these tend to be “blind”, in the sense that variations are made randomly, and only their effects are evaluated. With the criteria presented above, the search for solutions can be guided with a certain aim. However, if the relationship between the satisfaction of the elements and the satisfaction of the system is too obscure, “blind” methods remain a good alternative.

In general, the Control should explore different alternatives, trying to constantly increase $\sigma_{sys}$ by minimizing friction and maximizing synergy. This is a constant process, since a self-organizing system is in a dynamic environment, producing “solutions” for the current situation. Note that a mediator will not necessarily maximize the satisfaction of the agents. However, it should try to do so for the system.

4.2.2 Dividing the problem. If the system is to deal with many parameters, then it can be seen as a cognitive system [Gershenson 2004a]. It must “know” or “anticipate” what to do according to the current situation and previous history. Thus, the main problem, i.e. what the elements should do, could be divided into the problems of communication, cooperation, and coordination [Gershenson and Heylighen 2004].

For a system to self-organize, its elements need to communicate: they need to “understand” what other elements, or mediators, “want” to tell them. This is easy if the interactions are simple: sensors can give meaning to the behaviors of other elements. But as interactions turn more complex, the cognition [Gershenson 2004a] required by the elements should also be increased. New meanings can be learned [Steels 1998; de Jong 2000] to adapt to the changing conditions. These can be represented as “concepts” [Gärdenfors 2000], or encoded, e.g., in the weights of a learning neural network [Rojas 1996]. The precise implementation and philosophical interpretations are not relevant if the outcome is the desired one.

The problem of cooperation has been widely studied using game theory [Axelrod 1984]. There are several ways of promoting cooperation, especially if the system is designed. To mention mention only two of them: the use of tags [Riolo et al. 2001; Hales and Edmonds 2003] and multiple levels of selection [Michod 1997; Lenaerts 2003] have proven to yield cooperative behavior. This will certainly reduce friction and therefore increase $\sigma_{sys}$.

Elements of a system should coordinate while reducing friction, not to obstruct each other. An important aspect of coordination is the division of labour. This can promote synergy, since different elements can specialize in what they are good at and trust others to do what they are good at [Gaines 1994; Di Marzo Serugendo 2004]. This process will yield a higher $\sigma_{sys}$ compared to the case when every element is meant to perform all functions independently of how well each element performs.

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6Trust is also important for communication and cooperation.
each function. A good Control will promote division of labour by mediating a balance between specialization and integration: elements should devote more time doing what they are best at, but should still take into account the rest of the system. Another aspect of coordination is the workflow: if some tasks are prerequisites of other tasks, a mediator should synchronize the agents to minimize waiting times.

4.2.3 Trade-offs. A system needs to be able to cope with the complexity of its domain to achieve its goals. There are several trade-offs that can be identified to reach a balance and cope better with this complexity:

— **Complexity of Elements/Interactions.** The complexity of the system required to cope with the complexity of its domain can be tackled at one end of the spectrum by complex elements with few/simple interactions, and at the other by simple elements with several/complex interactions.

— **Quality/Quantity.** A system can consist at one extreme of a few complex elements, and at the other of several simple elements.

— **Economy/Redundancy.** Solving a problem with as few elements as possible is economical. But a minimal system is very fragile. Redundancy is one way of favoring the robustness of the system [von Neumann 1966; Fernández and Solé 2004; Wagner 2004; Gershenson et al. 2006]. Still, too much redundancy can also reduce the speed of adaptation and increase costs for maintaining the system.

— **Homogeneity/Heterogeneity.** A homogeneous system will be easier to understand and control. A heterogenous system will be able to cope with more complexity with less elements, and will be able to adapt more quickly to sudden changes. If there is a system of ten agents each able to solve ten tasks, a homogeneous system will be able to solve more than ten tasks robustly. A fully heterogeneous system would be able to solve more than a hundred tasks, but it would be fragile if one agent failed. Heterogeneity also brings diversity, that can accelerate the speed of exploration, adaptation, and evolution, since different solutions can be sought in parallel. The diversity is also related to the amount of variety of perturbations that the system can cope with [Ashby 1956], i.e. robustness.

— **System/Context.** The processing and storage of information can be carried out internally by the system, or the system can exploit its environment “throwing” complexity into it, i.e. allow it to store or process information [Gershenson et al. 2003].

— **Ability/Clarity.** A powerful system will solve a number of complex problems, but it will not be very useful if the functioning of the system cannot be understood. Designers should be able to understand the system in order to be able to control it [Schweitzer 2003].

— **Generality/Particularity.** An abstract Modeling will enable the designer to apply the Modeling in different contexts. However, particular details should be considered to make the implementation feasible.

There are only very relative ways of measuring the above mentioned trade-offs. However, they should be kept in mind during the development of the system.

In a particular system, the trade-offs will become clearer once the Simulation is underway. They can then be reconsidered and the Modeling updated.
4.3 Simulation

The aim here is to build computer simulation(s) that implement the model(s) developed in the Modeling stage, and test different scenarios and mediator strategies.

The Simulation development should proceed in stages: from abstract to particular. First, an abstract scenario should be used to test the main concepts developed during the Modeling. Only when these are tested and refined, should details be included in the Simulation. This is because particular details take time to develop, and there is no sense in investing before knowing whether the Modeling is on the right track. Details can also influence the result of the Simulation, so they should be put off until a time when the main mechanisms are understood.

The Simulation should compare the proposed solutions with traditional approaches. Ideally, the designer should develop more than one Control to test in the simulation. A rock-scissors-paper situation could arise, where no Control is best in all situations (also considering classic controls). The designer can then adjust or combine the Controls, and then compare again in the Simulation.

Experiments conducted with the aid of the Simulation should go from simple to extensive. Simple experiments will show proof of concepts, and their results can be used to improve the Modeling. Once this is robust, extensive studies should be made to be certain of the performance of the system under different conditions.

Based on the Simulation results and insights, the Modeling and Representation can be improved. A Simulation should be mature before taking the implementation into the real world.

4.4 Application

The role of this stage is basically to use the developed and tested model(s) in a real system. If this is a software system, the transition will not be so difficult. On the other hand, the transition to a real system can expose artifacts of a naive Simulation. A useful way to develop robust Simulations consists in adding some noise into the system [Jakobi 1997].

Good theoretical solutions can be very difficult/expensive/impossible to implement (e.g. if they involve instantaneous access to information, mind reading, tele-transportation, etc.). The feasibility of the Application should be taken into account during the whole design process. In other words, the designer should have an implementation bias in all the Methodology stages. If the proposed system turned out to be too expensive or complicated, all the designer’s efforts would be fruitless. If the system is developed for a client, there should be feedback between developers and clients during the whole process [Cotton 1996] to avoid client dissatisfaction once the system is implemented. The legacy of previous systems should also be considered for the design [Valckenaers et al. 2003]: if the current implementation is to be modified but not completely replaced, the designer is limited by the capabilities of the old system.

Constraints permitting, a pilot study should be made before engaging in a full Application, to detect incongruences and unexpected issues between the Simulation or Modeling stages and the Application. With the results of this pilot study, the Simulation, Modeling, and Representation can be fine-tuned.
4.5 Evaluation
Once the Application is underway, the performance of new system should be measured and compared with the performances of the previous system(s).

Constraints permitting, efforts should be continued to try to improve the system, since the requirements it has to meet will certainly change with time (e.g. changes of demand, capacity, etc.). The system will be more adaptive if it does not consider its solution as the best once and for all, and is able to change itself according to its performance and the changing requirements.

4.6 Notes on the methodology
—All returning arrows in the Figure 1 are given because it is not possible to predict the outcome of strategies before they have been tried out. All information and eventualities cannot be abstracted, nor emergent properties predicted before they have been observed. Emergent properties are a posteriori.

—The proposed Methodology will be useful for unpredictable problem domains, where all the possible system's situations cannot be considered beforehand. It could also be useful for creative tasks, where a self-organizing system can explore the design space in an alternative way.

—Most methodologies in the literature apply to software systems, e.g. [Jacobson et al. 1999; Jennings 2000]. This one is more general, since it is domain independent. The principles presented are such that can be applied to any domain for developing a functioning self-organizing system: Any system can be modeled as a group of agents, with satisfactions depending on their goals. The question is when is it useful to use this Methodology. Only application of the Methodology will provide an answer to this question. It should be noted that several approaches have been proposed in parallel, e.g. [Capera et al. 2003; De Wolf and Holvoet 2005], that, as the present work, and are part of the ongoing effort by the research community to understand self-organizing systems.

—The proposed Methodology is not quite a spiral model [Boehm 1988], because the last stage does not need to be reached to return to the first. This is, there is no need to deploy a working version (finish a cycle/iteration) before revisiting a previous stage, as for example in extreme programming. Rather, the Methodology is a “backtracking model”, where the designer can always return to previous stages.

—It is not necessary to understand a solution before testing it. In many cases understanding can come only after testing, i.e., the global behavior of the system is irreducible. Certainly, understanding the causes of a phenomenon will allow the modelers to have a greater control over it.

A detailed diagram of the different substeps of the Methodology can be appreciated in Figure 2.

5. CASE STUDY: SELF-ORGANIZING TRAFFIC LIGHTS
Recent work on self-organizing traffic lights [Gershenson 2005] will be used to illustrate the flow through the different steps of the Methodology. These traffic lights are called self-organizing because the global performance is given by the local rules
followed by each traffic light: they are unaware of the state of other intersections and still manage to achieve global coordination.

Traffic modeling has increased the understanding of this complex phenomenon [Prigogine and Herman 1971; Wolf et al. 1996; Schreckenberg and Wolf 1998; Helbing et al. 2000; Helbing 1997; Helbing and Huberman 1998]. Even when vehicles can follow simple rules, their local interactions generate global patterns that cannot be reduced to individual behaviors. Controlling traffic lights in a city is not an easy task: it requires the coordination of a multitude of components; the components affect one another; furthermore, these components do not operate at the same pace over time. Traffic flows and densities change constantly. Therefore, this problem is suitable to be tackled by self-organization. A centralized system could also perform

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the task, but in practice the amount of computation required to process all the data from a city is too great to be able to respond in real time. Thus, a self-organizing system seems to be a promising alternative.

Requirements. The goal is to develop a feasible and efficient traffic light control system.

Representation. The traffic light system can be modelled on two levels: the vehicle level and the city level. These are easy to identify because vehicles are objects that move through the city, establishing clear spatiotemporal distinctions. The goal of the vehicles is to flow as fast as possible, so their “satisfaction” $\sigma$ can be measured in terms of their average speed and average waiting time at a red light. Cars will have a maximum $\sigma$ if they go as fast as they are allowed, and do not stop at intersections. $\sigma$ would be zero if a car stops indefinitely. The goal of the traffic light system on the city level is to enable vehicles to flow as fast as possible, while mediating their conflicts for space and time at intersections. This would minimize fuel consumption, noise, pollution, and stress in the population. The satisfaction of the city can be measured in terms of the average speeds and average waiting times of all vehicles (i.e. average of $\sigma_i$, \forall i), and with the average percentage of stationary cars. $\sigma_{sys}$ will be maximum if all cars go as fast as possible, and are able to flow through the city without stopping. If a traffic jam occurs and all the vehicles stop, then $\sigma_{sys}$ would be minimal.

Modeling. Now the problem for the Control can be formulated: find a mechanism that will coordinate traffic lights so that these will mediate between vehicles to reduce their friction (i.e. try to prevent them from arriving at the same time at crossings). This will maximize the satisfactions of the vehicles and of the city ($\sigma_i$’s and $\sigma_{sys}$). Since all vehicles contribute equally to $\sigma_{sys}$, ideally the Control should minimize frictions via Compromise.

Simulation. A simple simulation was developed in NetLogo [Wilensky 1999], a multi-agent modeling environment. The “Gridlock” model [Wilensky and Stroup 2002] was extended to implement different traffic control strategies. It consists of an abstract traffic grid with intersections between cyclic single-lane arteries of two types: vertical or horizontal (similar to the scenarios of [Biham et al. 1992; Brockfeld et al. 2001]). Cars only flow in a straight line, either eastbound or southbound. Each crossroad has traffic lights that allow traffic flow in only one of the intersecting arteries with a green light. Yellow or red lights stop the traffic. The light sequence for a given artery is green-yellow-red-green. Cars simply try to go at a maximum speed of 1 “patch” per timestep, but stop when a car or a red or yellow light is in front of them. Time is discrete, but not space. A “patch” is a square of the environment the size of a car. The simulation can be tested at the URL http://homepages.vub.ac.be/~cgershon/sos/SOTL/SOTL.html. At first, a tentative model was implemented. The idea was unsuccessful. However, after refining the model, an efficient method was discovered, named sotl-request.

Modeling. In the sotl-request method, each traffic light keeps a count $\kappa_i$ of the number of cars times time steps (c*ts) approaching only the red light, independently of the status or speed of the cars (i.e. moving or stopped). $\kappa_i$ can be seen as the integral of waiting/approaching cars over time. When $\kappa_i$ reaches a threshold $\theta$, the opposing green light turns yellow, and the following time step it turns red with
\( \kappa_i = 0 \), while the red light which counted turns green. In this way, if there are more cars approaching or waiting before a red light, the light will turn green faster than if there are only few cars. This simple mechanism achieves self-organization as follows: if there is a single or just a few cars, these will be made to stop for a longer period before a red light. This gives time for other cars to join them. As more cars join the group, cars will be made to wait shorter periods before a red light. Once there are enough cars, the red light will turn green even before the oncoming cars reach the intersection, thereby generating “green waves”. Having “platoons” or “convoys” of cars moving together improves traffic flow, compared to a homogeneous distribution of cars, since there are large empty areas between platoons, which can be used by crossing platoons with few interferences. The SOTL-Request method has no phase or internal clock. Traffic lights change only when the above conditions are met. If no cars are approaching a red light, the complementary light can remain green.

**Representation.** It becomes clear now that it would be useful to consider traffic lights as agents as well. Their goal is to “get rid” of cars as quickly as possible. To do so, they should avoid having green lights on empty streets and red lights on streets with high traffic density. Since the satisfactions of the traffic lights and vehicles are complementary, they should interact via cooperation to achieve synergy. Also, \( \sigma_{\text{sys}} \) could be formulated in terms of the satisfactions of traffic lights, vehicles, or both.

**Modeling.** Two classic methods were implemented to compare their performance with SOTL-Request: *marching* and *optim*.

*Marching* is a very simple method. All traffic lights “march in step”: all green lights are either southbound or eastbound, synchronized in time. Intersections have a phase \( \varphi_i \), which counts time steps. \( \varphi_i \) is reset to zero when the phase reaches a period value \( p \). When \( \varphi_i = 0 \), red lights turn green, and yellow lights turn red. Green lights turn yellow one time step earlier, i.e. when \( \varphi = p - 1 \). A full cycle of an intersection consists of \( 2p \) time steps. “Marching” intersections are such that \( \varphi_i = \varphi_j, \forall i, j \).

The *optim* method is implemented trying to set phases \( \varphi_i \) of traffic lights so that, as soon as a red light turns green, a car that was made to stop would find the following traffic lights green. In other words, a fixed solution is obtained so that green waves flow to the southeast. The simulation environment has a radius of \( r \) square patches, so that these can be identified with coordinates \((x_i, y_i)\), \( x_i, y_i \in [-r, r] \). Therefore, each artery consists of \( 2r + 1 \) patches. In order to synchronize all the intersections, red lights should turn green and yellow lights should turn red when

\[
\varphi_i = \text{round}(\frac{2r + x_i - y_i}{4})
\]

and green lights should turn to yellow the previous time step. The period should be \( p = r + 3 \). The three is added as an extra margin for the reaction and acceleration times of cars (found to be best, for low densities, by trial and error).

These two methods are *non-adaptive*, in the sense that their behavior is dictated beforehand, and they do not consider the actual state of the traffic. Therefore, there cannot be cooperation between vehicles and traffic lights, since the latter...
ones have fixed behaviors. On the other hand, traffic lights under the *sotl-request* method are sensitive to the current traffic condition, and can therefore respond to the needs of the incoming vehicles.

**Simulation.** Preliminary experiments have shown that *sotl-request*, compared with the two traditional methods, achieves very good results for low traffic densities, but very poor results for high traffic densities. This is because depending on the value of $\theta$, high traffic densities can cause the traffic lights to change too fast. This obstructs traffic flow. A new model was developed, taking this factor into account.

**Modeling.** The *sotl-phase* method takes *sotl-request* and only adds the following constraint: a traffic light will not be changed if the time passed since the last light change is less than a minimum phase, i.e. $\varphi_i < \varphi_{\min}$. Once $\varphi_i \geq \varphi_{\min}$, the lights will change if/when $\kappa_i \geq \theta$. This prevents the fast changing of lights$^7$.

**Simulation.** *Sotl-phase* performed a bit less effectively than *sotl-request* for very low traffic densities, but still much better than the classic methods. However, *sotl-phase* outperformed them also for high densities. An unexpected phenomenon was observed: for certain traffic densities, *sotl-phase* achieved full synchronization, in the sense that no car stopped. Therefore, speeds were maximal and there were no waiting times nor sopped cars. Thus, satisfaction was maximal for vehicles, traffic lights, and the city. Still, this is not a realistic situation, because full synchronization is achieved due to the toroidal topology of the simulation environment. The full synchronization is achieved because platoons are promoted by the traffic lights, and platoons can move faster through the city modulating traffic lights. If two platoons are approaching an intersection, *sotl-phase* will stop one of them, and allow the other to pass without stopping. The latter platoon keeps its phase as it goes around the torus, and the former adjusts its speed until it finds a phase that does not cause a conflict with another platoon.

**Modeling.** Understanding the behavior of the platoons, it can be seen that there is a favorable system/context trade-off. There is no need of direct communication between traffic lights, since information can actually be sent via platoons of vehicles. The traffic lights communicate *stigmergically* [Theraulaz and Bonabeau 1999], i.e. via their environment, where the vehicles are conceptualized as the environment of traffic lights.

**Simulation.** With encouraging results, changes were made to the Simulation to make it more realistic. Thus, a scenario similar to the one of [Faieta and Huberman 1993] was developed. Traffic flow in four directions was introduced, alternating streets. This is, arteries still consist of one lane, but the directions alternate: southbound-northbound in vertical roads, and eastbound-westbound in horizontal roads. Also, the possibility of having more cars flowing in particular directions was introduced. Peak hour traffic can be simulated like this, regulating the percentages of cars that will flow in different roads. An option to switch off the torus in the simulation was added. Finally, a probability of turning at an intersection $P_{\text{turn}}$ was included. Therefore, when a car reaches an intersection, it will have a probability $P_{\text{turn}}$ of reducing its speed and turning in the direction of the crossing street. This can cause cars to leave platoons, which are more stable when $P_{\text{turn}} = 0$.

$^7$A similar method has been used successfully in the United Kingdom for some time, but for isolated intersections [Vincent and Young 1986].
The results of experiments in the more realistic simulation confirmed the previous ones: self-organizing methods outperform classic ones. There can still be full synchronization with alternating streets, but not without a torus or with \( P_{\text{turn}} > 0 \).

**Modeling.** Another method was developed, *sotl-platoon*, adding two restrictions to *sotl-phase* for regulating the size of platoons. Before changing a red light to green, *sotl-platoon* checks if a platoon is not crossing through, not to break it. More precisely, a red light is not changed to green if on the crossing street there is at least one car approaching at \( \omega \) patches from the intersection. This keeps platoons together. For high densities, this restriction alone would cause havoc, since large platoons would block the traffic flow of intersecting streets. To avoid this, a second restriction is introduced. The first restriction is not taken into account if there are more than \( \mu \) cars approaching the intersection. Like this, long platoons can be broken, and the restriction only comes into place if a platoon will soon be through an intersection.

**Simulation.** *Sotl-platoon* manages to keep platoons together, achieving full synchronization commonly for a wide density range, more effectively than *sotl-phase* (when the torus is active). This is because the restrictions of *sotl-platoon* prevent the breaking of platoons when these would leave few cars behind, with a small time cost for waiting vehicles. Still, this cost is much lower than breaking a platoon and waiting for separated vehicles to join back again so that they can switch red lights to green before reaching an intersection. However, for high traffic densities platoons aggregate too much, making traffic jams more probable. The *sotl-platoon* method fails when a platoon waiting to cross a street is long enough to reach the previous intersection, but not long enough to cut its tail. This will prevent waiting cars from advancing, until more cars join the long platoon. This failure could probably be avoided introducing further restrictions. In more realistic experiments (four directions, no torus, \( P_{\text{turn}} = 0.1 \), *sotl-platoon* gives on average 30% (up to 40%) more average speed, half the stopped cars, and seven times less average waiting times than non-responsive methods. Complete results and graphics of the experiments discussed here can be found in [Gershenson 2005].

**Representation.** If priority is to be given to certain vehicles (e.g. public transport, emergency), weights can be added to give more importance to some \( \sigma_i \)'s.

A meso-level might be considered, where properties of platoons can be observed: their behaviors, performance, and satisfaction and the relationships of these with the vehicle and city levels could enhance the understanding of the self-organizing traffic lights and even improve them.

**Simulation.** Streets of varying distances between crossings were tested, and all the self-organizing methods maintained their good performance. Still more realistic simulations should be made before moving to the Implementation, because of the cost of such a system. At least, multiple-street intersections, multiple-lane streets, lane changing, different driving behaviors, and non-homogeneous streets should be considered.

**Application.** The proposed system has not been implemented yet. Still, it is feasible to do so, since there is the sensor technology to implement the discussed methods in an affordable way. Currently, a more realistic simulation is being developed in cooperation with the Brussels Ministry of Mobility and Public Works.
to study its potential application in the city of Brussels. A pilot study should be made before applying it widely, to fine tune different parameters and methods. External factors, e.g. pedestrians and cyclists, could also affect the performance of the system.

Pedestrians could be taken into account considering them as cars approaching a red light. For example, a button could be used to inform the intersection of their presence, and this would contribute to the count $\kappa_i$.

A mixed strategy between different methods could be considered, e.g. *sotl-platoon* for low and medium densities, and *sotl-phase* or *marching* for high densities.

**Evaluation.** If a city deploys a self-organizing traffic light system, it should be monitored and compared with previous systems. This will help to improve the system. If the system would be an affordable success, its implementation in other cities would be promoted.

6. DISCUSSION

As could be seen in the case study, the backtracking between different steps in the Methodology is necessary because the behavior of the system cannot be predicted from the Modeling, i.e. it is not reducible. It might be possible to reason about all possible outcomes of simple systems, and then to implement the solution. But when complexity needs to be dealt with, a mutual feedback between experience and reasoning needs to be established, since reasoning alone cannot process all the information required to predict the behavior of a complex system [Edmonds 2005].

For this same reason, it would be preferable for the Control to be distributed. Even when a central supercomputer could possibly solve a problem in real time, the information delay caused by data transmission and integration can reduce the efficiency of the system. Also, a distributed Control will be more robust, in as much as if a module malfunctions, the rest of the system can still provide reliable solutions. If a central Control fails, the whole system will stop working.

The Simulation and Experiments are strictly necessary in the design of self-organizing systems [Edmonds 2005]. This is because their performance cannot be evaluated by purely formal methods [Edmonds and Bryson 2004]. Still, formal methods are necessary in the first stages of the Methodology. I am not suggesting a trial-and-error search. But since the behavior of a complex system in a complex environment cannot be predicted completely, the models need to be contrasted with experimentation before they can be validated. This Methodology suggests one possible path for finding solutions.

Now the reader might wonder whether the proposed Methodology is a *top-down* or a *bottom-up* approach. And the answer is: it is both and neither, since (at least) higher and lower levels of abstraction need to be considered simultaneously. The approach tests different local behaviors, and observes local and global (and meso) performances, for local and global (and meso) requirements. Thus, the Methodology can be seen as a *multi-level* approach.

Since “conflicts” between agents need to be solved at more than one level, the Control strategies should be carefully chosen and tested. A situation as in the prisoner’s dilemma [Axelrod 1984] might easily arise, when the “best” solution on one level/timescale is not the best solution on another level/timescale.
Many frictions between agents are due to faulty communication, especially in social and political relations. If agents do not “know” the goals of others, it will be much more difficult to coordinate and increase $\sigma_{sys}$. For example, in a social system, knowing what people or corporations need to fulfill their goals is not so obvious. Still, with emerging technologies, social systems perform better in this respect. Already in the early 1970s, the project Cybersin in Chile followed this path [Miller Medina 2005]: it kept a daily log of productions and requirements from all over the country (e.g. mines, factories, etc.), in order to distribute products where they were needed most; and as quickly as possible. Another step towards providing faster response to the needs of both individuals and social systems can be found in e-government [Layne and Lee 2001]. A company should also follow these principles to be able to adapt as quickly as possible. It needs to develop "sensors" to perceive the satisfactions and conflicts of agents at different levels of abstraction, and needs to develop fast ways of adapting to emerging conflicts, as well as to changing economic environment. A tempting solution might be to develop a homogeneous system since, e.g., homogeneous societies have fewer conflicts [Durkheim 1984]. This is because all the elements of a homogeneous system pursue the same goals. Thus, less diversity is easier to control. However, less diversity will be less able to adapt to sudden changes. Nevertheless, societies cannot be made homogeneous without generating conflicts since people are already diverse, and therefore already have a diversity of goals. The legacy [Valckenaers et al. 2003] of social systems gives less freedom to a designer, since some goals are already within the system. A social Control/mediator needs to satisfy these while trying to satisfy those of the social system.

7. CONCLUSIONS
This paper suggests a conceptual framework and a general methodology for designing and controlling self-organizing systems. The Methodology proposes the exploration for proper Control mechanisms/mediators/constraints that will reduce frictions and promote synergy so that elements will dynamically reach a robust and efficient solution. The proposed Methodology is general, but certainly it is not the only way to describe self-organizing systems.

Even if this paper is aimed mainly at engineers, it is rather philosophical. It presents no concrete results, but ideas that can be exploited to produce them. Certainly, these ideas have their roots in current practices, and many of them are not novel. Still, the aim of this work is not for novelty but for synthesis.

The Methodology strives to build artificial systems. Still, these could be used to understand natural systems using the synthetic method [Steels 1993]. Therefore, the ideas presented here are potentially useful not only for engineering, but also for science.

The backtracking ideology is also applicable to this Methodology: it will be improved once applied, through learning from experience. This Methodology is not final, but evolving. The more this Methodology is used, and in a wider variety of areas, the more potentially useful its abstractions will be. For example, would it be a good strategy to minimize the standard deviation of $\sigma$’s? This might possibly increase stability and reduce the probability of conflict, but this strategy, as any other, needs to be tested before it can be properly understood. It is worth noting
that apart from self-organizing traffic lights [Gershenson 2005], the Methodology is currently being used to develop Ambient Intelligence protocols [Gershenson and Heylighen 2004] and to study self-organizing bureaucracies.

Any system is liable to make mistakes (and will make them in an unpredictable environment). But a good system will learn from its mistakes. This is the basis for adaptation. It is pointless to attempt to build a “perfect” system, since it is not possible to predict future interactions with its environment. What should be done is to build systems that can adapt to their unexpected future and are robust enough not to be destroyed in the attempt. Self-organization provides one way to achieve this, but there is still much to be done to harness its full potential.

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