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An Adaptive Sanctioning Enforcement Model for Normative Multiagent Systems

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Abstract

The increasing interest on greater agent's autonomy in addition to its adaptability, bounded rationality, and heterogeneity features, and the necessity of interaction and cooperation may bring Multiagent Systems (MASs) to exhibit undesirable global behaviors. It may become even worse especially when they involve human agents who are less manageable and predictable in their actions, like in Sociotechnical Systems (STSs). These characteristics render an effective governance an essential aspect of these systems. The normative approach has been proposed as a prominent means to achieve this effectiveness, wherein *norms* provide a socially realistic view of interaction among autonomous parties that abstracts away low-level implementation details. Overlaid on norms is the notion of a *sanction* as a reaction to potentially any violation of or compliance with an expectation. Although norms have been well investigated in the context of MASs, sanctions still lack a more comprehensive inspection. We address the above-mentioned gap by proposing, first, a typology of sanctions that reflects the interplay of relevant features of STSs, second, a sanctioning enforcement process describing the functions of the diversity of components and their relationships, and third a sanctioning evaluation model that enables agents to evaluate and choose the most appropriate sanction to apply depending on a set of factors. In particular, this evaluation model enables the selection between formal or social sanctions based on how much the sanctioner can influence the social group of the sanctioned agent. This model is used to evaluate mono-type and multi-type sanctioning policies in a Smart Grid energy trading case study. Our results show that multi-type sanctioning policies do not always increase the level of norm compliance compared to mono-type sanctioning policies, yet multi-type policies are less costly.

Keywords: Sanctions. Enforcement Mechanisms. Normative Multiagent Systems. Multiagent Systems. Agent-Based Modeling.

Resumo

O crescente interesse em prover uma maior autonomia a agentes artificiais, além da sua capacidade de adaptação, racionalidade limitada, heterogeneidade, e necessidade de interação e cooperação podem fazer com que Sistemas Multiagentes (MASs) apresentem comportamentos globais indesejáveis. Esse cenário pode agravar-se, em especial quando esses sistemas envolvem a participação de humanos, uma vez que esses agem de forma menos controláveis e previsíveis, por exemplo, Sistemas Sócio-Técnicos (STSs). Essas características tornam a governaça desses sistemas um aspecto essencial para sua eficácia. A abordagem normativa é considerada uma proposta promissora para o atendimento desse requisito em tais sistemas. Nesse, *normas* fornecem uma visão socialmente realista das interação entre agentes autônomos abstraindo os detalhes de baixo nível. Suportada pelas normas está a noção de sanção como uma reação a potencialmente qualquer violação ou cumprimento de uma expectativa. Embora as normas já tenham sido extensamente investigadas no contexto de MASs, o conceito de sanção ainda carece de uma melhor inspeção. Esse carência é suprida nesse trabalho, primeiramente, propondo uma tipologia de sanções que captura as características relevantes de STSs, segundo, um processo adaptativo de sancionamento com a descrição das funções de seus componentes e inter-relacionamentos, e terceiro, um modelo adaptativo de avaliação de sancionamento que permite aos agentes decidirem qual sanção aplicar em cada situação. Em particular, esse model de avaliação permite a seleção entre sanções formais e informais dependendo de quanto o agente pode influenciar o grupo social do agente objeto da sanção. Esse modelo é usado na avaliação de políticas de sanção única ou múltiplas em um estudo de caso de transação de energia elétrica no contexto de uma rede elétrica inteligente. Conclui-se dos resultados obtidos que sistemas que disponibilizam políticas de sancionamento com múltiplas sanções não aumentam em todos os casos o nível de cumprimento das normas quando comparado com políticas de sancionamento com sanção única. Entretanto, políticas com multíplas sanções são menos custosas.

Palavras-chaves: Sanção. Mecanismos de Controle. Sistemas Multiagentes Normativos. Sistemas Multiagentes. Modelagem Baseada em Agentes.

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List of abbreviations and acronyms

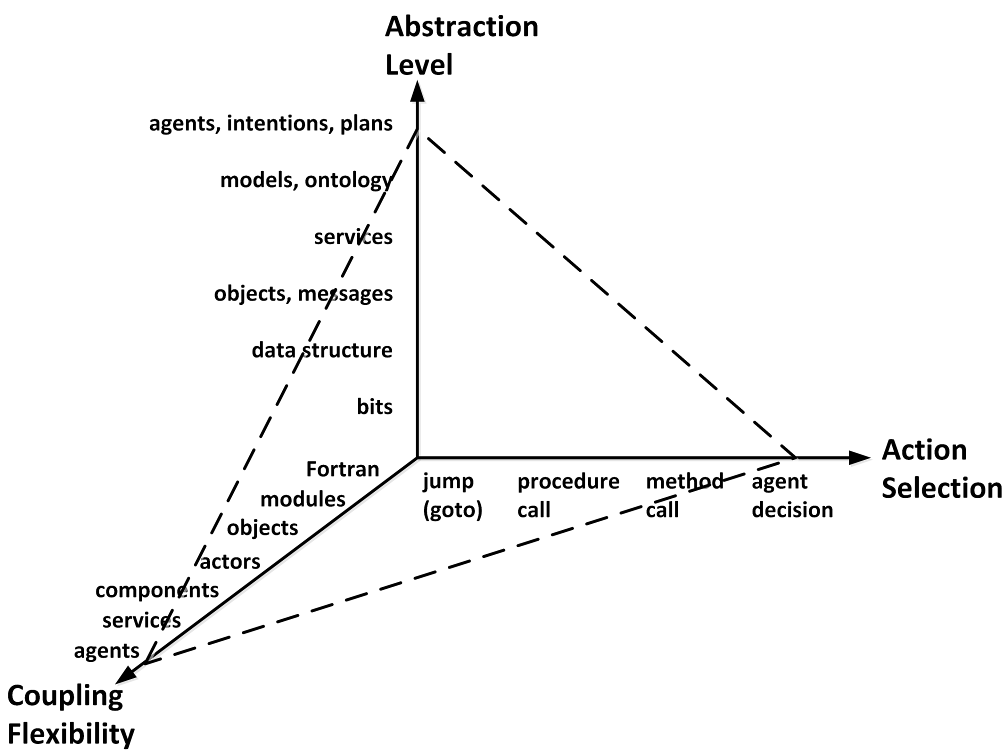
ABM	Agent-Based Modeling
BDI	Belief-Desire-Intention
BOID	Beliefs-Obligations-Intentions-Desires
CS	Contextual Specification
DOE	U.S. Department of Energy
EI	Electronic Institution
EMIL-A	EMergence In the Loop
ETP	European Technology Platform
FS	Functional Specification
G	Governor
HCI	Human-Computer Interface
IEA	International Energy Agency
IM	Institution Manager
IT	Information Technology
MAS	Multiagent System
MDP	Markov Decision Process
$\mathcal{MOISE}^{+}$	Model of Organization for multI-agent SystEms
NMAS	Normative Multiagent System
NS	Normative Specification
OE	Organizational Entity
OPERA	Organizations per Agents
OS	Organizational Specification
PowerTAC	Power Trading Agent Competition
SG	Smart Grid
SM	Scene Manager
STS	Sociotechnical System
SS	Structural Specification
TM	Transition Manager
TTP	Trusted Third Party

Contents

1 Introduction

Analyzing the computing evolution from the general programming perspective, Briot (2009) classifies it through a common referential composed of three dimensions: *abstraction level*, *coupling flexibility* and *action selection*. Figure 1 illustrates this referential in which the dimensions evolve beginning from the origin towards the end of the axes. This evolution indicates an increase in the abstraction level of the paradigms for the design and the development of systems, as well as an increase in the coupling flexibility and in their components autonomous decisions (i.e., action selection). According to this analysis, the *agent paradigm* – represented by the dimensions' value linked by the dashed line in Figure 1 – currently provides the highest abstraction level for systems modeling, coupling flexibility and their components autonomy, the agents.

Figure 1 – Computing evolution from the general programming perspective in which the dimensions evolve beginning from the origin towards the end of the axes (BRIOT, 2009).



Lately, there is an increasing interest on greater agent *autonomy*. Although autonomy is a spectrum, it refers here to the agent's ability of choosing and performing actions without the intervention of humans or other systems in order to meet its delegated goals (WOOLDRIDGE, 2009, p. 23).

Such interest is motivated partially because there is a general consensus that autonomy is central to the notion of agent (WOOLDRIDGE, 2009, p. 21) and partially as a consequence of a belief that the increase in autonomy results in improved system's properties (e.g., performance, stability, etc.), which is a desirable goal (SIERHUIS et al., 2012). As asserted by Sierhuis et al. (2012), however, such belief may be misleading for systems comprised of multiple agents participating in complex joint activities, such as Multiagent Systems (MASs), in which increased autonomy may eventually lead to degraded properties whenever the conditions necessary for an effective *governance* of their members interdependence are neglected. MAS properties can become even worse specially when involving not only artificial, but also human agents who are less manageable and more unpredictable in their actions. Sociotechnical Systems (STSs) are an example of this kind of MAS as they incorporate the interactions of multiple autonomous participants (human and artificial) mediated by Information Technology (IT), whose success relies on an effective governance of their interactions (SINGH, 2013; WHITWORTH, 2006).

Greater agents' autonomy in addition to (i) adaptability, (ii) bounded rationality, (iii) heterogeneity, and (iv) the necessity of interaction and cooperation may cause the system to exhibit undesirable global behaviors (CONTE, 2001). The incompatibility between agents' and global system's behaviors represents a dilemma to MAS, which is usually analyzed under the concept of *social order* (CONTE; DELLAROCAS, 2001). According to Castelfranchi (2000), social order "should be conceived as any form of systemic phenomenon or structure which is sufficiently stable, or better either self-organizing and self-reproducing through the actions of the agents, or consciously orchestrated by (some of) them."

Castelfranchi's definition implies two classic and extreme governance approaches through which social order may be achieved in MASs: the *emergent approach* and the *designed approach*. In the emergent approach, the system's global properties arise from agents' actions and interactions. The characteristic of this approach is that agents' behaviors are simple and predefined, while the system's behavior emerges from their interactions, rendering the global system outcome not even minimally predictable. In the designed approach, however, agents are controlled by an authoritative entity responsible for maintaining the social order and solving the problem that would arise due to the dichotomy between agents' individual and social interests (CONTE, 2001). While aligned with the characteristics of MAS, these classical approaches either (i) render difficult the prediction of the systems' global properties (emergent approach), or (ii) limit agents' autonomy (designed approach).

Along with these extreme approaches, the *normative approach* has attracted particular attention, especially in the last two decades, as an intermediary means for governing MASs. This attention derives from the fact that it is expected that normative concepts may play a key role in prescribing and guiding agents' behaviors, as they already play among humans (CONTE; CASTELFRANCHI, 1995; CASTELFRANCHI, 1998; CONTE; CASTELFRANCHI; DIGNUM, 1999; VERHAGEN, 2000; BOELLA; TORRE; VERHAGEN, 2006; BOELLA; TORRE; VERHAGEN, 2008; HOLLANDER; WU, 2011; ANDRIGHETTO et al., 2013).

In addition of being in line with how the social order problem is tackled in human organizations (CONTE, 2001), the interest in the normative approach is also a consequence of its greater flexibility that comes from the fact that the agents' behaviors are regulated through *norms*. We understand norms as guides of conduct prescribing how members of a group ought to behave in a given situation (ULLMANN-MARGALIT, 1977; CONTE; ANDRIGHETTO; CAMPENNÌ, 2013). They provide a common expectation that an entity has about others' behaviors. Thus, a set of norms comprises an explicit and formal specification of the expected agents' behaviors, which then renders the system's global properties (more) predictable.

Normative Multiagent Systems (NMASs), which are a combination of normative concepts and MAS, are proposed for establishing a balance between autonomy and control in MASs (VERHAGEN, 2000). They are based on normative actions, which considers that agents are members of a group and there is an expectation that they behave according to the norms established by that group (HABERMAS, 1984). In NMASs, norms can be autonomously recognized, adopted and complied with by agents through their normative decision processes (CONTE; CASTELFRANCHI; DIGNUM, 1999; HOLLANDER; WU, 2011; CONTE; ANDRIGHETTO; CAMPENNÌ, 2013). These decision processes provide certain autonomy to agents with respect to their action selection and execution, while an overall predictability of the system's global behavior is achieved in case agents act in accordance to the specified norms.

Nonetheless, agents may deliberately decide not to accept or comply with (i.e., violate or deviate from) the specified norms as they have autonomy in selecting their actions and goals. In NMASs, these situations are usually handled through two distinct types of enforcement approaches (MINSKY, 1991; JONES; SERGOT, 1993; GROSSI; ALDEWERELD; DIGNUM, 2007): (i) *regimentation*, in which a norm violation is made physically impossible, or (ii) *regulation*, in which agents can violate the norms, and the system or its member agents are usually endowed with some enforcement mechanism in order to influence themselves and other agents' behaviors conferring on them some sort of control.

Analyzing from the NMAS perspective, the regimentation limits agents' autonomy and resemble the designed approach described above. The regulation enforcement approach, therefore, is seen as the most adequate approach to NMASs due to the fact that it provides greater autonomy to agents, yet providing some control on them. There are several possible forms of implementing such approach, being one possibility the use of *sanctions* (i.e., sanctioning enforcement).

Sanction is a reaction triggered by the violation or compliance with a norm, whose intent is to promote compliance with such norm (GIBBS, 1966). A sanction provides a foundation for how participants in a NMAS may seek to influence each others' decision-making and to steer the system in a preferred direction. Although norms have been studied in regards to governance of NMASs (SAVARIMUTHU; CRANEFIELD, 2011; MAHMOUD et al., 2014), sanctions have not been comprehensively addressed yet.

1.1 Motivation

Enforcement is one of the central puzzles in the social order and social control theories. Sanctioning is an enforcement mechanism that provides incentives, positive or negative, to norm compliance. It has been addressed for a long time from a vast set of perspectives and disciplines, such as philosophy (BECCARIA; INGRAHAM, 1819; BENTHAM, 1823; MILL, 1871), law (AUSTIN, 1832; KELSEN, 1945; HART, 1968), economics (BECKER, 1968; STIGLER, 1970; LANDES; POSNER, 1975; ELLICKSON, 1991; POSNER; RASMUSEN, 1999; POLINSKY; SHAVELL, 2007), political sciences (DAHL, 1970; KIRSHNER, 2002), sociology (RADCLIFFE-BROWN, 1934; MORRIS, 1956; LOCKWOOD, 1964; GIBBS, 1966) and social psychology (SKINNER, 1938; CARLSMITH; DARLEY; ROBINSON, 2002; PETERSEN et al., 2012). In this wide literature, different categories of sanctions (i.e., emotional, informational, reputational and material sanctions (POSNER; RASMUSEN, 1999)) are reported being used by individuals and institutions for enforcing and promoting compliance with norms.

In human societies, these different categories of sanctions are usually used simultaneously and have an effective impact on making people comply with norms. This statement is supported by several empirical studies, such as Anderson, Chiricos and Waldo (1977), Jacob (1980), Hollinger and Clark (1982), Kean (1992), and more recently complemented by laboratory experiments with human subjects, such as Masclet (2003), Noussair and Tucker (2005), Kube and Traxler (2011). These studies provide empirical evidence that the availability and the possibility of using multiple categories of sanctions benefits in inducing people to comply with norms.

In MASs, and particularly in NMASs which is the focus of this work, the enforcement mechanisms use mostly two categories of sanctions (i.e., material and reputational sanctions) in spite of the existence of other proposals based on mechanisms like emotions (FIX; SCHEVE; MOLDT, 2006).

Material sanctions impose restrictions or grant permissions to an agent concerning some kind of resource in order to influence its behaviors. Usually, this category of sanction imposes direct tangible costs or grants direct tangible benefits to the sanctioned target agent. For instance, fining an agent is assumed a material sanction as it inflicts a cost to the target agent by constraining the use of its own money in other activities.

Reputational sanctions are based on the spreading of evaluation about others' past behaviors. Reputation has become a common approach to support the interaction in distributed environments as it may influence the target's future behavior in spite of not inflicting any direct tangible costs or granting direct tangible benefits to it. Thus, it is a means to discourage unwanted and foster desired behaviors among agents (CONTE; PAOLUCCI, 2002; SABATER-MIR; SIERRA, 2005; LU et al., 2007; CASTELFRANCHI; FALCONE, 2010; PINYOL; SABATER-MIR, 2013). It is based on the idea of indirect sanctioning, because instead of acting directly on agents' tangible resources, reputation carries information about others' past behaviors and can be used for evaluating how they might perform in the future. A positive performance history thereby is supposed to lead to higher reputation that the agent will perform well in the future again, whereas a negative one results in the opposite.

Despite the availability of different categories of sanctions, currently most NMAS sanctioning enforcement mechanisms do not enable the use or deal with them simultaneously. Generally, the available mechanisms enable the use of a single category of sanction at a time. Although providing some improvements in shaping or inducing agents' behavior, they may not be completely adequate to systems in which humans and artificial agents interact, such as in STSs, once these systems interrelate social and technical aspects that need to be tackled in an integrated fashion (HOUWING; HEIJNEN; BOUWMANS, 2006; FIADEIRO, 2008).

Hence, an adequate sanctioning enforcement model for NMASs applied to STSs should not only enable simultaneous use of multiple categories of sanctions, but also the selection of the most appropriate ones depending on the agent's current situation and goals.

1.2 Objectives

This work develops and evaluates an adaptive enforcement model for NMASs using the notion of sanctions. In particular, this enforcement model is tailored to facilitate the use of NMASs to model systems that integrate humans and artificial agents, like in STSs.

In order to be considered adaptive, this sanctioning enforcement model enables (i) the integrated use of different categories of sanctions, and (ii) the change of the set of sanctions associated to the norms, (iii) the selection of the most appropriate sanctions to apply, depending on their current situation and goals.

The fulfillment of these features requires the achievement of two specific objectives:

1. *Development of a typology of sanctions*

   Although the concept of norms has been well investigated in the context of NMASs (VERHAGEN, 2000; BOELLA; TORRE; VERHAGEN, 2008; HOLLANDER; WU, 2011; ANDRIGHETTO et al., 2013; MAHMOUD et al., 2014), *the concept of sanctions still lacks a more comprehensive inspection in* NMAS*s*. Despite the existence of several works devoted to the study of enforcement (PASQUIER; FLORES; CHAIB-DRAA, 2005; GROSSI; ALDEWERELD; DIGNUM, 2007; CARDOSO; OLIVEIRA, 2011; BALKE; VILLATORO, 2012; CRIADO et al., 2013), neither of them investigate deeply the concept of sanctions in the context of NMASs; they focus primarily on norms and refer to sanctions as a secondary aspect. Moreover, they usually focus on a single norm perspective or a specific approach, rather than performing a more comprehensive analysis that could consider a greater number of viewpoints.

   This work tackles this gap in the literature by developing a typology of sanctions that provides a set of dimensions to distinguish different categories of sanctions, in particular those useful for STSs modeled as NMASs, where norms are adopted to coordinate both humans and artificial agents actions.

2. *Development of a model enabling agents to adapt and choose among different possible sanctions*

   There are several categories of sanctions that can be used to influence agents' behaviors in NMASs; however, most of NMASs empower their agents to use only one category of sanction. Even those that enable the use of different categories impose some constraints on agents, e.g., they are not allowed to decide which sanctions to apply in each situation. Moreover, the relationship between norms and sanctions is specified in design time, constraining the agents' adaptability and autonomy. This limited use of sanctions in NMASs does not corroborate with the reality of human systems in which individuals have available a set of possible sanctions to apply and they usually decide and choose those most appropriate depending on their current situation and goals. Thus, they are assumed not completely adequate for representing systems that integrates humans and artificial agents, as they do not take into account humans adaptability and flexibility with respect to sanctioning.

1.3 Methodology

The methodology employed in the development of this work consisted first of elaborating a STS motivational scenario (i.e., a scenario in which humans and artificial agents may interact) to guide the development of the work and illustrate a possible application domain (Chapter 2).

Next, a literature review on NMASs was carried out to identify the necessary features for modeling this scenario as a NMAS (Chapter 3). Sanctioning was assumed to be the main aspect required in the scenario. Thus, a comprehensive review on sanctions and enforcement mechanisms on several social sciences disciplines and NMAS was carried out (Chapter 4). This literature review enriched the understanding of the concept of sanctions and the existent sanctioning enforcement mechanisms in disciplines more used in dealing with these kind of issues (i.e., social sciences).

These reviews, which took into account the application of enforcement mechanisms in scenarios comprised of humans and artificial agents, allowed the identification of two main limitations in existing NMAS sanctioning enforcement mechanisms: (i) a limited definition of sanctions, and (ii) a non-adaptive and inflexible agents' process with respect to sanctions. They have also facilitated the development of the comprehensive typology of sanctions (Chapter 5) for overcoming the first identified limitation (i.e., lack of a more comprehensive understanding of sanctions).

An adaptive sanctioning enforcement model was specified and implemented (Chapter 6) based on the features identified during the development of the typology of sanctions. This model describes and formally specify the main components and interrelationships of a sanctioning enforcement process model that enables agents to assess and adapt the possible sanctions to apply. Moreover, it implements a sanctioning evaluation model in charge of assess the agent's context and decide the most appropriate sanction to apply depending on a set of sanctioning decision factors.

The sanctioning enforcement model implementation was then used to develop a case study in the Smart Grid (SG) application domain (Chapter 7), in which agents representing households interact to trade energy. Several experiments were conducted through the Agent-Based Modeling (ABM) methodology as currently SG networks are not available to evaluate the usefulness of the proposed model in this application domain.

Finally, some possible future perspectives on how to exploit and expand the results obtained in this thesis were proposed (Chapter 8).

1.4 Contributions

This thesis contributes to the advancement of NMASs in distinct aspects:

1. developing an adaptive sanctioning enforcement model for NMAS that enables
   - (i) agents to adapt their sanctioning behavior by enabling the modification of the sanctions and their associations to norms,

(ii) agents to choose among different categories of sanctions the most appropriate ones to apply depending on a set of sanctioning decision factors, and

(iii) the modeling of agents behavior in different domain applications, in particular those integrating humans and artificial agents;

2. illustrating the use of NMAS and the developed adaptive sanctioning enforcement model in a STS application domain, more specifically in the SG domain.

1.5 Thesis Structure

This thesis is structured in other seven chapters subdivided in three parts and one appendix:

- *Chapter 2* introduces a motivational scenario in which humans and agents interact for trading renewable energy. It illustrates several situations where sanctions may apply and identifies these situations' main features.

- **Part I** provides the foundations and an overview of the state-of-the-art regarding norms, sanctions and sanctioning enforcement mechanisms in the social sciences and computing perspectives, in particular NMAS. *Chapter 3* presents the foundations and the state-of-the-art of NMAS for contextualizing the type of MAS to which the proposed sanctioning enforcement model shall be applicable. *Chapter 4* highlights the main characteristics of the notion of sanctions from various social sciences discipline perspectives. Next, it presents a literature review of sanctioning enforcement mechanisms in NMAS and evaluates them with respect to the identifiable limitations they would present if applied in systems involving interaction between humans and artificial agents.

- **Part II** presents our main contribution, in which a typology of sanctions is developed and an adaptive sanctioning enforcement model that enables agents to reason and decide about which sanctions to apply. In *Chapter 5*, the typology of sanctions is detailed, identifying the typology's dimensions and providing an evaluation of its applicability in NMASs. *Chapter 6* presents an adaptive sanctioning enforcement model and describe its main components characteristics and functioning, as well as some considerations about its actual implementation.

- **Part III** describes a SG simulation model in which the typology and adaptive sanctioning enforcement model were applied. *Chapter 7* describes the fitness of the proposed sanctioning enforcement model to the SG application domain and the use of the ABM approach to evaluate the efficacy of different types of policies to promote cooperation among consumers and small producers of renewable energy. It includes also a description of the experimental methodology, the simulation model, the experiments performed and the obtained results.

- Finally, *Chapter 8* concludes our research on sanctioning enforcement in NMASs and provides some possible perspectives to exploit and expand the work presented in this thesis.

- Appendix A provides the instructions to install, compile and run the SG energy trading model developed for evaluating the adaptive sanctioning enforcement model.

2 Motivating Scenario

This chapter details the motivational scenario that inspired the development of the adaptive sanctioning enforcement model developed in this work. It consists of a Sociotechnical System (STS), thus assumes the interrelation between social and technical aspects, which is illustrated through possible situations in a fictional Smart Grid (SG) renewable energy trading scenario. In Sections 2.1 and 2.2, the characteristics of STSs and SGs are respectively highlighted. Then, the SG motivational scenario is described in Section 2.3 illustrating its main governance requirements, in particular a set of situations in which sanctions may apply. Finally, the main features of the enforcement mechanisms required to support the outlined scenario are discussed in Section 2.4.

2.1 Sociotechnical Systems

Information Technology (IT) is becoming an integral part of everyone's life. Individuals are increasingly depending on it to interact, which is making interactions migrate from physical environments to Sociotechnical Systems (STSs).

STS is at the highest level in the Whitworth's (2009) hierarchical classification of systems (i.e., Hardware, Software, Human-Computer Interface (HCI) and STS), meaning that it has to deal with the requirements of all the beneath levels (i.e., *physical*, *information*, *personal* and *communal*). STSs, however, concentrate particularly on involving individuals not only as users, but as participants in these systems. It concerns with the role that individuals play in the system and the ability of such systems in adapting to individuals' needs. They represent a perspective on systems which considers the social and technical aspects together (HOUWING; HEIJNEN; BOUWMANS, 2006). These aspects are not simply co-located, yet they integrate into a higher level system with emergent global properties.

We understand STSs as complex adaptive systems in which social and technical aspects co-evolve. They are comprised of a number of computational and physical resources, and multiple autonomous stakeholders, whose interests are typically at best imperfectly aligned (SINGH, 2013).

The main challenge raised by these systems resides in the fact that their complexity derives from the number and nature of interactions that characterize their behavior (FIADEIRO, 2008). The success of a STS thus relies upon effective *governance*, which pertains to how the above-mentioned interactions are controlled, especially with a view to achieving relevant participant objectives, both technical (e.g., performance) and social (e.g., fairness of access to common resources) (BALKE; VILLATORO, 2012).

The normative approach has been proposed as a good candidate for governing STSs due to its flexibility and successfulness in governing human's behavior (SINGH, 2013). This approach guides individuals on how to behave under certain circumstances by prescribing what is permitted, obligatory and prohibited (SAVARIMUTHU; GHOSE, 2013).

Governance is achieved by norms being established among the participants and sanctioning occurring with respect to such norms. As an example, let Alice and Bob be two parties. A norm captures an expectation of Alice that Bob will behave in a certain manner, for instance Alice expects Bob to conserve power by switching off the office space heater when leaving the office. In essence, Alice holds Bob accountable for the given norm. Even if the participants in a STS are peers, in general, they play different roles with distinct privileges and liabilities, expressed via distinct norms that apply between them (SINGH, 2013).

A participant can potentially (1) *comply* with a norm by behaving as expected (e.g., turning the heater off), or (2) *violate* a norm by failing to behave as expected (e.g., leaving the heater on when leaving the office). *Sanctions* may then be applied aiming to promote norm's compliance. We understand sanction as a reaction to a norm compliance and violation, which aims to promote compliance with the norm. Hence, it provides a foundation for how participants in a STS influence each others' decision-making.

Traditional examples of STSs include the Internet, the global financial system, health systems, telecommunication networks, next-generation power grids, environmental systems, and regional and global transportation systems. This work focuses primarily on next-generation power grids, also known as Smart Grid, illustrating a STS.

2.2 Smart Grids

SG is an electrical grid that supports bi-directional flows of electricity and information between all network nodes, such as power plants and appliances. The SG enables real-time market transactions and seamless interfaces between people, buildings, industrial plants, generation facilities and the electrical network (VU; BEGOUIC; NOVOSEL, 1997; DOE, 2003).

SG serves as a STS because it involves multiple self-interested stakeholders collaborating with respect to their computational and physical resources, which raises a number of key governance issues (MAH et al., 2012). Although a well-established definition of SG is not yet available, but the existing ones agree its main characteristics are (IEA, 2011):

- *Enabling informed participation by consumers*

  The bi-directional flow of data and energy influences consumers behavior and participation. These behavioral changes come as a result of consumers having choices motivating their patterns of behavior.

- *Accommodating all generation and storage options*

  SG comprises a large set of distributed energy resources managed by consumers that are also small-scale energy producers. The integration of these resources into the infrastructure demands a distributed control all along the value chain, from suppliers to market and to consumers.

- *Enabling new products, services and markets*

  Consumers have more choices and are more informed about available opportunities and services. Markets are more dynamic and regulators, owners/operators and consumers should have flexibility to enforce and modify the business rules to suit operating and market conditions.

- *Providing the power quality for the range of needs*

  The quality of service provided may be customized to each type of consumer. Thus, a SG is able to supply varying grades (and prices) of energy depending on the consumers needs. Advanced control methods are used to monitor the infrastructure and fulfill the required quality levels.

- *Optimizing asset utilization and operating efficiency*

  Optimization is possible due to the communication infrastructure available, which provides the support for the spreading of management and preventive data that enables the selection of least-cost energy delivery system through system-control devices.

- *Providing resiliency to disturbances, attacks and natural disasters*

  Resiliency refers to the ability of a system to recover quickly from unexpected events by isolating problematic elements while the rest of the system is restored to normal operation. These self-healing actions result in reduced interruption of service to consumers and help service providers to better manage the delivery infrastructure.

These characteristics pose a number of challenges, not only technically related, but also concerning social aspects. Furthermore, they make evident that users play a key role in SGs. Reports of several governmental agencies, such as U.S. Department of Energy (DOE, 2003), European Technology Platform (ETP, 2012), and International Energy Agency (IEA, 2011), recognize these social challenges and the crucial importance of the users.

The European Technology Platform specifically acknowledges the need of new market models and regulations mechanisms in which consumers play a more active role. It also identifies the importance of technological, psychological, sociological, and economical aspects for an active consumer participation.

Next, we illustrate a SG scenario in which consumers play a crucial role in the system's dynamics. That happens because they are not only involved with energy demand and supply, but have also an active role in regulating the system through sanctioning.

2.3 Smart Grid Scenario

To demonstrate our ideas, we consider a fictitious SG trading scenario, which is partially inspired by the current Power Trading Agent Competition (PowerTAC)[1] (KETTER; COLLINS; REDDY, 2013; KETTER et al., 2014), a competitive simulation that models transactions among the members of a power grid.

Figure 2 – SG motivational scenario.

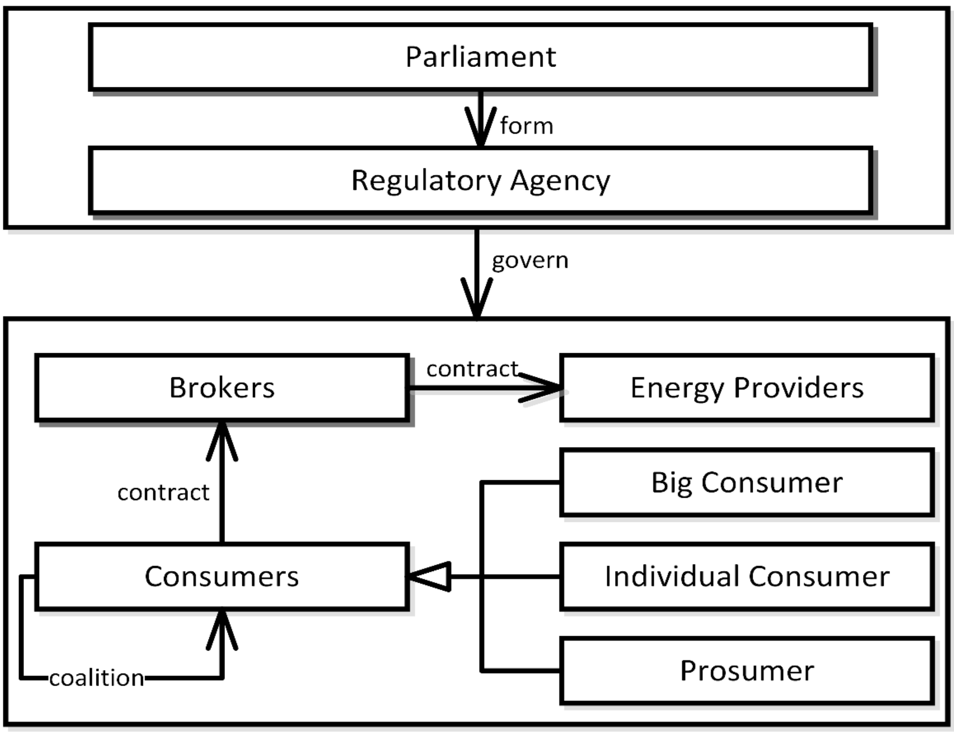


Figure 2 shows the main entities in our motivational scenario. An *energy provider* generates (a large amount of) energy with high stability. *Consumers* may be classified as: (i) *big consumers* (e.g., a factory or an amusement park that consumes a large amount of energy); (ii) *individual consumers* (e.g., a house or a small office that consumes a small amount of energy); (iii) *prosumers* (e.g., a house with solar panels or a farm with wind generators that generates and consumes small amounts of energy, and whose generation is

[1] <http://www.powertac.org>.

quite unpredictable, particularly due to the vagaries of the weather); or (iv) *coalitions* (e.g., two or more consumers working as one consumer to buy and sell energy).

A *broker* mediates energy transactions between energy providers or prosumers, and consumers. The *regulatory agency* is a distinguished authority that promulgates and enforces norms on the dealings between providers, consumers and brokers. The *Parliament* is the entity that constitutes the regulatory agency.

The regulatory agency formally governs the interactions among energy providers, brokers and consumers, which can also monitor each others' behaviors with respect to the established norms and sanction each other.

For concreteness, consider three neighbors (John, Joseph and Mary) connected to the same power network, whose monthly individual energy consumption is around $1000\ kWh$. Each of them has installed solar panels with a capacity of around $400\ kWh$ per month, characterizing them as prosumers. They have entered into separate energy buying contracts with a broker, which in turn has a buying contract with an energy provider. The broker may also buy renewable energy generated by prosumers at a price of $\$0.05$ per kWh for a minimum of $1000\ kWh$ per month, or at $\$0.02$ per kWh otherwise. The broker has a selling contract with a factory (big consumer). We refer to John, Joseph, Mary and the factory jointly as the broker's *consumers*.

The norms ruling this scenario establish that (i) the seller is obliged to (uninterruptedly) supply the committed amount of energy to the buyer; (ii) a coalition member is obliged to (uninterruptedly) supply the amount of energy agreed with the coalition; and (iii) the buyer is obliged to pay for the amount of energy supplied by the seller.

Based on such SG scenario, consider the following possible situations in which sanctions may apply:

2.3.1 Situation 1: Energy Provider Failure

Due to a human error, the energy provider fails to fulfill its commitment of supplying energy without interruption to its consumers, which in turn causes the brokers that negotiated the energy supply to also fail to fulfill its commitments with these consumers. Consumers become unsatisfied with the service provided and may decide to take one or more of the following actions:

S1.1 Blame themselves for selecting the service from this broker;

S1.2 Take legal actions against the broker;

S1.3 Spread negative ratings about the broker; or

S1.4 Switch to another broker.

Subsequently, the broker may also sanction the energy provider as its credibility and finances suffer due to the energy provider's fault. An option would be simply to switch to another provider; however, this is impossible since this energy provider is the only energy concessionary in the region capable of supplying the required amount of energy. The broker's choices, therefore, are limited to reactions stipulated in its contract with the provider. Thus, the broker may decide to take the following action:

S1.5 Sue the energy provider.

Additionally, the regulatory agency, after observing consumers not receiving adequate power, decides to evaluate the broker and energy provider's liabilities and responsibilities in order to determine the sanctions to impose on them. The possible sanctions are:

S1.6 Fine the energy provider between 1% and 5% of its monthly profit; or

S1.7 Suspend the broker from signing new contracts for a period up to 30 days.

2.3.2 Situation 2: Coalition Formation

John, Joseph and Mary decide to take a vacation at the same time. Joseph realizes that their broker buys renewable energy at a higher price from prosumers who can generate more than $1000\ kWh$ per month. He suggests they form a coalition to which they would each contribute at least $350\ kWh$ for one month. John and Mary agree with his proposal. Since they would profit from his initiative, they may react by:

S2.1 Thanking Joseph; or

S2.2 Spreading Joseph's good reputation due to his initiative.

2.3.3 Situation 3: Coalition Failure

Upon returning from their vacation, they notice that Mary's solar panel malfunctioned because she did not follow the manufacturer's service recommendations. Since their coalition failed to generate energy exceeding $1000\ kWh$, they obtained only a reduced price from the broker, as specified in their contract. John and Joseph may decide to do nothing as they understand that hardware failures are difficult to control and Mary has a good cooperation history, or they (and Mary) may react according to one or more of the ways:

S3.1 Mary blames herself for the solar panel's malfunctioning;

S3.2 John and Joseph suggest that Mary have her solar panel serviced on a regular basis;

S3.3 John and Joseph reduce their trust in Mary as a partner;

S3.4 John and Joseph request compensation from Mary; or

S3.5 John and Joseph tell others that Mary is an unreliable partner.

2.3.4 Situation 4: Coalition Success

During next year's vacation, John, Joseph and Mary again form a coalition to sell energy to the same broker. However, because of unforeseen circumstances (John's mother suffered a heart attack), John cancels his vacation and returns home accompanied with his mother, who requires special care and equipment that consumes a lot of energy. Conscious that he will not be able to supply the committed amount of energy for the coalition to reach $1000\ kWh$, he requests his friend George to replace him in the coalition. George agrees to John's request, and Joseph, Mary and George together generate more than $1000\ kWh$ of energy, thus meeting their contracted threshold for receiving the higher rate. Hence, Joseph and Mary may react by:

S4.1 Thanking George for coming to their rescue;

S4.2 Praising George to others;

S4.3 Praising John to others as he had proposed a successful alternative to his fault; or

S4.4 Deciding not to form a coalition with John in the future, even though they recognize that John's behavior was justified.

2.3.5 Situation 5: Broker Failure

To meet unanticipated market demands, a factory decides to operate an additional shift. Thus, it requests from the broker additional energy; the broker agrees to provide this additional energy, but at a higher rate. Since the energy supplied by the energy provider is limited, the broker reduces the energy supplied to John, Joseph and Mary and redirects it to the factory. Unhappy with the failure of the broker in fulfilling the consumers commitments, the latter may react similarly to the options listed in the Situation 1 (**S1.1** to **S1.4**). In contrast, the big consumer on receiving extra energy supply may:

S5.1 Increase its trust in the broker as a service provider; or

S5.2 Tell others of the willingness of the broker to meet increased demand.

2.4 Discussion

Analyzing the foregoing scenario from the perspective of sanctioning enforcement mechanisms, the main features that it brings out are the following:

1. *Sanctions are loosely coupled to norms, since multiple sanctions categories are possible*. The affected parties (i.e., the parties affected by norm violation or compliance) are not forced to apply a fixed sanction to the violating party due to its behavior, they have a list of available options (i.e., loosely coupled to norms). In Situation 1, for instance, unsatisfied consumers can blame themselves for contract the failing broker, take legal actions against it, spread negative ratings about it or, ultimately, switch to another broker. Furthermore, the available sanctions are of different types, such as legal actions, ostracism or rating spread (i.e., availability of different categories of sanctions).

2. *A sanctioning party may consider a variety of factors in determining whether and which sanctions to apply*. Situation 3 illustrates this feature as John and Joseph take into account not only Mary's fault, but her history as an energy supplier (i.e., Mary's reputation) and what caused her to violate (i.e., hardware malfunction) her commitment in order to decide whether to sanction or not. Deciding on sanctioning her, they may take into account the same factors to decide which of the available sanctions to apply.

These features demand the following requirements for a STS sanctioning process:

R1 Support for multiple categories of sanctions;

R2 Potential association of multiple sanctions with a norm violation or compliance;

R3 Adaption of the sanction content depending also on the context; and

R4 Decision about the most adequate sanction to apply depending on the context.

In the next sections, we review the existing literature of sanctions both in NMAS and social sciences, aiming to propose a conceptual model that supports scenarios of the above kind and that fulfills these identified requirements.

Part I

Foundations and State-of-the-Art

3 Normative Multiagent Systems

In this chapter, the definition and characteristics of Normative Multiagent Systems (NMASs) are presented. First, the foundations and definitions of NMAS with a special emphasis on norms are described in Section 3.1. In Section 3.2, normative processes supporting norms life cycle are detailed. A review of NMASs according respectively to the institutional and social approaches is presented in Sections 3.3 and 3.4. Finally, a summary of the characteristics of NMAS is provided in Section 3.5.

3.1 Introduction

Multiagent Systems (MASs) are systems composed of a set of autonomous and heterogeneous *agents* situated in a shared *environment* that *interact* among themselves and with the environment for achieving their (delegated) goals (WOOLDRIDGE, 2009). They may also *organize* themselves according to different organizational paradigms (HORLING; LESSER, 2004; DIGNUM, 2009).

MASs may be classified as *closed* or *open* systems. Closed MASs are those in which all agents know each other and interact among themselves via structured and predictable protocols following specific patterns. These systems are usually designed with a specific purpose in mind. Conversely, Open MASs are general purpose systems in which (1) agents' behaviors and interactions cannot be known in advance, (2) their internal architecture as well as beliefs and goals are not shared, and (3) they can join and leave the system at any time (ARTIKIS; PITT, 2009; HEWITT, 1991).

These properties entails that open MASs global macro-behavior is *unknown* in advance (Property 1), in which agents can be heterogeneous and non-cooperative as they may have different beliefs and goals (Property 2). They also implies that these systems are *dynamic* and their organizational structure may change over time (Property 3).

Open MASs properties render difficult to assure that all agents will behave as expected for the system to exhibit desirable global properties (e.g., stability, efficacy). Thus, the use of certain mechanisms to steer the system in a preferred direction becomes very important, yet maintaining certain level of agents' autonomy (PASQUIER; FLORES; CHAIB-DRAA, 2006). One possible strategy to achieve this goal is governing agents' behaviors through normative systems (i.e., normative constraints), as in human societies.

Normative systems reflect the idea of normative action (HABERMAS, 1984), which considers individuals as members of a group with an expectation that they respect the norms of that group:

> The central concept of complying with a norm means fulfilling a generalized expectation of behavior. The latter does not have the cognitive sense of expecting a predicted event, but the normative sense that members are entitled to expect a certain behavior. This normative model of action lies behind the role theory that is widespread in sociology. (HABERMAS, 1984, p. 85)

In computer science, normative systems are redefined as those in which "norms play a role and which need normative concepts in order to be described or specified" (MEYER; WIERINGA, 1993, preface). Drawing upon Von Wright (1963), and a long tradition of deontic philosophy and logic-based theory of action, normative systems define the global desired properties of the system by means of norms that specify obligations, prohibitions and permissions.

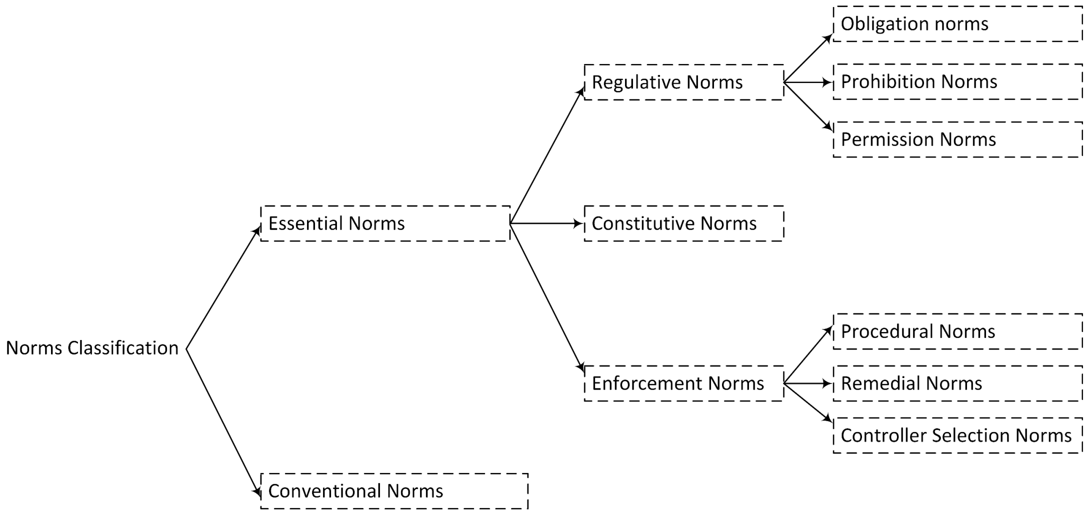
Norms do not have a universal definition as the term has been studied in a variety of research domains from different perspectives. Conte and Castelfranchi (1995), however, provide three different functional perspectives on the use of norms in MASs: (i) norms as constraints on behavior, (ii) norms as ends (or goals), and (iii) norms as obligations. These uses are reflected in the literature in which norms refer to constraints on behavior (SHOHAM; TENNENHOLTZ, 1992), solutions to macro-level problem (ZHANG; LEEZER, 2009), obligations (VERHAGEN, 2000), and regulatory and control devices for decentralized systems (SAVARIMUTHU; PURVIS; PURVIS, 2008).

Despite the varying definitions and perspectives on norms (HORNE, 2001), Hollander and Wu (2011) identify some common features. Norms are (i) patterns of behavior accepted by the majority of the group, (ii) acquired through interactions with others and the environment, and (iii) enforced through different mechanisms. Hence, they represent the standards of correct behavior that each party in a system expects from others and may be willing to enforce.

Accordingly, we refer to norms as guides of conduct prescribing how members of a group ought to behave in a given situation according to the majority of its members (ULLMANN-MARGALIT, 1977). Norms specify actions that are permitted, obligatory or prohibited under a given set of conditions, as well as the effects of complying with or violating them (BALKE; VILLATORO, 2012).

There are many different types of norms that vary in different aspects (GIBBS, 1965). Looking at the literature, various typologies (MORRIS, 1956; GIBBS, 1965; INTERIS, 2011) and classifications (ELLICKSON, 1991; COLEMAN, 1998; DIGNUM, 1999; BOELLA; TORRE, 2008) have been proposed. These classifications vary according to the scope (DIGNUM, 1999) and the purpose of the norm (ELLICKSON, 1991; BOELLA; TORRE, 2008). Figure 3 illustrates a classification integrating both perspectives.

Figure 3 – Norms classification, according to scope (DIGNUM, 1999) and purpose (ELLICKSON, 1991; BOELLA; TORRE, 2008) of the norm.



Coleman (1998) categorize norms in *Conventional* and *Essential* norms. Conventional norms are customary, expected and self-enforcing patterns of behavior that everyone has interest in complying with as its violation represents a punishment in itself. Thus, conventions solve coordination problems only when there is no conflict between individual and collective interests.

Conversely, essential norms solve or ease collective problems in the presence of conflicts between individual and collective interests (VILLATORO et al., 2011). Boella and Van der Torre (2008), in a pragmatic perspective, categorizes essential norms in

- *Regulative* norms specify the expected behavior of agents by means of obligations, prohibitions and permissions.
- *Constitutive* norms specify the *count-as* (SEARLE, 1995) relations and are used to support regulative norms by introducing *institutional facts*. These facts exist solely due to their collective acceptance and recognition by the agents. The constitutive norms refer also to how roles define power and responsibilities in organizational structures, and how hierarchies structure groups and individuals.
- *Procedural* norms are instrumental norms aimed to encourage agents to comply with the regulative and constitutive norms. They express how decisions are made and are addressed to agents playing a role in the system. Thus, they define a practical link between the regulative and constitutive norms and the effects on complying with or violating them.

Ellickson (1991) proposes a slightly different classification comprised of five types of norms. His *substantive* and *constitutive* norms correspond exactly to the regulative and constitutive norms proposed by Boella and Van der Torre (2008). Nonetheless, the Boella and Van der Torre's procedural norm, also known as *enforcement* norms, is divided into

- *Procedural* norms specify how evidence is weighted and reactions administered once a norm is complied with or violated. It refers to the activities of gathering and assessing information that support the decision whether to enforce or not a norm.
- *Remedial* norms specify the nature and the magnitude (i.e., type and strength of the remedy) of the punishment (or reward) that an enforcer should use when deemed necessary.
- *Controller selection* norms specify which enforcers should be chosen to react upon a norm compliance or violation.

Thus, these enforcement norms (i.e., procedural, remedial, and controller selection) determine whether, how and whom should react to a violation or compliance with the substantive and constitutive norms.

Normative Multiagent System (NMAS) revolves around the idea that, like in human societies, individual and collective behaviors are affected (i.e., governed) by norms. Thus, they are a combination of normative systems and MAS, aiming to govern MASs and establishing the balance between the agents' interests and the desired global system's properties (SHOHAM; TENNENHOLTZ, 1992; CASTELFRANCHI, 1998; VERHAGEN, 2000; BOELLA; TORRE, 2003).

There have been a few definitions of NMAS over time. Initially, Carmo and Jones (2002) defined NMAS as "sets of agents (human or software) whose interactions can be regarded as norm-governed, whereby the norms prescribe how the agents should and should not ideally behave."

Although valid, Carmo and Jones definition has proved very limited and unfitted for MAS as it does not make any reference to the norm dynamics (i.e., norms life cycle). Boella, Van der Torre and Verhagen (2006) defined NMAS as "MAS together with normative systems in which agents, on the one hand, can decide whether to follow the explicitly represented norms, and on the other hand, the normative systems specify how and in which extent the agents can modify the norms."

More recently, however, there was a shift of interest from a more static view (i.e., *legalistic view*) to a more dynamic view (i.e., *interactionist view*) on norms.

The legalistic view to NMAS represents an approach in which the power structures among the agents are fixed. The norms specify the allowed agents' interactions, which are explicitly created by the system designer or a representative agent. The agents, however, are autonomous to comply with or violate the norms, thus the system (i.e., NMAS infrastructure components) implements enforcement mechanisms to govern the agents' behavior.

In the interactionist view, norms also specify the expected behavior of agents, yet they may emerge from agents interactions. Thus, governance cannot be completely delegated to the NMAS infrastructure and a different approach to enforcement is deemed necessary.

Due to this change of interest, Boella, Van der Torre and Verhagen (2008) propose an updated definition of NMAS in which they shift the emphasis from norm representation issues to the mechanisms used by the agents to govern themselves. Hence, they define NMASs as:

> a MAS organized by means of mechanisms to represent, communicate, distribute, detect, create, modify and enforce norms, and mechanisms to deliberate about norms and detect norm violation and fulfillment (BOELLA; TORRE; VERHAGEN, 2008).

Next, we describe in more detail these mechanisms and how they organize to create a process oriented model of norm life cycle.

3.2 Normative Processes

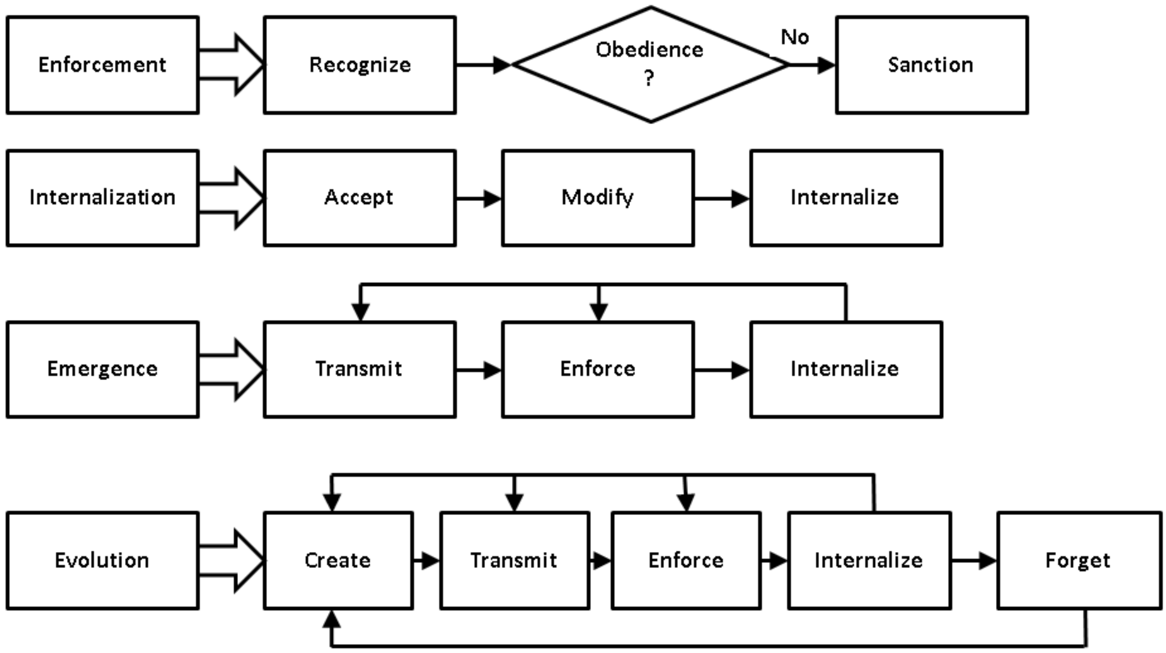
The interactionist view presumes that NMAS involves a set of norms and learning mechanisms based on reflecting upon actions' results. During a system lifetime, norms emerge and evolve to adapt to changes in the environment.

Hollander and Wu (2011), in line with this norms' dynamism, propose an evolutionary norm life cycle model based on a process oriented approach, as illustrated in Figure 4. The model is comprised of a set of processes structured in three main super-processes (*Enforcement*, *Internalization*, and *Emergence*) embedded in an end-to-end process (*Evolution* process).

This norm life cycle model begins with the creation (*Create* process) of potential norms as part of an evolutionary process (*Evolution* process). These new potential norms then spread through passive or active transmission mechanisms (*Transmit* process) and are enforced (*Enforce* process) in order to be internalized (*Internalize* process). The interaction among these processes constitute the *Emergence* process. A norm emerges whenever it has been accepted by a sufficient number of agents in the population.

The Emergence process makes use of the *Enforcement* and *Internalization* processes to encourage agents, via coercion (e.g., punishments) or incentives (e.g., rewards), to acquire and internalize norms. The internalization of a norm requires its acceptance

Figure 4 – Normative processes of norms' life cycle (HOLLANDER; WU, 2011).



(*Accept* process) and the change of the already existing set of norms to accommodate the new one (*Modify* process). Once internalized, the norm is reinforced by means of the Enforcement process. This process observes and infers the norms in the group (*Recognize* process), detects violating behaviors (*Obedience?*) and sanctions those that violated them (*Sanction* process).

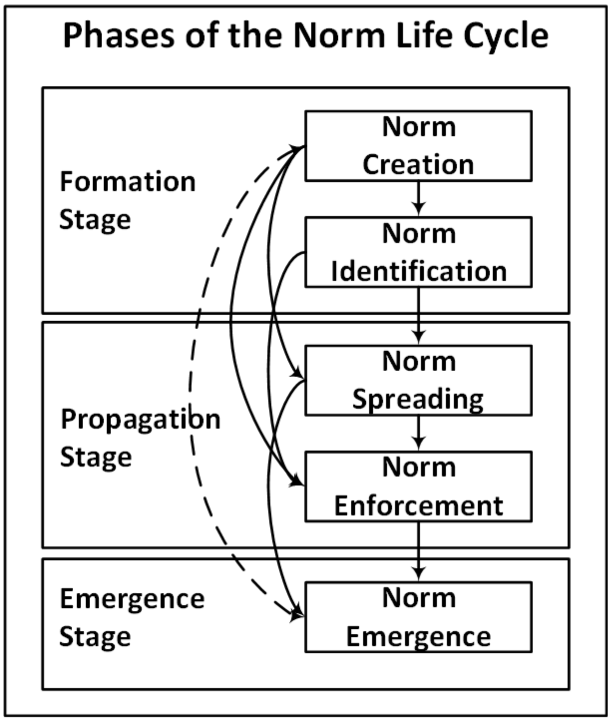
Eventually, an internalized norm may become invalid due to condition changes, thus becoming a candidate to be forgotten (*Forget* process). The creation and forgetting processes stand for the evolutionary characteristic of the proposal.

In this norm life cycle model, the enforcement mechanism plays an important role as it is involved in the dynamics of the two main processes of the norm life cycle (i.e., emergence and internalization). It thus influences directly agents behaviors and promote the stability and robustness of the norm life cycle.

Savarimuthu and Cranefield (2011) propose a similar norm life cycle model composed of three important stages (Figure 5). The *Formation stage* addresses how agents can create norm in a society and how individual agents can identify those that have been created. The *Propagation stage* explains how norms might spread and be enforced in the society. Finally, the *Emergence stage* determines the extent of the spread of a norm in the society. These stages of norms are realized through five phases:

1. *Norm Creation* represents the phase in which norms are defined, which may be done: (i) off-line by a designer, (ii) by a norm-leader, or (iii) by a normative agent.

Figure 5 – Phases of norm life-cycle (SAVARIMUTHU; CRANEFIELD, 2011).



2. *Norm Identification* represents mechanisms allowing the agents to recognize norms in the environment based on interaction with other agents. They may be based on (i) some learning mechanism, such as imitation, or (ii) inference in which the agents create its own notion of what the norms are according to their expectations, beliefs and goals.

3. *Norm Spreading* is the transmission of the norm among the society through spreading mechanisms, such as leadership, entrepreneurship, cultural and evolutionary.

4. *Norm Enforcement* is the discouraging of norm violation through a some form of sanctioning in order to sustain the norms in a society. The mechanisms usually used to enforce norms are punishment (or rewards), or reputation.

5. *Norm Emergence* is defined to be the reaching of a certain level of norm spreading and acceptance in the society. The emergence of the norm can be reversed whenever a norm decrease its acceptance of the norm and a new norm replaces the former among a significant threshold of agents.

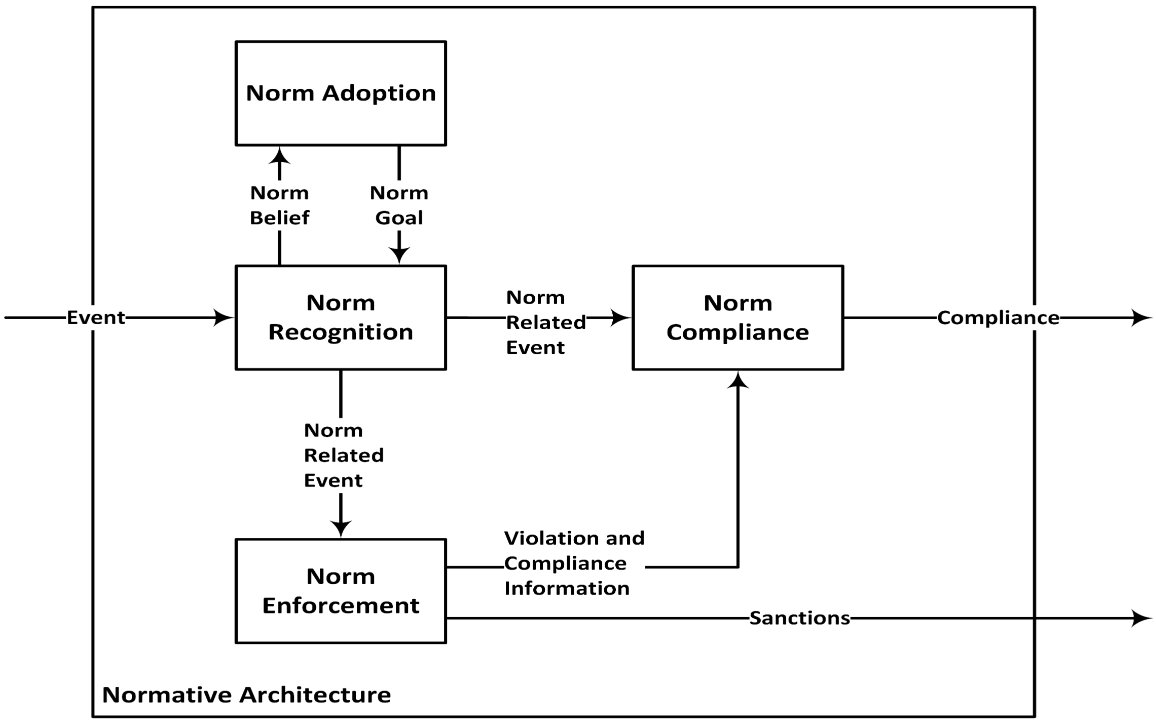
Looking from a cognitive perspective, Conte, Andrighetto and Campennì (2013) explain that norms influence agents by immerging in their "minds" and shaping their mental representations (i.e., beliefs, goals and intentions). It demands that the agents must be endowed with reasoning abilities to process and manage normative concepts (LUCK et al., 2013). Conte, Andrighetto and Campennì (2013) refer to these concepts as:

- *Normative Beliefs*: beliefs that a given behavior, in a given context, for a given set of agents, is either forbidden, obligatory or permitted (CONTE; CASTELFRANCHI, 2006).
- *Normative Goals*: goals associated to normative beliefs. A goal is pursued whenever a given set of world-state or events is held to be true or it is expected to be true in the future. They are dropped, however, as soon as they become false or unattainable, or because they conflict with more important goals.
- *Normative Actions*: actions resulting from the conversion, under certain conditions, of normative goals into intentions, i.e., executable goals.

These normative concepts are then produced and processed by different normative processes: (i) *norm recognition*, that produces normative beliefs; (ii) *norm adoption*, that possibly produces normative goals based on normative beliefs; (iii) *norm compliance*, that possibly converts normative goals into normative actions; and (iv) *norm enforcement* that monitors and motivates norm compliance.

Figure 6 illustrates an agent normative architecture that considers these processes and the interrelationship among them.

Figure 6 – Normative processes architecture based on (CONTE; ANDRIGHETTO; CAMPENNÌ, 2013).



3.2.1 Norm Recognition

Norm recognition refers to the ability of an agent to infer that a certain norm is in force in a group via observation and interaction with others (CONTE; CASTELFRANCHI; DIGNUM, 1999). More specifically, agents potentially acquire normative beliefs when they are exposed to the behaviors of others and to their explicit or implicit normative requests.

Norm recognition mechanisms are mostly inspired on the learning and cognitive approaches, similarly to the Norm Identification phase in Savarimuthu and Cranefield (2011). The learning processes are based on the *imitation* approach in which the agent mimics how the majority of the other agents in the group behave, or *social learning* approach in which the agent uses machine learning mechanisms for identifying possible patterns of behavior as norms. Conversely, the cognitive approach explores the mental capabilities of the agents to recognize a norm.

3.2.2 Norm Adoption

Norm adoption refers to the mechanism of accepting recognized norms that will influence the agents practical reasoning. It is a non-deterministic process in which the agent can decide to adopt or not a norm based on various endogenous and exogenous factors, leading to the formation of normative goals. Conte and Castelfranchi (1995) describe at some length the general mechanism by which an agent would adopt a norm. They identify that an agent adopts a norm (i) if it believes that this norm helps in a direct or indirect way to achieve one of its goals (*Instrumental* norm adoption), or (ii) for the simple fact that it is a norm (*Terminal* norm adoption).

The adoption of new norms may cause conflicts with existing norms and may render impossible for the agent to choose an action that is norm-consistent as complying with one causes the violation of another. Kollingbaum and Norman (2003b) define three adoption consistency levels: (i) the *strong consistency* in which the adoption of a new norm does not cause any conflict with previous adopted ones, (ii) the *weak consistency* in which the adoption of a new norm may possibly lead to an inconsistency, and (iii) the *strong inconsistency* in which the inclusion of the new norm will certainly conflicts with another.

3.2.3 Norm Compliance

Adopting a norm, however, does not mean that the agent will automatically comply with it. Norm compliance implies a normative process in which the agent decision to comply with a norm depends on a variety of other criteria (CONTE; CASTELFRANCHI; DIGNUM, 1999).

The agent may refuse to comply with a norm if it conflicts with a more important goal or with other norms that it has already decided to comply with. A goal deriving from a normative goal, therefore, does not necessarily lead to an actual normative action. A goal can be abandoned for a variety of reasons also. If a normative goal is not abandoned, it is transformed into a normative intention, and the agent will execute it, either by complying with or by defending the norm (i.e., promoting and enforcing the norm in its social group).

Conversely, if an agent refuses to comply with a norm, enforcing mechanisms may be applied for regulating its behavior and promoting norm compliance.

3.2.4 Norm Enforcement

Norm enforcement refers to the process in which agents monitor and encourage others to comply with the norms. The degree to which a norm is enforced plays a crucial role in its dynamics as it conveys a great deal of norm-relevant information that affects norm recognition, adoption and compliance processes. Thus, norm enforcement is a reinforcement mechanism that guarantees the stability and robustness of the norm life cycle.

Sanctioning is a means of norm enforcement in which a non-compliant behavior is potentially negatively sanctioned and a compliant behavior positively sanctioned. Sanction is a reaction triggered as a response to a violation or a compliance with a norm. Thus, it provides a foundation for how agents may seek to influence each other's normative decision-making. Two traditional approaches to the enforcement of norms are:

- *Institutional Approach*: This approach assumes a central authority that observes, controls or enforces agents' actions and interactions, and sanctioning them in case of normative behaviors. This approach ensures a high level of control over the actions and interactions.
- *Social Approach*: In this approach agents themselves are capable of sanctioning normative behaviors. To achieve such distributed control agents must be endowed with mechanisms for monitoring others, evaluate their behaviors and apply sanctions whenever appropriate.

It is important to remark that these approaches are complementary, and they can be employed simultaneously for the enforcement of norms. Chapter 4 describes in more detail some sanctioning norm enforcement mechanisms in social and computer sciences, in particular those that have been applied in NMASs.

We detail in the next two sections how these two perspectives have been applied on the implementation of NMASs. First, an institutional view of NMASs is presented in which a central authority is responsible for enabling and regulating agents interaction (Section 3.3). Next, a social perspective is provided in which the focus lies on normative agent architectures responsible for processing normative concepts (Section 3.4).

3.3 Normative Institutions Frameworks

The term institution has a variety of theoretical definitions that at best accounts for overlapping fields of social phenomena (MILLER, 2012). In line with Scott (2001), we refer to (normative) institutions as stable, yet changeable, social structures composed of a set of agents, as well as normative and regulative elements, which aims to enable and govern agents interactions.

A normative institution provides a normative system of reference under which the agents are encouraged to cooperate. When joining the institution, the agent implicitly abides to the set of norms that enable and regulate its possible interactions.

These features and the development levels of NMAS proposed by Boella, Torre and Verhagen (2008) leads to the understanding that normative institutions are a class of NMAS. Next, we present three frameworks implementing the concepts of normative institutions.

3.3.1 Electronic Institutions

Electronic Institution (EI) is a NMAS enabling the coordination of collective activities among autonomous agents in which their behaviors are influenced by norms supervised through an enforcement mechanisms (NORIEGA, 1997; ESTEVA et al., 2000). Its constructs mimic the coordination support that conventional human institutions provide (FORNARA et al., 2013). The conceptual core model of the EI includes a set of constructs that allow agents' actions and interactions (ESTEVA, 2003):

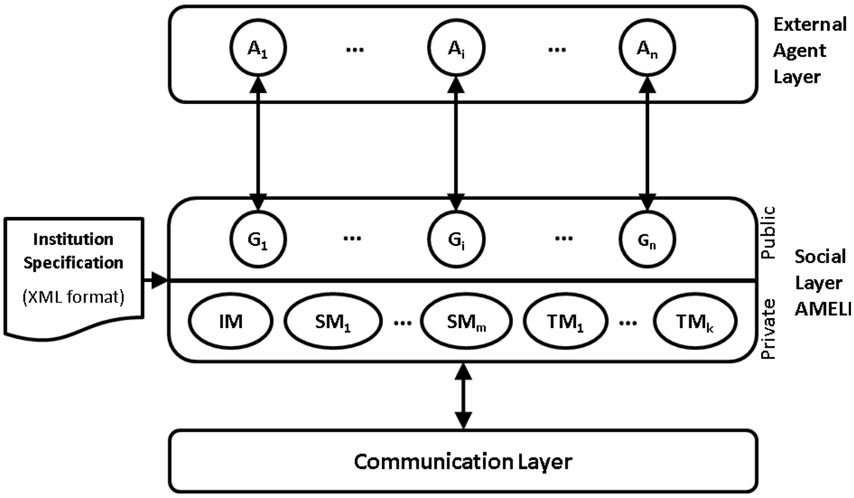
- *Agents and roles*. Agents are black-boxes, heterogeneous, self-motivated entities that are allowed to enter or leave the institution at any time, whereas roles define expected patterns of behaviors of the agents adopting them. Each role has a set of actions associated to it, which delineates the actions agents adopting the role may perform.
- *Dialogical framework*. The dialogical framework is a structure that consists of a set of roles and their relationship structure (social model), a set of language communication constructs that define the messages expressiveness (language model), and the institutional information state (information model).
- *Scenes*. Scenes represent interactions, defined through a well-defined communication protocol, among agents performing a specific role. An agent can participate in different scenes simultaneously.
- *Performative structure*. The performative structure defines the network of interconnected scenes and their transition conditions.

- *Normative rules*. The normative rules define the pre- and post-conditions of agents actions in a scene. It imposes constraints on the movement of agents between scenes, which affects their possible paths within the performative structure.

The agents' actions and interactions define the operational semantics of the EI, which requires the support of a computational architecture for its operationalization. This conceptual model can be implemented in different ways and AMELI (ESTEVA et al., 2004) is an implementation for the execution of EIs.

AMELI is a centralized institutional architecture for mediating agents interactions and it provides an interface for the agents to participate in the institution. Additionally, it controls the agents interaction by acting as an institutional enforcement mechanism (i) guaranteeing the correct evolution of each scene execution by filtering erroneous communications, (ii) guaranteeing that agents' movements between scenes comply with the specification, and (iii) controlling the acquired and fulfilled agents obligations.

Figure 7 – *Electronic Institution* architecture using AMELI (ESTEVA et al., 2004).



This architecture is composed of three layers (Figure 7): (i) the *External Agent Layer* that represents the agents participating in the institution, (ii) the *Social Layer* that implements the control functions of the institution infrastructure, and (iii) the *Communication Layer* that provides the data transport service. These layers are populated with four different types of agents (ESTEVA et al., 2004; FORNARA et al., 2013):

- *Institution Manager* (IM) initializes and terminates the institution. It also authorize the entry of agents into the institution and manages the creation and execution of new scenes. It keeps information about all participants and scenes executed. Each institution has one IM.

- *Transition Manager* (TM) manages the transition of agents between scenes by controlling which transitions and agent moves are allowed.

- *Scene Manager* (SM) controls a scene execution by starting and closing the scene, keeping track of agents that enter and leave the scene, updating the state of the scene, and coordinating with the TM to let agents in or out. Each scene execution is controlled by one SM.
- *Governor* (G) mediates agents' participation in the institution by mediating all the communications between the institution and agents. There is one G for each participating agent in the institution.

The original EI design proposes a regimented mechanism for enforcing norms. Thus, all communications with the institution are checked to identify whether they comply with the established norms. If a norm violation is detected, the communication is dropped by the infrastructure before being processed by the institution. This prevents any violation to happen in the institution.

Due to the restrictiveness of this mechanism, García-Camino (2010) proposes an extension known as AMELI$^+$ to address the regulation of the behavior of autonomous agents in the EI. In AMELI$^+$, agents may violate norms; however, even though the infrastructure does not block the violations, it detects them and thus can react accordingly. Although incorporating such flexibility, the EI infrastructure is still responsible for controlling all the actions that are going to be executed in the context of the institution.

3.3.2 OperA

Dignum (2004) proposes the OperA (Organizations per Agents) framework, which is an organizational specification model for MAS that governs how member agents should act according to social requirements. This model aims to integrate the global goals of an organization with its autonomous and heterogeneous member agents goals.

The model allows the specification of organizations in a conceptual level using the notions of *groups* and *scenes*. A group is a set of roles. Roles are described in terms of objectives (i.e., what an agent playing the role is expected to achieve), and norms (i.e., how the agent is expected to behave). A role has rights associated to it. There are two types of roles, *institutional* and *external* roles. An institutional role can only be performed by a member of the organization, whilst an external role does not hold this constraint.

A scene is composed of a set of roles or groups, a set of final states that the agents should achieve by executing these roles, a set of actions that allow the agents to achieve such states and a set of norms that govern the agents behaviors in a scene.

The OperA architecture is composed of three main components (Figure 8):

- The *Organizational Model* specifies the organizational structure of a society in terms

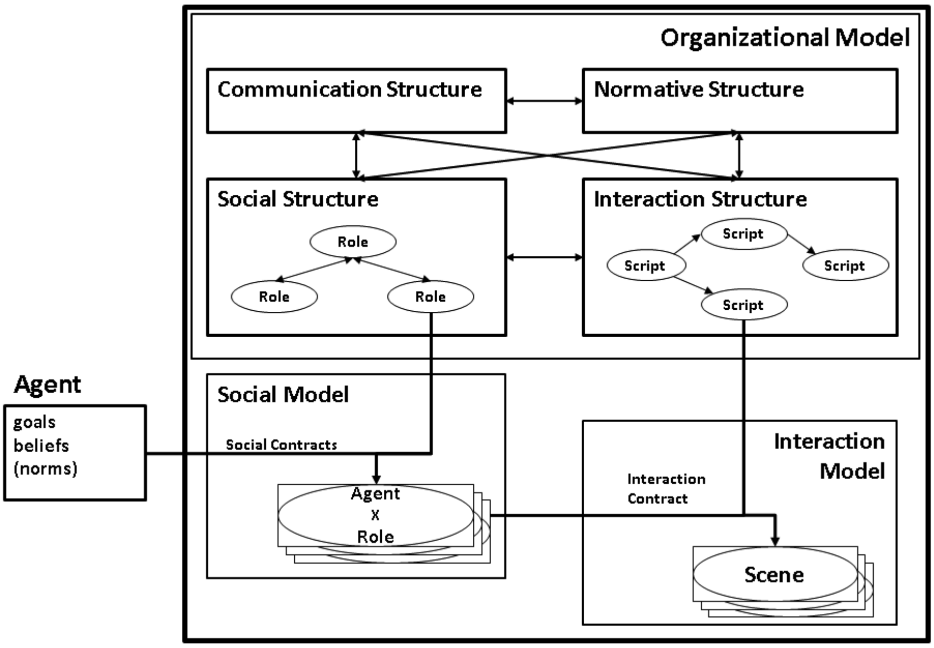


Figure 8 – OperA architecture (DIGNUM, 2004).

of four structures: (i) the *Social Structure* that specifies the objectives of the society, the possible roles available, and the model governing its coordination, (ii) the *Interaction Structure* that specifies the tasks requiring the coordinated actions of several roles and the sequence of scenes to execute, (iii) The *Normative Structure* that specifies the social norms and regulations in terms of roles and interaction norms, and (iv) The *Communicative Structure* that specifies the ontologies describing the application domain and the communication structures.

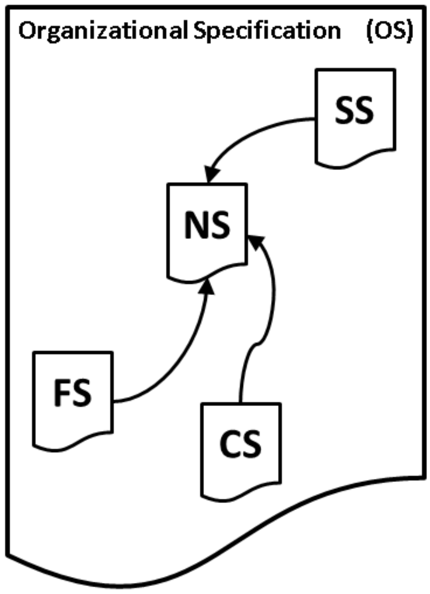
- The *Social Model* specifies the enactment of roles by individual agents. The enactment is done through social contracts that describes the capacities and responsibilities of the agent within the organization. A social contract defines the activities that the agents are allowed to perform in the organization.
- The *Interaction Model* allows the creation of concrete interaction scenes by agents enacting a role, based on the scripts specified in the organizational model.

The admissible actions of each scene are regulated by a set of norms. These norms are associated to reactions, i.e., sanctions, which are applied in case of norm violation. In OPERA, the task of checking whether an action complies with or violates a norm is performed by a monitoring infrastructural agent, named Trusted Third Party (TTP). This agent monitors the system at run-time and whenever it detects a violation, it applies the predefined sanctions associated to the violated norms. Nonetheless, the TTP does not have the autonomy to decide which sanction to apply in each situation.

3.3.3 $\mathcal{MOISE}^{Inst}$

The $\mathcal{MOISE}^{Inst}$ model (GÂTEAU et al., 2005; GÂTEAU, 2006; GÂTEAU, 2007) is an extension of the $\mathcal{MOISE}^{+}$ (Model of Organization for multI-agent SystEms) model (HÜBNER; SICHMAN; BOISSIER, 2002). The $\mathcal{MOISE}^{+}$ is an organization model whose structure is specified in terms of *roles*, *groups* and *links*. The $\mathcal{MOISE}^{Inst}$ extends this model by including *norms* to govern agents' behaviors.

Figure 9 – $\mathcal{MOISE}^{Inst}$ organizational model overview (GÂTEAU, 2007).



The $\mathcal{MOISE}^{Inst}$ organization model (Figure 9) is specified by an *Organizational Specification* (OS) that is formed by a *Structural Specification* (SS), a *Functional Specification* (FS), a *Contextual Specification* (CS) and a *Normative Specification* (NS).

The SS specifies the organization structure expressed by a set of *roles*, *groups* and *links*. A group is a set of roles and links. A role specifies constraints to the agents' behaviors, while a link connects two roles in the same group.

The FS specifies the collective objectives to be achieved by the organization in terms of *social schemes*. A social schema is a tree structure composed of goals/subgoals and missions. It specifies the sequence of steps that agents must perform to achieve the specified organizational objectives.

The CS captures constraint on the organization evolution as a set of *contexts* and possible transitions among them. Contexts express the conditions an agent playing a role have to respect. Transitions represent the changes from one context to another due to the occurrence of certain events.

The NS specifies a set of norms that links the SS, FS and eventually a CS via a context, an issuer, a bearer, a mission and a deontic operator. Norms determine a right or a duty of a role or a group in a specific context and mission. Norms are specified using deontic logic and they express permissions, obligations and prohibitions of missions referring to goals. NS also allows the specification of a special kind of norm, i.e., *sanction* norm, that is linked to a main norm. This norm specifies the actions to be performed if the main norm constraints are violated.

These four specifications form the OS, whose instance forms an *Organizational Entity* (OE). The OE is built by instantiating the OS through a set of agents playing roles, organizing themselves and behaving as specified in the OS. Besides, agents are governed by an arbitration system, $\mathcal{S}YNAI$ (GÂTEAU et al., 2005).

$\mathcal{S}YNAI$ is an arbitration system that manages and controls the functioning of the OE. It is composed of a set of manager agents supervising the (application) agents actions. These supervising agents serve as an interface between the application agents and the organization. Thus, they are capable of monitoring all the agents communications with the organization. Nonetheless, $\mathcal{S}YNAI$ allows agents to execute actions that violates norms, but due to the certainty of violation detection, every violation is enforced by applying the sanctions specified in the NS (identical approach used in AMELI$^+$).

3.4 Normative Agent Architectures

Unlike the institutional approach, norm-govern agency implies that individuals have the capacity of dealing with explicit representations of normative concepts. This is realized through normative agent architectures that enable agents to regulate their behavior by means of norms. In the next sections, several normative agent architectures are described.

3.4.1 BOID

The BOID (Beliefs-Obligations-Intentions-Desires) architecture (BROERSEN et al., 2001; BROERSEN et al., 2002) deals with the decision of selecting goals in a noisy environment, where the agent is overloaded with input data.

This architecture extends the Belief-Desire-Intention (BDI) architecture by introducing the explicit notion of *obligations* representing norms (i.e., external motivational attitudes) as mental states. Obligations interact with beliefs, desires and intentions to generate candidate goals. Conflicts among mental attitudes are solved based on overriding mental states, in which a mental attitude is used at the expense of another. According to the different overriding priorities that are specified in terms of ordering functions, a set of agent types is defined: *realistic*, *stable*, *selfish* and *social* (BROERSEN et al., 2001).

BOID agents' always consider norms in the same manner; that is, they cannot decide to comply with or violate a given norm according to their circumstances (LUCK et al., 2013). Hence, they do not take into account any aspect of norm enforcement due to the impossibility of violating norms.

3.4.2 NOA

The NOA architecture (KOLLINGBAUM; NORMAN, 2003a) also extends the classic BDI (Belief-Desire-Intention) architecture by considering the representation of new normative elements: *obligation*, *permissions* and *prohibitions*. NOA agents use obligations as the main element influencing their actions, while prohibitions and permissions constrain the agents' actions by filtering those forbidden and those that would produce forbidden effects. Permissions supersede prohibitions.

NOA agent's behaviors are based on reactive planning and they are determined by beliefs, norms and plans. The beliefs are used as input to (de)activate obligations, which motivate the achievement of a state of affairs or the performance of primitive actions. Plans are then selected and instantiated so the agent may achieve the state of affairs, or execute the specified primitive actions affecting the world or updating the agent's beliefs.

Even though not explicitly mentioned, the filtering of plans plays a role as norm enforcer and its implementation is important to define how the enforcement is performed. A filter mechanism that removes all forbidden actions or plans prevents agents from violating norms. Otherwise, if it only labels those violating actions as forbidden, it allows agents to deliberate and decide whether or not to execute them instead of preemptively block them. No further detail, however, is provided in the NOA literature with respect to the norm enforcement process.

3.4.3 EMIL-A

EMIL-A (EMergence In the Loop) is a normative agent architecture which consider the norms' dynamics as a complex loop (ANDRIGHETTO et al., 2007; CONTE; ANDRIGHETTO; CAMPENNÌ, 2013). This architecture enables agents to (i) learn norms governing their environment and (ii) recognize the degree of relevance of a norm within their social group; that is, the norm salience (ANDRIGHETTO; VILLATORO; CONTE, 2010; VILLATORO et al., 2011; CONTE; ANDRIGHETTO; CAMPENNÌ, 2013).

The norm salience measures how strongly a norm is perceived within a group and it is updated according to the behaviors of the own agent and the behavior of other agents in its group. Formally, the norm salience is updated according to the Equation 3.1.

$$Sal_t^n = Sal_{t-1}^n + \frac{1}{\alpha \times \phi}\left(w_c + O \times w_o + NPV \times w_{npv} + P \times w_p + S \times w_s + E \times w_e\right) \quad (3.1)$$

where, Sal_{t-1}^n is the salience of norm n at time $t-1$, α is the number of neighbors that the agent has, ϕ is the normalization value, w_x is the weight specified in Table 1, and O, NPV,

P, S and E corresponds to the number of occurrences of each cue observed at time t. The resulting salience $Sal_t^n \in [0, 1]$ is subjective to each agent.

Table 1 – Norm salience weight values (ANDRIGHETTO; VILLATORO; CONTE, 2010).

Cue	Description	Weight
C/V	Own Norm Compliance/Violation	$w_c = (+/-)0.99$
O	Observed Norm Compliance	$w_o = +0.33$
NPV	Non-Punished Violators	$w_{npv} = -0.66$
P	Observed/Applied/Received Punishment	$w_p = +0.33$
S	Observed/Applied/Received Sanction	$w_s = +0.99$
E	Observed/Applied/Received Norm Invocation	$w_e = +0.99$

EMIL-A agents are endowed with cognitive modules that allow them to (i) infer new norms (i.e., normative beliefs) from observation and interactions (*Norm Recognition* module), (ii) decide whether or not to adopt normative beliefs as normative goals, i.e., normative beliefs to be pursued (*Norm Adoption* module), and (iii) determine whether or not to comply with normative goals converting them into normative intentions, i.e., normative actions (*Norm Compliance* module).

These modules' operation is influenced by the salience of the norm, which plays a major role in the acceptance or rejection of the norms, as well as in the decision whether to comply with or violate them. The agent behavior in turn may use enforcement mechanisms that are used to spread norms to other agents, thus influencing them in changing their norms salience. Hence, the more a behavior is believed to be salient, the more it will be complied with, and the more the corresponding norm will be enforced. This complex loop leads to the stability and robustness of the normative process that may culminate with the norm internalization.

The norm enforcement mechanism plays a significant role in the EMIL-A agents' behavior, as it is the mechanism whereby agent implicitly signals the importance it attributes to the norm. Andrighetto, Villatoro and Conte (2010) implements a norm enforcement mechanism in which an agent may sanction a norm violator by means of two different types of sanctions: *strategic* and *normative*. Both negatively affects the utility of the punished violator; however, the normative sanction is also accompanied by a deontic message making explicit the existence of a norm. Although enabling different types of sanctions, agents are hard-wired with a specific type of sanction at design-time. More recently, Villatoro et al. (2011) improved this mechanism by allowing agents to adapt the strength of the sanction based on the number of observable violators.

3.4.4 Normative AgentSpeak(L)

Normative AgentSpeak(L) (MENEGUZZI; LUCK, 2009) is an extended AgentSpeak(L) (RAO, 1996) interpreter that includes mechanisms allowing agents to adapt at runtime to norms constraining their behavior. This adaptation is achieved by enabling agents to enact behavior modification in response to newly accepted norms. These modification mechanism works exclusively with prohibition and obligation norms. For prohibition norms, the mechanism temporarily remove the violating plans from the plan library. For the obligations, new plans are created to enable the agent to accomplish the norms.

The Normative AgentSpeak(L)'s modification mechanism enforces compliance with norms, preventing the agent from violating them. Equivalently to the BOID architecture, Normative AgentSpeak(L) does not consider any aspect of norm enforcement in its specification.

3.4.5 MDP Architecture

Fagundes, Billhardt and Ossowski (2010) propose an architecture for normative rational self-interested agents capable of reasoning about the possibility of violating norms. This agent architecture uses the Markov Decision Process (MDP) framework to represent the agent's knowledge about norms and sanctions. Due to the acceptance of a new norm, agents generate *would be* worlds and their expected utility considering the norm and its sanctions. The agent decides to violate the norm if the expected utility by violating is greater than by complying with the norm.

More recently, the authors developed a norm enforcement mechanism based on the detection of violating states in terms of imperfect observations (FAGUNDES; OSSOWSKI; MENEGUZZI, 2014). Thus, the mechanism detects violations with a certain probability, yet whenever detected the violator is materially sanctioning (i.e., a cost is inflicted on the violator).

3.5 Discussion

In this chapter, we described the main features and processes comprising the NMASs and two implementation perspectives to NMASs were presented: the institutional and the social. The institutional perspective corresponds to a centralized approach in which the control of the agents actions are performed by a central infrastructural component, which gives complete control to the system, yet rendering it inflexible.

The social perspective focuses on the normative agent architecture and, specifically, in the agents reasoning to comply with or violate a norm. Regarding the normative processes described in Section 3.2, the norm enforcement process was the least tackled by the analyzed architectures despite its importance as highlighted.

As our aim is develop an sanctioning enforcement model to NMASs, in the next chapter we present a review of the terms “sanction” and “enforcement mechanism” employed in social and computer sciences.

4 Sanctioning Enforcement

In this chapter, the notion of sanction and its use within sanctioning enforcement mechanisms gleaned from diverse disciplines is presented. First, a general definition of sanction is provided in Section 4.1. Next, in Section 4.2 the aspects of sanctions and sanctioning enforcement prevailing in the perspective of social sciences is described. Similar analysis from the computational perspective is presented in Section 4.3. Finally, a comparative analysis of both perspectives, showing their similarities and dissimilarities, is shown in Section 4.4.

4.1 Sanction Definition

Etymologically, the term *sanction* has its origins in two roots, the Latin words *sanctionem* and *sanctus*, that date back to the 14^{th} and 15^{th} centuries, respectively. The former means the "act of decreeing", and the latter, which *sanctionem* apparently derives from, means "to decree, confirm, ratify, or make sacred" (HARPER, 2010). More recently, however, the term sanction has also assumed a different connotation, meaning the imposition of a penalty for disobeying a norm or granting a reward in case of complying with it. The American Heritage Dictionary (PICKET, 2011) recognizes these meanings:

> (i) To give official authorization or approval to, as when a legislature sanctions a presidential action;
> (ii) To encourage or tolerate by indicating approval;
> (iii) To penalize, as for violating a moral principle or international law.

These meanings clearly put in evidence the conflicting aspect within the concept of sanctions. In one hand, definition (i) implies that sanctions are the provisioning of an authorization, e.g., the sanctioning of a law by the president; on the other hand, definitions (ii) and (iii) imply respectively the granting of rewards (i.e., encourage or tolerate) and the imposition of punishments (i.e., penalize). These meanings are reflected in the literature on sanctions, with the computing literature emphasizing the definition (iii).

In the next two sections, the existing literature of sanctions is reviewed from the social and computer sciences perspectives, respectively, aiming to propose an enriched typology of sanctions in Chapter 5 and an adapted sanctioning enforcement model in Chapter 6.

4.2 Sanctions in Social Sciences

The concept of sanction has been the focus of study in a wide range of social sciences disciplines like Law, Sociology, Psychology, Economics and Political Sciences. Reviewing the literature reveals a variation in the meaning and use of the concept between, and within, these disciplines, each of which is discussed next.

4.2.1 Law

Law has several legal theories, among which the two great traditions are *natural law theory* and *legal positivism* (PATTERSON, 2010). These theories basically differ on the role played by morality in determining the authority of legal norms. In *natural law theory*, the authority of legal standards necessarily derives, at least in part, from considerations associated to the moral merit of those standards (FINNIS, 2011). In *legal positivism*, however, the existence and content of law depend on social facts and not on its merits (no connection between law and morality) (GARDNER, 2001; PATTERSON, 2010, ch. 14).

Legal positivism is nowadays dominant among the various legal theories (PATTERSON, 2010). In this tradition, law is an instrument of social order, but one that emanates from the state and is enforced through legal sanctions by recognized state institutions. These features distinguish law from other forms of social control, such as religion, moral codes and customs. Firstly, because it requires the existence of a sovereign entity, the state, without which it is impossible to maintain the social order. It has originally been proposed in the work *Leviathan* of Thomas Hobbes (1651) that considers the state as the primary source for creating rules and enforcing them into the society. Secondly, because it distinguishes legal sanctions from other kinds of sanctions by requiring that the enforcer institutions possess specific powers granted by the state.

Hence, legal sanctions are reactions enforced by the state or empowered entities that seek to induce individuals to comply with legal rules (GARNER, 2010). Although reactions may be negative or positive, law frequently considers negative reactions as the only means to enforce obedience (SCHWARTZ; ORLEANS, 1967). Legal sanctions can be of different forms and types, such as imprisonment, probation, fine, community service, suspension, or revocation of business, professional or hobby licenses.

Some legal theorists, e.g., Ellickson (1991), Posner and Rasmusen (1999), Posner (2000), Meares, Katyal and Kahan (2004), oppose the interpretation of sanctions as enforced only by the state. They argue that informal forms of regulation (i.e., those enforced by peers), such as gossip, disapproval and ostracism, remain important. Posner and Rasmusen, for instance, identify several of these sanctions: (i) *Automatic* – the sanction is the direct consequence of the violator's action not being coordinated with the actions of others, (ii) *Guilt* – the violator feels bad by knowing that he has behaved in an inappropriate way, without others coming to know about it, (iii) *Shame* – the violator feels bad because he perceives his action has reduced the others' evaluation about himself, (iv) *Informational* – the violator unintentionally provides information about himself that he would not like others to know, (v) *Bilateral costly* – punishment inflicted on the violator by a second-party or third-party, and (vi) *Multilateral costly* – punishment inflicted on the violator by a second-party and third-parties, or only by third-parties.

Legal and informal sanctions may be complementary or conflicting, producing some cases of interaction between both as noted by Panther (2000), Baker and Choi (2014): (i) the informal sanction may adapt to the legal one reinforcing it, (ii) the informal sanction shapes the creation of a legal sanction, (iii) the informal sanction may substitute the legal sanction, or vice-versa, meaning that relying more on one kind of sanction reduces the need for the other, or (iv) a special situation in which an informal sanction may be illegal with respect to the current legal one.

Regardless of the universal adoption of (legal or informal) sanctions for enforcing compliance, there is still an open debate in law and philosophy revolving around the question 'What justifies the infliction of sanction (punishment) on people?'. According to Hart (1968, p. 1-27), such answer should address three distinct issues: (i) What justifies the creation and maintenance of a sanctioning system? (ii) Who may be sanctioned? (iii) How should the appropriate amount of sanction be determined? Existing theories differ in how they address these concerns (DAVIS, 2009).

holding that the consequences of one's conduct are the ultimate basis for any judgment about the rightness or wrongness of that conduct.

The *consequentialist* theory justifies sanctioning by reference to its consequences, in which individuals are discouraged to misbehave due to the fear of being sanctioned. A form of consequentialism is *utilitarianism*, which views sanctioning as a cost-effective means to prevent future misbehaviors (BECCARIA; INGRAHAM, 1819; BENTHAM, 1823; MILL, 1871). Typical consequentialist mechanisms include (CAVADINO; DIGNAN, 2002, ch. 2):

- *Deterrence* that involves causing fear among potential violators. It is subdivided into (i) *individual deterrence*, in which an individual after being sanctioned avoids misbehaving, and (ii) *general deterrence*, in which an individual that observes someone being sanctioned will have an incentive for not behaving similarly in the future (NAGIN, 1998). Respective examples are (1) an energy broker being levied a fine for violating a commitment to provide a certain amount of energy, presumably leading it to create internal controls to avoid future violations, and (2) brokers who observe another broker being penalized may develop controls to avoid such violations themselves.

- *Incapacitation* that prevents future misbehavior temporarily or permanently. For example, imprisonment incapacitates a would be perpetrator by restricting his movements. In a trading scenario, for instance, a trader's account may be temporarily suspended restricting his capacity to misbehave.

- *Reform* that improves a violator's character or behavior to make him less likely to violate the norm in the future. For instance, the obligation of attending extra driving classes after being caught by police driving in high speed multiple times, or demand an energy provider to train its employees in order to reduce the risk of future power interruptions.

Conversely, the *retributive* theory seeks to sanction an offender proportionally to the magnitude of his misbehavior and does not consider the possible future consequences of the sanctioning. It scales the level of sanction to the severity of the misbehavior. Thus, in case of an energy blackout caused by an energy provider, the penalty would be calculated based on the aggregate damage that such interruption of energy caused to its consumers.

4.2.2 Sociology

Radcliffe-Brown (1934) may have been the first sociologist to define sanctions. He defines them as a society's (or a "considerable number" of its members) reaction to an approved or disapproved behavior. Gibbs (1966), however, states that not all reactions to a behavior can count as sanctions and defines a set of criteria under which it counts as such. A sanction (i) requires a *referential*, typically a set of norms, (ii) is applied by at least one *enforcer*, (iii) is associated with a *prescription*, (iv) specifies its *enforcer*'s role, and (v) specifies whether it is to be *perceived* to be a sanction by its target.

Generally, sanctions are used to ensure the compliance of individuals to desirable norms, i.e., prescribed behaviors shared and enforced by a community (BICCHIERI, 2006). Sanctions therefore include not only legal punishments, but also informal rewards and esteem by community members.

Radcliffe-Brown (1934) proposed a first classification of sanctions. A sanction may be *positive* or *negative*. A sanction may be *diffuse* (i.e., individual action) or *organized* (i.e., applied according to some social tradition and recognized procedure). For example, a legal sanction would be *negative* and *organized* since it is enforced by a recognized authority.

Morris (1956) proposes a classification of sanctions that includes six dimensions: *reward-punishment* ("more reward than punishment" to "more punishment than reward"), *severity* ("light, unimportant" to "heavy, important"), *enforcing agency* ("specialized, designated responsibility" to "general, universal responsibility"), *extent of enforcement* ("lax, intermittent" to "rigorous, uniform"), *source of authority* ("rational, expedient, instrumental" to "divine, inherent, absolute, autonomous"), and *degree of internalization* ("little, external enforcement, required" to "great, self-enforcement, sufficient").

Gibbs (1966) proposes an alternative classification of sanctions based on four dimensions:

- *Type*. Defined as *internal* or *external* with respect to the individual who enforces it (MILL, 1871, ch. 3). An *internal* sanction comes from the individual's own mind, involves feelings resulting from personal morals, and whether or not the individual internally regrets a prior action. An *external* sanction reflects disapproval from others, such as peers or governmental institutions (i.e., police and judiciary).
- *Direction*. A *positive* sanction is a reward granted for compliance with a norm; a *negative* sanction is a punishment inflicted because of violation of a norm.
- *Source*. A *formal* sanction is applied by a recognized social institution and an *informal* sanction by a peer.
- *Effect*. A *preventive* sanction has the purpose of influencing behavior to promote compliances or prevent violations. The *inducement* of individuals to comply is a form of a preventive sanction. A *deterrent* is a sanction applied prior to compliances or violations. Examples are sanctions based on the *hedonic* conception, which involve physical or moral pain, or positive stimulation.

More recently, Clinard and Meier (2008) proposed a simpler classification of sanctions based on two dimensions. *Direction* can be *positive* or *negative*. *Source* can be *informal* or unofficial, *formal* or official.

Although sociology emphasizes informal sanctions, it recognizes the need for multiple forms of sanctions to coexist for effective social control, and that institutionalized (legal) sanctions can be more effective for social control rather than informal ones (MEIER, 1982; MIETHE; LU, 2005).

Traditionally, three basic mechanisms are used for tackling the social control issue: (i) the *government* that has the power to impose penalties to non-compliant behavior, (ii) the *market* that provides incentives to productive activity, and (iii) the *education* which enables the internalization of appropriate values and reduces the dependence on the government and the market.

Horne (2009), in addition, proposes a relational theory of enforcement that highlights the importance of social relations and the importance of peers to social control. This theory and empirical evidences support that people care not only about the consequences and meanings of a typicality of behavior, but also about their relations (e.g., dependence, influence, persuasion power) with others and their reactions to sanctions.

4.2.3 Psychology

Psychology sees sanctioning as essential for the maintenance of social life (CARLSMITH, 2006). Indeed, sanctions are studied in psychology from the perspectives both of the sanctioner and the sanctionee. Regarding sanctioners, the primary psychological approach emphasizes understanding individuals' motivations and justifications for punishing (GABRIEL; OSWALD, 2007; CARLSMITH; DARLEY; ROBINSON, 2002; PETERSEN et al., 2012). Regarding sanctionees, operant conditioning (SKINNER, 1938) involves modifying an individual's behavior as a consequence of the sanction.

More specifically, psychological-based sanction theories approach the following questions: 'Why and when do people tend to punish behavior that violates legal or informal norms of society? Which type of sanction do people use to punish? How severely do people want to punish? What are they trying to achieve?' (CARLSMITH; DARLEY; ROBINSON, 2002; PETERSEN et al., 2012). Hence, it seeks to identify the factors that influence people's punishment decisions.

Recalling the distinction between *deterrence* and *retribution* (see Section 4.2.1), Carlsmith (2006) conducted experiments from which he concluded that individuals' sentencing decisions are affected primarily by retribution, even though they express preference for utilitarian goals (deterrence) when legislating. That is, individuals relate the sanctions and their severity to the harm they perceive from a violation: a more serious misbehavior calls for a more severe sanction.

Extending the idea of proportionality, Petersen et al. (2012) argue that individuals base their decisions about sanctions and their severity on two factors: the seriousness of an offense and the offender's long-term value as an associate. These factors depend upon environmental cues, such as the offender's violation history, status (in-group or out-group), past contributions, expression of remorse, and kinship with the individual judging. According to experimental results, an individual's decision on whether to sanction depends upon the offender's value to them and not only on the seriousness of the offense. In contrast, the seriousness of the offense determines the intensity of sanction applied. Therefore, an individual may apply a rehabilitative sanction to an offender when the former perceives the latter to hold some social worth.

4.2.4 Economics

The economic theory analyzes sanctions under the economic theory of law enforcement, which assumes that individuals are rational utility maximizers influenced by deterring incentives (BECKER, 1968). This utilitarian characteristic is what mainly distinguish the economic approach to others. Accordingly, it assumes that the individuals violate legal rules if the expected gains obtained by violating them exceed its costs. Becker (1968) models the expected utility (EU) of a violation as

$$EU = p \times (b - f) + (1 - p) \times (b) \tag{4.1}$$

where, p is the probability of being sanctioned, b is the gains obtained with the violation (if undetected), and f is the sanction severity.

The core conclusion drawn from Equation 4.1 is that violation is discouraged by increasing the probability of detection (p) or the severity of sanction (f). For example, by allocating more resources to law enforcement, the state would increase the certainty of sanction, which would reduce the violation gains, causing the reduction of the number of violations. Hence, the economic theory of optimal law enforcement supports that sanctions should be maximal, so that the probability of detection could be reduced to a minimal, reducing consequently the amount of law enforcement resources needed (STIGLER, 1970; GAROUPA, 1997).

The optimal law enforcement theory, however, disregards the costs associated with sanctioning. Whenever taken into account, the maximal sanction is not anymore always an optimal solution and the trade-off between the probability and severity of sanction should be evaluated. Polinsky and Shavell (2007) identify four major sanctioning criteria that influence such balance:

- *Rule* determines the violators that should be sanctioned based on liability, *strict* or *fault-based*. The strict liability implies that the violator is sanctioned whenever he has been found to cause a harm. In the fault-based liability, sanction is applied only if the violator harm is due to the violation of a standard behavior.
- *Form* determines the form of sanction to employ: *monetary* (i.e., fines), *non-monetary* (i.e., imprisonment) or a combination of both. The main difference between monetary and non-monetary sanctions is their cost of application.
- *Magnitude* determines the severity of the sanctions for each type of violation.
- *Resource* determines the amount of resources allocated for detecting and sanctioning violators.

Generally, these criteria are set differently depending whether the entity responsible for the law enforcement is *public* or *private*. Their differences regard their final goals and source of the resources for enforcing the law. The public law enforcement uses governmental institutions and agents to enforce the law (i.e., police, prosecutors, and judges) and its main goal is the maximization of the social welfare; whilst the private law enforcement uses private resources and agents instead (i.e., security guards) and has as its main goal the profit (POLINSKY; SHAVELL, 2007).

Becker and Stigler (1974) suggests that private law enforcement is more advantageous than public in all situations. Nonetheless, Landes and Posner (1975) oppose to their general approach stating that private law enforcement is more effective to certain types of violations, primarily those that can be detected and punished at near zero cost (i.e., identity of violators are easily available). Public law enforcement, however, is preferred in cases that involves the identification, the gathering of private information or the capturing of the violator.

A clear distinction of these two types of law enforcement is observable between contract law and criminal law enforcement (KLÖHN, 2011). In contract law, contracts are usually enforced by the involved parties as they are the best observers of violations and can better evaluate whether, when and how to enforce a violation. A hybrid strategy may also be employed in which once the disagreement is not solved privately, it is assigned to a public law enforcement institution resolution. In criminal law, however, the process involves the identification and the capture of the violator requiring a great effort that may not motivate private enforcers due to the low profitability or the required infrastructure and authoritative power needed.

4.2.5 Political Sciences

In political sciences, sanctions are considered as "a punishment or the permission to act, depending on its context" (SULLIVAN, 2009). The term thereby often refers to political, military and economic sanctions (KIRSHNER, 2002), i.e., penalties or some coercive measures (negative sanctions), designed to influence the conduct of a group or a country. Examples of such (negative) sanctions are trade and arms embargoes, travel restrictions and revoking diplomatic ties.

Often three different aspects of sanctions and sanctioning enforcement are discussed in political sciences: (i) the reasons for sanction, including thresholds for when it should be applied (LEKTZIAN; SPRECHER, 2007), (ii) the target and executors of a sanction, i.e., whom the sanction is aimed to and who executes it (e.g., who revokes diplomatic ties) (DREZNER, 2000; BARRETT, 1999), and (iii) the success of the sanction with respect to its intention (CORTRIGHT, 2001; DORUSSEN, 2001).

The latter aspect has been heavily discussed in the political science literature, as there is no agreement on the efficiency and success of negative sanctions, and whether positive coercion as stimulant for 'correct' behavior should be considered under the term sanction (BALDWIN, 1971). Thus, most political scientists pay little attention to the distinction between positive and negative sanctions or explicitly reject the idea (DAHL, 1970, p. 32-33).

4.3 Sanctions in Normative Multiagent Systems

As pointed out by Balke (2009) with respect to sanctioning, the NMAS literature builds on traditional areas such as sociology, economics, psychology and cognitive sciences. Although used in many works in NMAS, a more comprehensive understanding of the term sanction has been neglected or, at least, not broadly addressed yet. In the next sections, we present works related to sanctions in the context of NMASs.

4.3.1 Typologies of Sanction

The literature on NMAS offers few proposals of typology of sanctions. Pasquier, Flores and Chaib-draa (2005) propose a typology along three dimensions:

- *Direction*, which specifies the content of a sanction, *negative* or *positive*, respectively representing punishments or rewards.
- *Type*, which specifies the nature of a sanction as *automatic* (i.e., when a violator action carries its own penalty) or *non-automatic*. The non-automatic sanction is divided in other three types: *material* (i.e., physical sanctions that directly affects its target's future behavior), *social* (i.e., spreading of social values that indirectly influences its target's future behavior) or *psychological* (i.e., internal emotional feelings that impacts the agent's future behavior).
- *Style*, which specifies the target agent's awareness of the application of the sanction, and may be *implicit* (i.e., the sanction is not made clearly known not even among the interacting parties and agents have to discover whether or not they have been sanctioned) or *explicit* (i.e., the sanction is publicly known at least among the interacting parties).

Cardoso and Oliveira (2009) synthesize Pasquier, Flores and Chaib-draa's dimensions into two broad categories of sanctions:

- *direct, material*, which have an immediate effect on the (material) resources of a target agent, e.g., by imposing fines, and
- *indirect, social*, which may have a future effect on the agents' interactions, e.g., by changing the agent's reputation.

These few and simple categorization proposals evidences the lack of importance given to this aspect on the study of sanctions in NMAS. Conversely, most of the works in NMAS focuses on sanctioning, that is the use of sanction as an enforcement mechanism.

They are detailed here by presenting a classification taxonomy (Section 4.3.2), an enforcement process proposal (Section 4.3.3) and a review of a set of enforcement mechanisms (Section 4.3.4).

4.3.2 Balke's Enforcement Taxonomy

Some NMASs rely upon an enforcement mechanism that assumes that agents can be controlled and non-compliant actions can be prevented, that is, a violation is not possible. Jones and Sergot (1993) term such a mechanism *regimentation*, as do Grossi, Aldewereld and Dignum (2007); others call it *control-based enforcement* (PINNINCK, 2010, p. 14). Minsky (1991) distinguishes two modes of regimentation, namely, by *interception* (i.e., controlling the messages an agent is able to send), and by *compilation* (i.e., controlling the mental states of an agent).

Jones and Sergot (1993) term the complementary mechanism *regulation* wherein violations may occur, yet whenever a violation is detected, reactions (i.e., sanctions) may be applied to the violator. Others call this *incentive-based enforcement* (PINNINCK, 2010, p. 16).

Balke (2009) extends this classification and proposes a taxonomy based on the works by Ellickson (1998) and Grossi, Aldewereld and Dignum (2007). Her taxonomy has two dimensions (Figure 10). The *observer* dimension that identifies the entity responsible for monitoring others' behaviors and detecting their norm compliance or violation, and the *enforcer* dimension that identifies the entity authorized for applying sanctions.

The observer dimension has five distinct categories, in which the observation of the environment is performed by: (i) a NMAS infrastructure component (*Infrastructure*), (ii) an agent instantiated by the infrastructure (*Infrastructural entity*), (iii) any other agent in the system (*Third-party*), (iv) a transaction partner agent (*Second-party*), or (v) the agent itself (*First-party*).

The enforcer dimension has also five distinct categories, in which the sanction is applied by: (i) a NMAS infrastructure component that may constrain the target agent of having non-compliant mental states (*Infrastructure (mental states)*), or it may filter out the execution of the target agent's non-compliant actions (*Infrastructure (agent action)*), (ii) an agent instantiated by the infrastructure (*Infrastructural entity*), (iii) any other agent (*Social enforcement*), (iv) a transaction partner agent (*Second-party enforcement*), or (v) the agent itself (*First-party enforcement*).

The intersection between these two dimensions creates the taxonomy shown in Figure 10 (Column *Taxonomy)*. The recognized types of enforcement mechanisms are:

Figure 10 – Balke's enforcement mechanisms taxonomy (BALKE, 2009)

	Observer	Enforcer	Sanctions	Taxonomy
Regimentation	Infrastructure	Infrastructure (mental states)	Impossible violations	Infrastructural control (*white box)*
		Infrastructure (agent actions)		Infrastructural control (*black box*)
Enforcement	Infrastructure entities	Infrastructural entities	Infrastructural sanction	Institutionalization of agents
	Third-party			Infrastructural assisted enforcement
		Social enforcement	Vicarious, Retaliation, Reciprocation	Informal Control
	Second-party	Second-party enforcement	Retaliation, Reciprocation	Promisee-enforced rules
		Infrastructural entities	Infrastructural sanction	Infrastructural assisted enforcement
	First-party	First-party enforcement	Self-sanction	Self-control

- *Infrastructure control (white box)*. An infrastructural component ensures that all the agent's mental states (e.g., beliefs and goals) are compliant to the norms as the infrastructure component has unrestricted access to analyze and alter the agents' "mind." It is a very pervasive approach as the agent has no autonomy on its own mental states.

- *Infrastructure control (black box)*. An infrastructural component analyzes all agents' actions and filters out those non-compliant to the norms. It is less pervasive than the previous type as it does not require unrestricted access to the agents' mental states rendering the agent more autonomous.

- *Institutionalization of agents*. Special agents empowered by the infrastructure (i.e., police agents) are employed for monitoring the behavior of other agents, detecting norm violations and applying sanctions. This type differs from previous types as the special agents cannot control all the actions of all other agents, yet they may react to their non-compliant actions to influence their future behavior.

- *Infrastructural assisted enforcement*. A second-party or third-party agent monitors other agents' behaviors and reports any violation to an infrastructural entity, which is responsible for applying sanctions.

- *Informal control*. A third-party agent monitors other agents and apply sanctions in case it observes a non-compliant action, even though it has not been affected by the action.

- *Promisee-enforced rules*. A second-party agent monitors the actions of a transaction partner and apply sanctions in case it observes a non-compliant action.

- *Self-control*. An agent monitors its own actions and applies sanctions to itself.

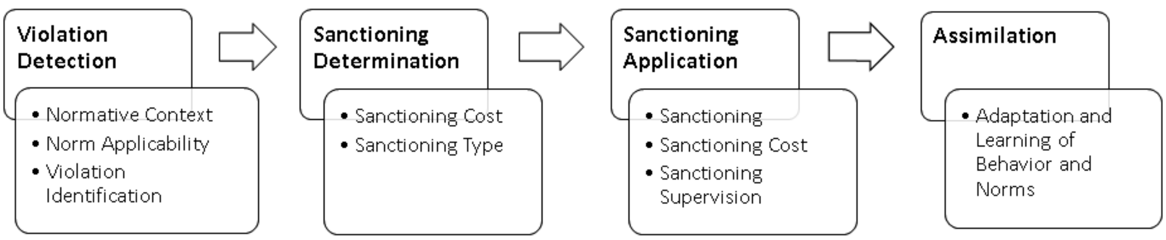
4.3.3 Balke and Villatoro's Enforcement Process

As a complementary approach to this taxonomy, Balke and Villatoro (2012) propose a process oriented model of sanctioning enforcement mechanisms composed by four phases: (i) *Violation detection* involves monitoring agents to check whether they comply with the norms. (ii) *Sanctioning determination* evaluates the norm deviation or compliance to determine whether to sanction or not. If so, (iii) *Sanctioning application* takes over. (iv) *Assimilation* involves monitoring the effects of the applied sanction to determine its efficacy.

Each phase involves distinct activities whose performers are agents playing particular roles. The roles involved in the sanctioning enforcement process are: (i) *Violator* – agent who performs a non-compliant action with respect to the norm, (ii) *Victim* – agent affected by the norm violation, (iii) *Profiteer* – agent who benefits from the norm violation consequences, (iv) *Observer* – agent who identifies norm violations, (v) *Judge* – agent capable of evaluate norm violations and determine the appropriate sanction to apply to the violator, (vi) *Executor* – agent who applies the sanction stipulated by the Judge to the Violator, (vii) *Controller* – agent who evaluates the efficacy of the applied sanctions, (viii) *Legislator* – agent who observes the system efficacy and creates new norms and sanctions. It is worth to note that a single agent can play several roles at the same time.

Figure 11 illustrates the proposed general four-phase sanctioning enforcement process.

Figure 11 – Sanctioning enforcement process (BALKE; VILLATORO, 2012)



The *Violation Detection* phase has two main goals: to detect and ascertain the occurrence of a violation and to identify the involved agents. The Observer agent collect evidences about the actions performed by the would be Violator and identifies the possible affected parties Victims and Profiteers.

The *Sanctioning Determination* phase evaluates the applicability of the norm in the context in which the supposed violation has happened. If applicable, it determines the appropriate sanction to apply to the Violator. In this phase, the agent who plays the Judge role receives the information collected in the previous phase and decides what sanction to apply to the Violator, if any.

The *Sanctioning Application* phase goal is to apply the sanctions determined by the Judge in the previous phase and checks its actual application. The agent playing the Executor role can be: (i) the agent that violated the norm, (ii) the Victim of the violation, (iii) a third-party observer, or (iv) an infrastructure agent. Thus it may happen situations in which the Violator is sanctioned by more than one Executor.

Finally, the *Assimilation* phase enables the adaptation of the process to new situations. The Controller evaluates the efficacy of the sanctions applied and based on this information the Legislator may propose new norms and sanctions, or adaptations to the current ones.

We present next two possible approaches that may be used by the sanctioning process as a mechanism of enforcement.

4.3.4 Sanctioning Enforcement Mechanisms

In NMASs, sanctions are a form of *social control*, which in turn are used for the achievement of *social order* (CASTELFRANCHI, 2000), which is akin to the notion of governance for NMAS adopted in this work. Social control and order are realized via two main complementary approaches, respectively, by trust and reputation, and by normative enforcement, each of which we discuss next.

4.3.4.1 Trust and Reputation

Trust and reputation are a means to discourage unwanted and foster desired behaviors among agents in NMASs.

Because trust functions as a decision criterion for an agent to engage in social activities, any action that potentially affects the trust placed in a party can possibly serve as a sanction on that party. These concepts are based on the idea of indirect sanctioning, because instead of acting directly against others (e.g., imposition of fines), agents use information about their past behavior to evaluate how they might perform in the future. A positive performance history thereby would ordinarily lead to higher trust that the agent will perform well in the future, whereas a negative history results in the opposite.

Dellarocas (2006) recognizes a dual role in the use of reputation: (i) the *sanctioning* role in which reputation is used for deterring moral hazards present in agreement settings where each party may gain from acting contrary to the outlined principles (e.g., online trading and "tragedy of the commons" (HARDIN, 1968)), and (ii) the *signaling* role in which reputation is used for reducing information asymmetries among interacting parties.

Due to the importance of trust and reputation for MAS (CASTELFRANCHI; FALCONE, 1998), several models have been proposed in the literature in the last decades, such as Histos and Sporas (ZACHARIA; MAES, 2000), MMH (Mui, Mohtashemi and Halberstadt) (MUI; HALBERSTADT; MOHTASHEMI, 2002), ReGreT (SABATER-MIR; SIERRA, 2002), Repage (CONTE; PAOLUCCI, 2002; SABATER-MIR; PAOLUCCI; CONTE, 2006), FIRE (HUYNH; JENNINGS; SHADBOLT, 2006), Wang & Singh (WANG; SINGH, 2010), L.I.A.R. (VERCOUTER; MULLER, 2010) and BDI+Repage (PINYOL et al., 2012). We did not try to be exhaustive here, but to provide a set of representative trust and reputation models available in the MAS literature. Further information about computational trust and reputation models can be found on Pinyol and Sabater-Mir (2013) and Hendrikx, Bubendorfer and Chard (2015).

Different ways to model trust and reputation include quantitative, e.g., Castelfranchi and Falcone (2010), and cognitive, e.g., Conte and Paolucci (2002), approaches. The latter helps to distinguish an agent's *image* (i.e., beliefs another individual has about a target) from its *reputation* (i.e., beliefs others collectively have about a target). Thus image is personalized, while reputation is an impersonal evaluation produced by sharing information about the target agent.

Image refers to the idea that the agent reacts to directly acquired beliefs when judging potential future interactions. Thus, in case of repeated interactions, gained beliefs can be used to identify agents that out-performed or under-performed, respectively, favoring or disfavoring their selection as a transaction partner. As a result, for example, when cheating another agent in one transaction, the cheater should consider the possibility that by doing so those agents that were cheated might construct a negative image of it, thereby hurting future prospects for transacting. The corresponding sanction is hence indirect and delayed.

Rodrigues and Luck (2007) propose a model for building others' image based on the Piaget's theory of exchange values (RODRIGUES; COSTA; BORDINI, 2003; PIAGET, 1995). Exchange values represent the gains and losses of agents in each direct interaction with others. These direct experiences are evaluated in terms of successful and unsuccessful interactions. The successfulness of an interaction is defined in terms of the balance between gains and losses: a successful interaction represent a situation in which the gains are equivalent or greater than the losses, and an unsuccessful interaction the opposite.

In Kalia, Zhang and Singh (2014), image about others is learned based on a probabilistic trust model. The model estimate agents' trust parameters from positive, negative and neutral interactions ruled by commitments (i.e., a social relationship between two agents giving a high-level description of what one agent expects from the other).

Reputation presumes information sharing, but otherwise functions somewhat like image. Reputation is a general opinion about a target, especially the target's ability to perform specific tasks, as shared across some population. In contrast to image, where agents act upon their own experiences, reputation requires the sharing of information. Such sharing can lead to a larger set of agents acquiring an opinion about a target. Similar to image, reputation function as sanction, but due to the inherent sharing involved, it takes the form of social control in which a large fraction of society accounts for past behavior.

The information sharing assumption, however, renders reputation a vulnerable mechanism due to (i) the lack of incentive for rational agents to report feedback as it would provide an advantage to the other agents, and (ii) the quality of the reports as agents may be dishonest, i.e., lie or share unreliable evaluation about others. Heitz, König and Eymann (2010) analyze different incentive mechanisms and identify that feedback reporting would be improved by setting a reward to those that share information. To overcome the quality issue, different factors should be taken into account as (i) to calculate reputation based on different ratings, and (ii) to normalize the reported information based on the recommender's trustworthiness and (iii) behavioral stability.

4.3.4.2 Normative Enforcement

Normative enforcement mechanisms are supported by norms. Sanctioning enforcement corresponds to mechanisms enable reacting to norms violation or compliance. These mechanisms, similar to the perspective of the normative computational models (i.e., institutional or social) described in Sections 3.3 and 3.4 are centralized or distributed.

Cardoso and Oliveira (2009) propose a centralized norm enforcement mechanism for contractual commitments, i.e., agreements binding two or more parties describing their mutual expectations, to the degree that to renege on the commitments will be costly. The mechanism uses only direct material sanctions implemented through fines as a deterrent. The main idea behind Cardoso and Oliveira's sanctioning mechanism is to base the severity of fines on statistics regarding violation: the severity of a fine is increased or decreased depending whether the number of violations is respectively greater or less than a specified threshold.

Cardoso and Oliveira's approach relies upon a centralized entity who tracks commitments among agents and judges them for their violation and compliance. In effect, the centralized entity restricts agents' autonomy by determining sanctions and their severity, and imposes them without regard to any subjective or contextual distinction.

Centeno, Billhardt and Hermoso's (2011, 2013) mechanism resembles Cardoso and Oliveira's approach, but accommodates contextual information to adapt sanctions to particular agents and situations. As in electronic institutions (Section 3.3.1), each external agent is associated with an institutional component for sanctioning, which adapts policies to promote norm compliance by agents. Similarly, Campos et al. (2013) propose an adaptation mechanism that modifies norm penalties according to agents' behaviors through the use of case-based reasoning (AAMODT; PLAZA, 1994) to learn the best ways to regulate them in each situation.

The foregoing mechanisms, though adaptable, require *a priori* knowledge not only about the global utility function, but also about whether the system is gaining or losing utility. The need for a global utility function renders these approaches unviable for systems in which not all the components are controllable, like STSs.

Daskalopulu, Dimitrakos and Maibaum (2002) introduce an architecture of contract performance monitoring with arbitration, by relaxing the centralized monitoring characteristic of the previous architectures. Contractual party agents hold a state diagram representation of the contract in terms of obligations. Whenever they disagree about obligations fulfillment, they present evidences supporting their view of what happened and what should have happened to an arbitrator agent, which undertakes a resolution. The arbitrator reasons about the evidences using Subjective Logic (JØSANG, 2001) and proposes a solution, i.e., resetting the agreement to its normal course. If there is no solution, agreements are terminated and litigation ensued to establish liability and award damages.

Extending the decentralization, Modgil et al. (2009) propose a general architecture for norm-governed systems that relies in infrastructural agents to monitor and sanction. The architecture comprises observer agents responsible for inspecting specific agent's actions and determining whether a norm violation has happened (FACI et al., 2008). If so, they report the violators and the violated norms to manager agents, who apply pre-specified sanctions to them.

Criado et al. (2013) propose MANEA, an architecture for enforcing norms that resembles Modgil et al.'s approach as enforcer infrastructural agents monitor and sanction (i.e., punishing or rewarding) application agents due to, respectively, norms' violation or compliance. Importantly, each norm is associated with specific penalty or reward sanctions. Hence, the norm enforcers are not autonomous: they are forced to act as specified and cannot reason to select the most appropriate sanction for a given situation.

To overcome limitations of centralized and infrastructural approaches, some works support second-party and third-party sanctioning, in which an agent who is affected by or observes a violation is responsible for identifying and sanctioning the violating agent, respectively. Pinninck, Sierra and Schorlemmer (2010) propose a distributed mechanism in which non-compliant agents can be ostracized from the society. In Pinninck's approach, agents monitor and spread information about each other as a way to build a reputation measure, which is used in the decision process to ostracize recurrent non-compliers (i.e., non-reputable agents).

López and Luck (2003) introduce a distributed norm enforcement mechanism in which the compliance or violation of a norm results in the triggering of an *enforcement norm*. The enforcement norm specifies the reward or punishment to be applied due to the violation or the compliance with the original norm, as well as the application criteria and the role of the agent responsible for applying it. Despite enabling the agents to monitor and sanction other agents, this mechanism pre-establishes the sanctions to be applied.

In contrast, adaptive sanctioning techniques enable agents to dynamically adapt the strength of a sanction. Whereas Villatoro et al.'s (2011) technique adapts the strength of the sanction based on the number of defectors, Mahmoud et al.'s (2012a) technique adapts it according to characteristics of the violation, such as magnitude and frequency. Mahmoud et al. (2012b) identify that due to lack of information these previous adaptive techniques fail to stop agents violating norms in partial observable environments. Hence, they introduce reputation as a means to enrich agents' knowledge about others and adapt the strength of a sanction. The drawback of these techniques is due to their limited use of a specific type of sanction, the material sanction.

Giardini, Andrighetto and Conte (2010) claim that this is an incomplete view of sanctioning and propose a cognitive model with distinct kinds of sanctioning behaviors. Andrighetto and Villatoro (2011) create a mechanism that takes into account this cognitive model and they evaluate two distinct enforcing strategies, the *Punishment* and the *Sanction* strategies. In the Punishment strategy, a sanction corresponds only to the imposition of a cost on the target (i.e., material sanction), whereas the Sanction strategy in addition to impose economic costs, also has a norm-signaling component. This additional component influences the target by signaling about the existence of the norm and that it should be respected. They show that the Sanction strategy is more effective in promoting compliance with the norm, as in addition to inflict a cost on the violator it signals that the norm is relevant to members of the social group.

4.4 Discussion

Social sciences in general recognize the need for multiple categories of sanctions for the maintenance of social order. In human societies, *informal* (trust and reputation) or *formal* (normative systems) sanctions coexist, as emphasized in the social sciences literature review (Section 4.2).

Psychological studies show also that humans usually reason about multiple factors before reacting to a violation. It is interesting that people reason differently depending upon whether they are creating legislation (promote deterrence, anticipating a potential violation) or reacting to a violation (engage in retribution). An individual would benefit from knowing about the applicable sanctions, their usual consequences, and how others sanction in similar situations. These characteristics also corroborate with the requirements exposed by systems involving humans (see Section 2.4), in which a set of possible sanctions are available and different sanctioning decision factors influence the sanctioning decision.

As these systems involve humans, it makes sense that norm enforcement mechanisms applied to them inherit characteristics that are observed in pure human systems. The main characteristic observed in the social sciences literature, i.e., fields that studies pure human systems, was a greater flexibility in the decisions to sanction. Thus, the advantages in using more flexible sanctioning mechanisms reside in the fact that (i) humans deal with and are sensible to different categories of sanctions, and (ii) different sanctions that differs in application costs may cause the same end result.

Thus analyzing from this outlook, the enforcement proposals of Section 4.3 suffer from some drawbacks that render them unsuitable for supporting the requirements identified in Section 2.4:

R1 Support for multiple categories of sanctions;

R2 Potential association of multiple sanctions with a norm violation or compliance;

R3 Adaption of the sanction content depending also on the context; and

R4 Decision about the most adequate sanction to apply depending on the context.

Table 2 summarizes the enforcement mechanisms described in Section 4.3 indicating their classification according to the Balke's enforcement taxonomy (see Section 4.3.2) and the requirements they fulfill (✔) to support the modeling of STSs (see Section 2.4).

Table 2 – Summary of classification and requirements fulfilled by the existing enforcement mechanisms.

Enforcement Mechanism	Enforcement Mechanism Classification*	Requirements			
		Multiple Sanctions (R1)	Multiple Categories (R2)	Sanction Adaptation (R3)	Sanction Decision (R4)
Cardoso and Oliveira (2009)	IoA	—	—	✔	—
Centeno, Billhardt and Hermoso (2011)	IoA	—	—	✔	—
Centeno, Billhardt and Hermoso (2013)	IoA	—	—	✔	—
Campos et al. (2013)	IoA	—	—	✔	—
Pinninck, Sierra and Schorlemmer (2010)	PER, SC	—	—	—	—
Daskalopulu, Dimitrakos and Maibaum (2002)	IAE	—	—	—	—
Modgil et al. (2009)	IAE	✔	✔	—	—
Criado et al. (2013)	IAE	✔	✔	—	—
López and Luck (2003)	IC, PER, SC	✔	✔	—	—
Villatoro et al. (2011)	IC, PER, SC	—	—	✔	—
Mahmoud et al. (2012a)	IC, PER, SC	—	—	✔	—
Mahmoud et al. (2012b)	IC, PER, SC	—	—	✔	—

* **IoA** – Institutionalization of Agents, **IAE** – Infrastructure Assisted Enforcement, **IC** – Informal Control, **PER** – Promisee-Enforced Rules, and **SC** – Self-Control.

Even though they involve multiple categories of sanctions (R1), such as reputation, ostracism and material sanction, each approach uses a single category, established at design time. For instance, Cardoso and Oliveira (2009), Centeno, Billhardt and Hermoso (2011), Centeno, Billhardt and Hermoso (2013) and Campos et al.'s (2013) approaches use only material sanctions, although they allow the adaptation of the sanction (R3). Hence, the approaches do not consider multiple categories of sanctions simultaneously (thus, failing R1 and R2) and do not support the enforcer's decision making (thus, failing R4). Pinninck, Sierra and Schorlemmer (2010) and Daskalopulu, Dimitrakos and Maibaum's (2002) approaches fail to fulfill all the requirements. López and Luck (2003) and Criado et al.'s (2013) mechanisms can support multiple categories of sanctions (R1 and R2). However, they model sanctioning as an automatic reaction, which limits agents' decision making and disregards context (thus, failing R3 and R4). Villatoro et al. (2011), Mahmoud et al. (2012a) and Mahmoud et al.'s (2012b) approaches enable agents to adjust their sanctions (R3), but are limited to material sanctions (thus, failing R1, R2 and R4). Even Mahmoud et al. (2012b) that use reputation, apply it only as a means to adjust the material sanction (i.e., as extra information) and not as a real sanctioning mechanism.

Therefore, existing mechanisms do not address a situation from our motivating scenario. Waiving a sanction, where the affected coalition members may decide not to sanction the violating agent (possible outcome of Situation 3) even though there is a set of possible sanctions (thus, failing R4) linked to the violation of the norm.

This work develops an adaptive sanctioning norm enforcement model that fulfill all the requirements through the use of various contextual factors, as explained in the next two chapters.

Part II

The Model

5 A Comprehensive Typology of Sanctions

This chapter develops a comprehensive typology of sanctions that includes human aspects into NMASs. Section 5.1 provides a brief overview about the classification and its importance. Section 5.2 details the dimensions of the proposed typology for classifying sanctions. To illustrate the concepts, the SG scenario presented in Section 2.3 is used. Finally, an evaluation of the proposed typology is presented in Section 5.3.

5.1 Introduction

The analysis of the literature in the previous chapters illustrates the rich variety of concepts that come together in sanctioning. Hitherto, however, there have only been few efforts aimed to elaborate a typology of sanctions to NMAS (see Section 4.3.1), and to the best of our knowledge, none has comprehensively tackled the integration of the variety of aspects deriving from the perspectives of different disciplines. This situation leads us to develop a *typology*, i.e., a systematic classification of types that have characteristics in common (PICKET, 2011) and highlights distinctions that can feature in a theory as independent and dependent variables (BAILEY, 1994).

The classification of sanctions can help map out the space of possibilities, supporting the assimilation of human aspects into NMAS. Furthermore, these categories may enable the identification of those sanctions that are more effective in reducing each kind of violation, thus supporting an improvement of the general level of compliance in the system.

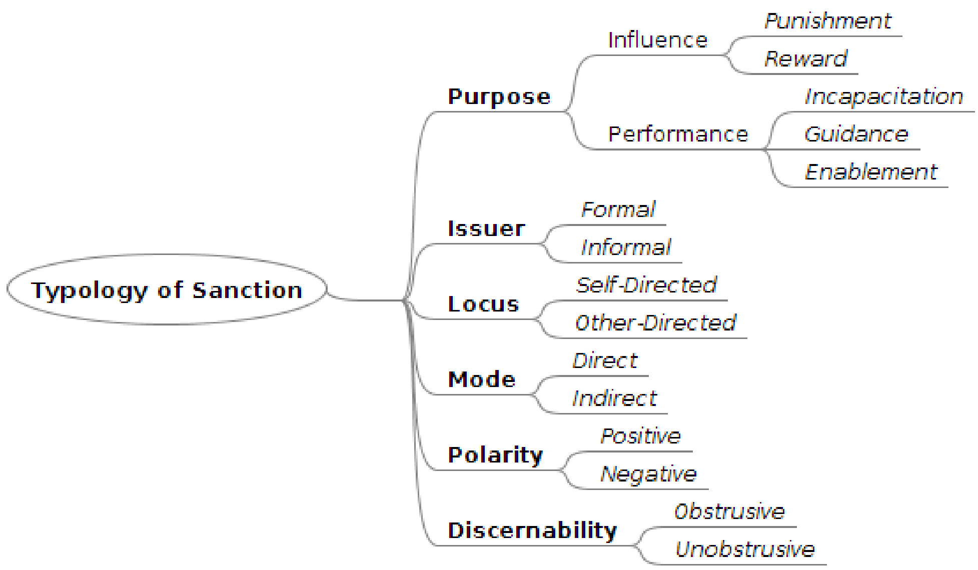
The analysis of existing typologies of sanctions (see Section 4.3.1) shows that they (i) use distinct terms for the same concept, (ii) use the same term to describe distinct concepts, and (iii) incorporate disparate dimensions, which could be consolidated.

Below, we describe a typology that lays the foundations for a comprehensive notion of sanctions as a possible means to prevent non-compliant acts in NMASs. Our typology seeks to advance the understanding of sanctioning in NMASs.

5.2 Dimensions

We now outline a typology of sanctions composed of six dimensions, as depicted in Figure 12, mostly based on the sociological literature, but extended to accommodate STSs. These dimensions are *Purpose*, *Issuer*, *Locus*, *Mode*, *Polarity* and *Discernability*.

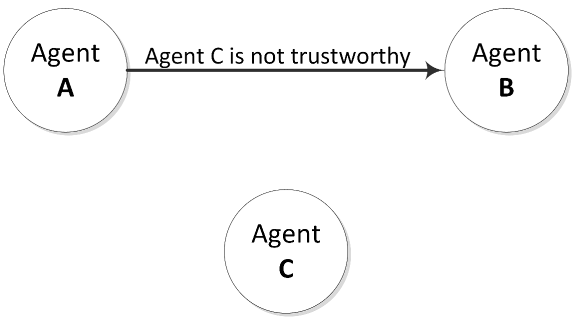
Figure 12 – Dimensions of the proposed sanction typology



Before detailing these dimensions, however, we define the terms *Source*, *Target*, *Sender* and *Receiver* that are used to describe some of these dimensions. The terms Source and Target refers to the content of the sanction: the Source indicates the agent that generates the sanction (probably, the affected agent or an observer third-party) and Target refers to the agent to whom the sanction is directed to. The terms Sender and Receiver refers to the agents participating in the sanction application, that is, the Sender is the agent that actually applies the sanction and the Receiver the one directly receiving and processing it.

Figure 13 illustrates a fictitious situation in which agent A sanctions agent C by spreading bad reputation about the latter to agent B. Thus, agent A is the Sender and the Source of the sanction, while agent B is the Receiver and agent C the Target.

Figure 13 – Agent A spreads a bad reputation about agent C to agent B. Agent A (*Source* and *Sender*) informs agent B (*Receiver*) that agent C (*Target*) is not trustworthy.



5.2.1 Purpose

Purpose categorizes sanctions based on the expectation about their function in the social environment. Drawing from the literature on sanctions, we identify five possible purposes, organized into two aspects or regions of the dimension, depending on when they apply.

1. The *influence* aspect deals with incentives (negative or positive) and ranges over two purposes subsequent to a target violation or compliance: *punishment* seeks to penalize the target and prevent potential norm violation (e.g., the imposition of a fine to the energy provider due to its failure in supply the contract amount of energy (S1.6)); *reward* seeks to promote and motivate targets towards compliant behavior (e.g., John and Mary thanking Joseph for his profitable coalition formation idea (S2.1); or, the factory spreading to others about the willingness of the broker to meet increased demand (S5.2)).

2. The *performance* aspect deals with capabilities and ranges over three purposes closely tied to the target's behavior. First, *incapacitation* seeks to restrict the target's actions rendering the norm violation impossible for bounded period, differing from regimentation in that respect (e.g., suspension of the broker from signing new contracts for a period of up to 30 days (S1.7)). Second, *guidance* seeks to change a target's behavior, through instructing the target as how to comply (e.g., John and Joseph suggesting that Mary have her solar panel serviced in a regular basis (S3.2)). Third, *enablement* seeks to provide an opportunity, and potentially the means, through which the target may comply and thus avoid sanctions (e.g., enable the broker to trade energy 24 hours a day without interruption instead of only 8 hours due to its last year's good performance). Whereas enablement supports repeating the sanctioned behavior, rewards provides only an incentive for the target to repeat the sanctioned action.

5.2.2 Issuer

The *Issuer* specifies whether the sanction's issuer or enforcer are recognized authorities. *Formal* sanctions are established, and generally also enforced by recognized authorities, such as governmental institutions. Formal sanctions may be imposed not only by the State, but also by suitably empowered institutions, such as regulatory agencies (e.g., Federal Energy Regulatory Commission) or traders (e.g., eBay and Amazon). A specific example are the penalties specified in a trading contract in which an affected party may pay a reduced energy due to a failure in the supply.

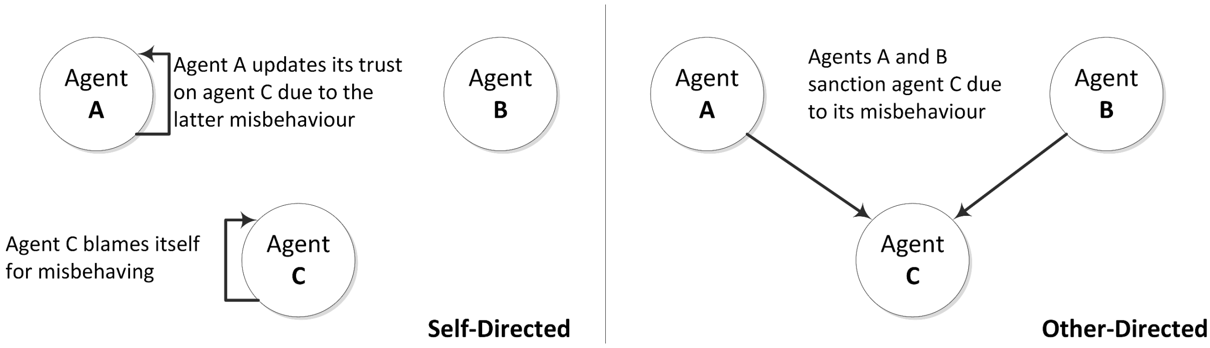
Informal sanctions are established or enforced unofficially by members of the society, and need not be specified in a formal code. Examples include ridicule, ostracism, awards, prizes, and damage to or promotion of reputation (e.g., the spread of negative ratings about a broker that has failed to fulfill the contract agreements (S1.3)).

In law, formal sanctions include fines, social service and imprisonment; there are no informal sanctions despite the fact that the former may facilitate the latter (BAKER; CHOI, 2014). In sociology, formal sanctions include not only fines and imprisonment, but also awards and bonuses. Informal sanctions include ridicule, ostracism and praise.

5.2.3 Locus

The *Locus* determines whether a sanction is *self-directed* (i.e., $Sender = Receiver$) or *other-directed* (i.e., $Sender \neq Receiver$) with respect to the individual that applies it (Figure 14). Locus does not make reference to the target of the sanction, but to its recipient.

Figure 14 – In the left, agent A updates its trust about agent C due to the latter misbehavior, and agent C reacts to her own misbehavior by blaming itself ($Sender = Receiver$). In the right, agents A and B sanction agent C for its misbehavior ($Sender \neq Receiver$).



A *self-directed* sanction is directed and affects only its sender (e.g., Mary blames herself for the solar panel's malfunctioning (S3.1)). A self-directed sanction can also refer to an action performed by another individual, which corresponds to a situation in which an individual sanctions himself because of others' action (e.g., vicarious shame as when someone becomes ashamed due to football fans from his country misbehave; or when John and Joseph reduce their trust on Mary as partner (S3.3)).

Other-directed sanctions correspond to a penalty or reward applied on another individual or group. It presumes an external action performed by the sanctioner toward the sanctionee. A classical example is the imposition of a fine due to misbehavior or the grant of an award due to compliance (e.g., John and Joseph request compensation to Mary (S3.4); or the consumers taking legal actions against the broker (S1.2)).

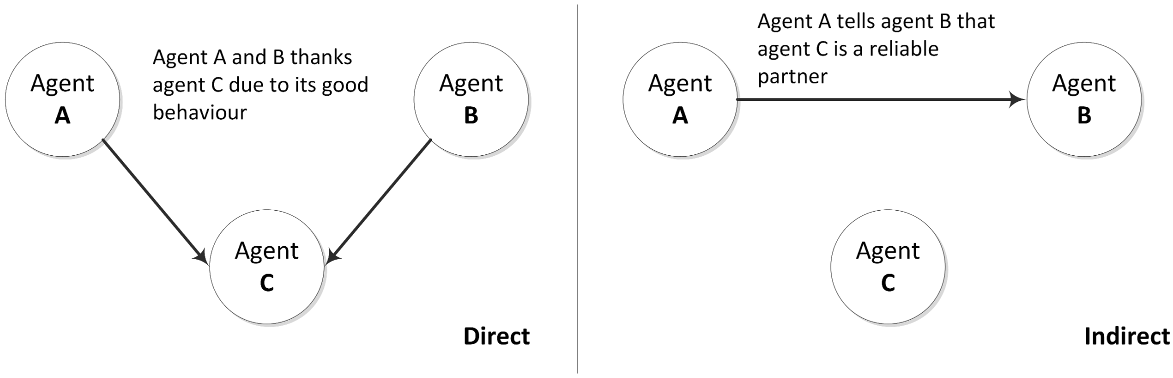
In law, other-directed sanctions include suspensions and fines, and there are no self-directed sanctions. In sociology, self-directed sanctions include guilt and trust, and other-directed sanctions include gossip and praise.

5.2.4 Mode

The *Mode* indicates how a sanction affects its target (Figure 15). A *direct* sanction affects its target directly and immediately (e.g., the levying of a fine; or, the consumers blaming themselves for selecting the service from an untrusting broker (S1.1)).

An *indirect* sanction affects its target indirectly, potentially influencing the future actions of others that will then affect the target (e.g., damaging the target's reputation, which would discourage others from transacting with the target; or, the spreading of Joseph's good reputation by John and Mary for the initiative of forming a coalition (S2.2)).

Figure 15 – In the left, agents A and B directly affects agent C by thanking it for its support in previous activities ($Target = Receiver$). In the right, agent A indirectly affects agent C by spreading the information that the latter is unreliable as a partner ($Target \neq Receiver$).



The distinction between *direct* and *indirect* sanction is observed only in sociology and psychology. These are the fields that put more emphasizes to informal rather than on the formal sanctions, which therefore have a higher propensity of having indirect characteristics, such as reputation and ostracism. All other disciplines are more focused on sanctions that directly affects the individuals' resources, whether financial or not.

5.2.5 Polarity

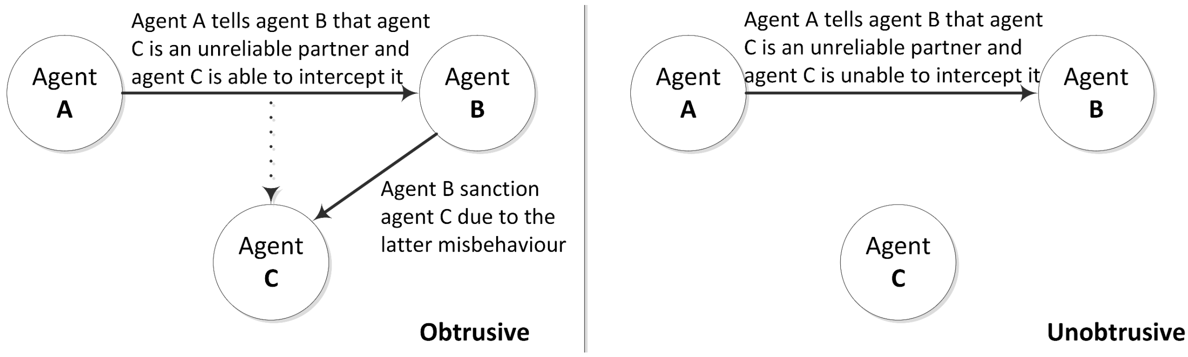
The *Polarity* of a sanction relates to its content: *positive* indicates a reward (e.g., Joseph and Mary praising George to others as George successfully replaced John in the coalition (S4.2)) and *negative* represents a penalty (e.g., John and Joseph requesting compensation from Mary for her non fulfillment of the coalition agreement).

The law primarily considers negative sanctions, as applied in cases of violation. However, it considers positive sanctions for individuals who report fraud or help catch wanted criminals. Sociology and psychology consider both negative and positive sanctions more evenly than law.

5.2.6 Discernability

Discernability indicates how noticeable a sanction is to its target (Figure 16).

Figure 16 – In the left, the sanction is obtrusive because agent C comes to know about the sanction agents A and B are applying to it. In the right, otherwise, agent C is unable to notice the sanction, thus it is unobtrusive.



An *obtrusive* sanction, whether a penalty or a reward, is noticeable by the target (e.g., Joseph and Mary thanking George for his successful help for the coalition to reach $1000kWh$ (S4.1)); an *unobtrusive* sanction, such as gossiping behind one's back, is not easily noticeable (e.g., John and Joseph reduce their trust in Mary as a partner (S3.3)). A target would not easily be able to associate an unobtrusive sanction with the action that provoked it.

5.3 Discussion

We now compare our typology's expressiveness with existing sanction typologies, as introduced in Sections 4.2 and 4.3. To this end, we adopt Jensen's (2002) *powerfulness* criterion, which states that a typology is more powerful than others if it creates categories that allow a better explanation of a set of empirical findings; that is, it allows data to be better explained. The more facts a typology permits to be explained, the more powerful, and the more scientifically valuable, it is.

We now evaluate the dimensions of our typology with respect to STSs, as exemplified by the motivational scenario introduced in Section 2.3. Table 3 summarizes the result of our comparison, which shows the relative advantages of our typology for STSs.

Our Purpose dimension accommodates concepts defined in the social sciences literature, thus going beyond Gibbs's (1966) conception of inducement and hedonic purposes. Our Purpose dimension provides sufficient granularity for STS participants to select sanctions that align with their goals.

The typologies proposed in sociology, but not in NMAS, include the Issuer dimension. This dimension suits STS well because they have aspects of both formal structure and informal relationships. A sanctioning agent can select a suitable issuer depending on the visibility or the seriousness of the sanction it wishes to apply, given its dealings with the target and with other agents.

Table 3 – Typologies dimensions mapping. A × mark indicates the dimensions proposed in our typology that each other existing sanction typology (identified in the top table row) is capable of expressing.

Dimension	**Typology**					
	Radcliffe-Brown (1934)	Morris (1956)	Gibbs (1966)	Pasquier et al. (2005)	Clinard and Meier (2008)	Cardoso and Oliveira (2011)
Purpose			×			
Issuer	×	×	×		×	
Locus		×	×			
Mode						×
Polarity	×	×	×	×	×	
Discernability				×		

The Locus dimension extends previous typologies by expanding self-directed sanctions based on another agent's behavior. Doing so presents the possibility for one agent to sanction itself and thus alter either its behavior or, more importantly, its associations with other agents as a result. For example, if John is embarrassed by his neighbors not conserving power, he may move out of the neighborhood.

The Discernability dimension was introduced as the Style dimension in Pasquier, Flores and Chaib-draa's (2005) typology. A power company would obtrusively sanction a consumer for non-payment via a fine with the Purpose of deterrence. Or, it may limit the consumer's consumption with the Purpose of punishment. However, some situations call for an unobtrusive sanction. For example, a consumer may not wish to obtrusively sanction a neighbor who fails to keep her commitment to supply power for their coalition, possibly to avoid retaliation.

Table 4 – Classification of the types of sanctions proposed in (POSNER; RASMUSEN, 1999).

Sanction	**Dimensions**					
	Purpose	**Issuer**	**Locus**	**Mode**	**Polarity**	**Discernability**
Automatic	—	—	—	—	—	—
Guilt	Punishment	Informal	Self-directed	Direct	Negative	Unobtrusive
Shame	Punishment	Informal	Self-directed	Direct	Negative	Unobtrusive
Informational	—	—	—	—	—	—
Bilateral costly	Punishment	Informal	Other-directed	Direct	Negative	Unobtrusive
Multilateral costly	Punishment	Informal	Other-directed	Direct	Negative	Unobtrusive

The Mode dimension is valuable for STSs since they involve interactions among autonomous participants. Participants, especially regulatory agencies, can apply direct sanctions. Ordinary participants can additionally apply indirect sanctions.

The Polarity dimension is common to the typologies we reviewed, except Cardoso and Oliveira (2011). It applies to STSs because positive and negative sanctions apply equally in general in regulating interactions among autonomous parties.

To give an example of the use of the proposed typology, we classify the types of sanctions proposed by Posner and Rasmusen (1999), which are summarized in Table 4. The Automatic and the Informational sanctions are not categorized because we do not understand them as sanctions. For instance, if we assume the Automatic sanction is an actual sanction, we would assume any action resultant of a norm violation is a sanction, even though the consequence of that action intends to promote the compliance to the norm. The Informational sanction equates an undesirable conveying of information as a sanction, but we understand sanction as the reaction of others regarding that information and not the information itself. Thus we would not consider an Information sanction, yet a Bilateral or Multilateral costly sanction. That said, we can understand that the other types of sanctions can form two groups, one in which the individuals emotionally punish themselves by what they have done (Guilt and Shame), and another in which a second-party or third-parties react to an action (Bilateral costly and Multilateral costly).

Table 6 classifies the possible sanctions identified in Section 2.3 according to our proposed typology. As noted in the scenario, an *affected party* is one affected by a norm violation or compliance; a *third-party* is one that observes a norm violation or compliance, and though not affected, reacts to it; a *enforcer* is one that applies the sanction. The affected parties and third-parties potentially can choose among multiple sanctions for reacting to each situation. The enforcer thus would apply such sanctions on a *(sanction) target*.

In order to facilitate the readability of Table 6, we repeat in Table 5 the different sanctions presented in Section 2.3.

Sanction S1.1 is classified as a self-directed locus (the sanction sender and the receiver are the same individual); direct mode; negative polarity (negative emotions); obtrusive; and of an informal source (there is no formal rule for guilt). Sanction S3.1 may be treated similarly.

In contrast, although Sanctions S3.3, S4.4 and S5.1 are of self-directed locus because they involve changing the affected agent's trust, even though they refer to another agent's behavior. Although the sanction is of self-directed locus, potentially the target is not aware of its lowered trust (unobtrusive discernability), hence it is indirectly affected (indirect mode). This happens because while the locus dimension refers to the affected or third-party, the discernability and mode dimensions refer to the target.

Sanctions S1.2, S1.5, S1.6, S1.7 and S3.4, being legal, have a formal source. Sanction S1.4 has an informal source as it is applied by consumers, which have the right to change service providers at any time.

Sanctions S1.3, S2.2, S3.5, S4.2, S4.3 and S5.2 involve spreading reputation (in-

Table 5 – Summary of the sanctions.

Sanction	Description
S1.1	John, Joseph and Mary blame themselves for selecting the service from this broker.
S1.2	John, Joseph and Mary take legal actions against the broker˙
S1.3	John, Joseph and Mary spread negative ratings about the broker.
S1.4	John, Joseph and Mary switch to another broker.
S1.5	The Broker sues the energy provider.
S1.6	The regulatory agency fines the energy provider between 1% and 5% of its monthly profit.
S1.7	The regulatory agency suspends the broker from signing new contracts for a period up to 30 days.
S2.1	John, Joseph and Mary thanks Joseph.
S2.2	John, Joseph and Mary spreads Joseph's good reputation due to his initiative.
S3.1	Mary blames herself for the solar panel's malfunctioning.
S3.2	John and Joseph suggest that Mary have her solar panel serviced on a regular basis.
S3.3	John and Joseph reduce their trust in Mary as a partner.
S3.4	John and Joseph request compensation from Mary.
S3.5	John and Joseph tell others that Mary is an unreliable partner.
S4.1	John and Mary thank George for coming to their rescue.
S4.2	John and Mary praise George to others.
S4.3	John and Mary praise John to others as he had proposed a successful alternative to his fault.
S4.4	John and Mary decide not to form a coalition with John in the future.
S5.1	The big consumer increases its trust in the broker as a service provider.
S5.2	The big consumer tells others of the willingness of the broker to meet increased demand.

Table 6 – Classification of sanctions identified in the motivational scenario situations

	Roles			Dimensions					
Sanction	**Affected Party** or **Third-Party**	**Sanction Target**	**Sanction Receiver**	**Purpose**	**Source**	**Locus**	**Mode**	**Polarity**	**Discernability**
S1.1	John/Joseph/Mary	John/Joseph/Mary	John/Joseph/Mary	Punishment	Informal	Self-directed	Direct	Negative	Obtrusive
S1.2	John/Joseph/Mary	Broker	Regulatory Agency	Punishment	Formal	Other-directed	Indirect	Negative	Obtrusive
S1.3	John/Joseph/Mary	Broker	Other Consumers	Punishment	Informal	Other-directed	Indirect	Negative	Unobtrusive
S1.4	John/Joseph/Mary	Broker	Broker	Punishment	Informal	Other-directed	Direct	Negative	Obtrusive
S1.5	Broker	Energy Provider	Regulatory Agency	Punishment	Formal	Other-directed	Indirect	Negative	Obtrusive
S1.6	Regulatory Agency	Energy Provider	Energy Provider	Punishment	Formal	Other-directed	Direct	Negative	Obtrusive
S1.7	Regulatory Agency	Broker	Broker	Incapacitation	Formal	Other-directed	Direct	Negative	Obtrusive
S2.1	John/Mary	Joseph	Joseph	Reward	Informal	Other-directed	Direct	Positive	Obtrusive
S2.2	John/Mary	Joseph	Other Consumers	Reward	Informal	Other-directed	Indirect	Positive	Unobtrusive
S3.1	Mary	Mary	Mary	Punishment	Informal	Self-directed	Direct	Negative	Obtrusive
S3.2	John/Joseph	Mary	Mary	Guidance	Informal	Other-directed	Direct	Positive	Obtrusive
S3.3	John/Joseph	Mary	John/Joseph	Punishment	Informal	Self-directed	Indirect	Negative	Unobtrusive
S3.4	John/Joseph	Mary	Mary	Punishment	Formal	Other-directed	Direct	Negative	Obtrusive
S3.5	John/Joseph	Mary	Other Consumers	Punishment	Informal	Other-directed	Indirect	Negative	Unobtrusive
S4.1	Mary/Joseph	George	George	Reward	Informal	Other-directed	Direct	Positive	Obtrusive
S4.2	Mary/Joseph	George	Other Consumers	Reward	Informal	Other-directed	Indirect	Positive	Unobtrusive
S4.3	Mary/Joseph	John	Other Consumers	Reward	Informal	Other-Directed	Indirect	Positive	Unobtrusive
S4.4	Mary/Joseph	John	Mary/Joseph	Incapacitation	Informal	Self-Directed	Indirect	Negative	Unobtrusive
S5.1	Big Consumer	Broker	Big Consumer	Reward	Informal	Self-directed	Indirect	Positive	Unobtrusive
S5.2	Big Consumer	Broker	Other Consumers	Reward	Informal	Other-directed	Indirect	Positive	Unobtrusive

formal and other-directed) differing only in their polarity. Reputation spreading can help influence future decisions by others (other-directed locus), but it is unobtrusive (the target is usually unaware of it) and of indirect mode. Sanctions S2.1, S3.2 and S4.1 are obtrusive and direct since they are communicated directly to the target.

We detail our proposal of a sanctioning model that takes the concepts of this typology into account to enforce normative behavior in NMASs that integrates human and artificial agents.

6 An Adaptive Sanctioning Enforcement Model

In this chapter, an adaptive sanctioning enforcement model addressing some of the drawbacks of the above-mentioned enforcement mechanisms is detailed. This model proposes (i) a sanctioning enforcement process that enables agents to reason about and adapt their sanctions, and (ii) a sanctioning evaluation model that enables them to choose the most appropriate sanctions to apply due to a set of factors. First, a brief overview of the model and its aims are outlined in Section 6.1. In Section 6.2, we describe and formally specify the sanctioning enforcement process model, its main components and interrelationships. The sanctioning evaluation model that takes into account a set of factors to decide whether to sanction and which sanction to apply is presented in Section 6.3. The requirements for the use of this model are highlighted in Section 6.4. Finally, Section 6.5 concludes by providing a discussion about how the typology of sanctions influenced the development of this adaptive sanctioning enforcement model.

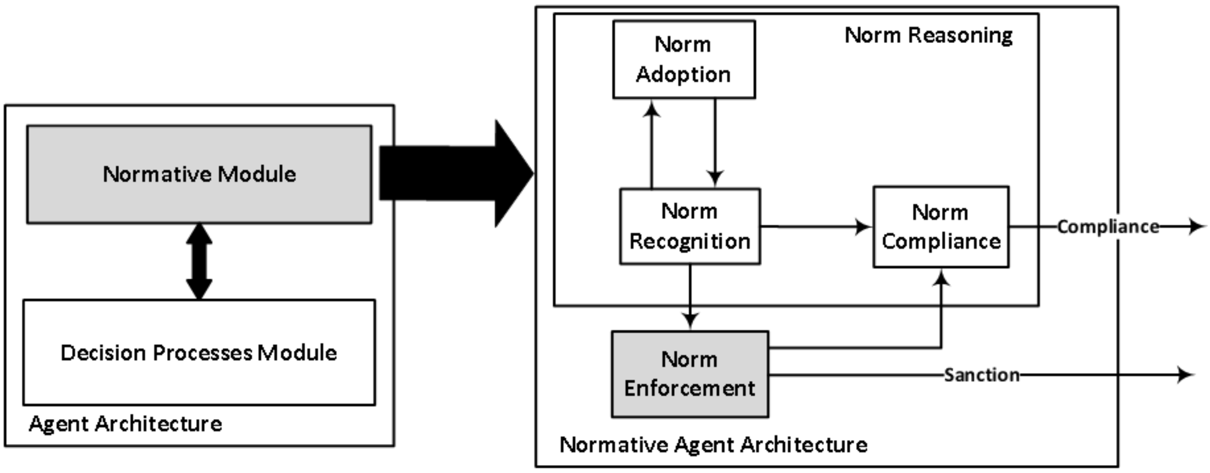
6.1 Introduction

The use of the MAS paradigm in systems' modeling and implementation has been motivated in certain measure to its high level of abstraction and flexibility as shown in Section 1. These properties are obtained thanks to the decentralization and the autonomy of its heterogeneous agents, meaning that information, resources and capabilities are distributed among them. The accomplishment of global tasks and individual goals, however, require some level of coordination among agents, which entails that they have to take others' actions into account while interacting.

Governance is thus essential in these systems. Governance refers to how the above-mentioned interactions among agents (humans or artificial) are controlled. The benefits of the normative approach to the governance of MASs has been detailed in Chapter 3 and two forms of dealing with it highlighted: the institutional approach (see Section 3.3) and the social approach (see Section 3.4).

The proposed adaptive sanctioning enforcement model is grounded on the social approach, which implies that agents perform themselves an adaptive and auto-organized control of one another. Moreover, agents base their decisions supported on norms and sanctions related to such norms. This suggests that agents have to be endowed with a normative component enabling them (i) to reason about norms (i.e., norm recognition, norm adoption and norm compliance), and (ii) to react to others' norm-based behaviors

Figure 17 – Modules composing a general normative agent architecture.



(i.e., norm enforcement). Figure 17 illustrates such agent architecture (left-side of Figure 17) comprised of a *Decision Processes Module* and a *Normative Module*.

The Decision Processes Module represents all agent's functions tightly linked to the application domain the agent was built for. The Normative Module (right-side of Figure 17) maintains and updates norm-related representations and information (see detail in Section 3.2) that are used to guide the decision-making in the Decision Processes Module.

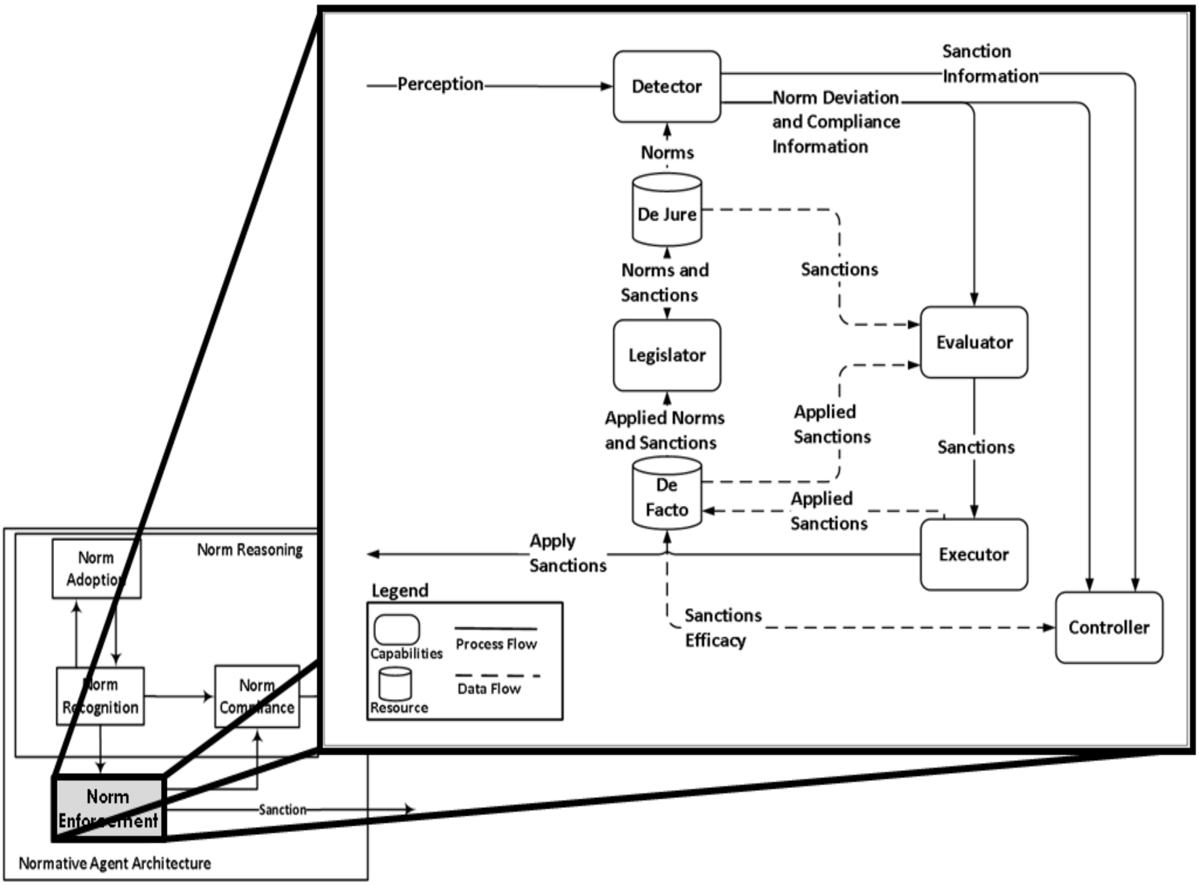
Here, we are interested in rendering the norm enforcement process more flexible and adaptable depending on the agent's current situation and goals. The proposed model has its foundation on a sanctioning enforcement process and a sanctioning evaluation model. The former details and formalizes the main components and capabilities that enable agents to specify, evaluate, choose and apply sanctions depending on their current situation and goals (see Section 6.2). The latter proposes an evaluation decision model used to select among a variety of sanctions the most appropriate ones based on normative, social and learning decision factors (see Section 6.3).

6.2 Sanctioning Enforcement Process

Our sanctioning enforcement process for NMAS is based on the one proposed by Balke and Villatoro (2012) (see Section 4.3.3). Their proposed process is composed of four stages: (i) *Violation detection* involves monitoring agents to check whether other agents comply with the norms; (ii) *Sanctioning determination* evaluates the violation or compliance with norms and determines a sanction; (iii) *Sanctioning application* takes over and applies the selected sanctions, if any; (iv) *Assimilation* involves monitoring the sanction application to determine its efficacy. We extend Balke and Villatoro's model by associating specific capabilities with each of these stages.

Figure 18 depicts our model, illustrating the above-mentioned stages being enacted by five capabilities (active entities: *Detector*, *Evaluator*, *Executor*, *Controller* and *Legislator*) using two resources (passive entities: the data repositories *De Jure* and *De Facto*). Note that these capabilities and resources may be realized in multiple ways, including in a fully centralized or a fully decentralized manner.

Figure 18 – Sanctioning enforcement process model.



The *De Jure* repository stores norms and sanctions known by the agent as well as links between them, i.e., which sanctions apply for what norm violation or compliance: the relationship between norms and sanctions can be many to many. These norms and sanctions are initially given, but the Legislator entity may include, remove or change them and their relations at run-time.

The *De Facto* repository stores information about the sanctions as applied, and relevant information such as the observed violations, which can be used to assess the efficacy of different sanctions in achieving their purpose in specific contexts.

Note that capitalization matters: De Jure and De Facto refer to the repositories; de jure and de facto are modifiers as in "de jure norms".

A significant benefit of our model is that it supports storing conflicting information in De Jure and De Facto. In particular, a sanction (and the underlying norm) specified in De Jure may not be apparent in De Facto, indicating the well-known idea of a discrepancy between what is conceived and what is realized. These information can then be used for updating the sanctions and their associations to the norms (see Legislator capability below).

An *agent* represents an entity capable of performing actions in its environment and, more importantly, of interacting with other agents. An agent's function is to represent the interest and perspective of a social entity in a given NMAS. An agent stands in for any social entity. Specific agents capabilities are as indicated in the model. Specifically, a *Detector* perceives the environment and detects any norm violation or compliance, and sanctions applied by other agents. In general, the environment would be only partially observable because of (i) its size and complexity, including the number of participants, (ii) the impossibility of identifying the executor of an action, and (iii) the confidentiality of some communications.

Assuming the Detector perceives an action, it determines whether the agent who performed it is governed by a de jure norm (e.g., given its capabilities in the NMAS) and, if so, whether the action violates or complies with the norm. Note we limit the Detector to work based on de jure norms, the idea being that all violations detected are given de jure status.

The *Evaluator* in addition obtains information from De Jure and De Facto in order to determine whether to apply a sanction and, if so, which. De Facto captures previous behaviors reported by the Controller and any sanctions applied in those cases, whether by the Evaluator or by other agents. The Evaluator's reasoning could incorporate the magnitude of the violation and an assessment of the success of previous sanctions with respect to their purposes. Importantly, De Facto is not necessarily a unitary entity. Hence, the Evaluator may access a portion of De Facto that captures not only the experiences shared among some members of the NMAS but also his personal experiences.

The *Executor* possesses the power to execute a sanction. In general, a formal sanction requires a more specific kind of executor than an informal sanction. For example, imprisonment must be executed by the police even though the Evaluator is a judge, whereas the ostracism may be executed by the same individuals who serve as Evaluators.

The *Controller* monitors the outcomes of applying a sanction, including the future behavior of the target, such as to evaluate the efficacy of the sanction. The Controller stores and reviews de facto sanctions to make its determinations. It may take advantage of the sanction's Purpose dimension defined in Section 5.2.1 in order to compare what was expected and the outcome of the sanction application. Moreover, it records in the De Facto the sanctions applied by other agents as a reaction to the violation or compliance with norms.

The *Legislator* updates de jure norms and sanctions based on an assessment of De Jure and De Facto along with the environment information. The updates, for instance, can be motivated to reduce misalignments between de facto and de jure norms and sanctions.

The following subsections, from 6.2.1 to 6.2.11, formally specify the sanctioning enforcement process model here outlined. It must be considered as part of a normative agent architecture, which acts under a NMAS specification (see Figure 17).

6.2.1 NMAS

A NMAS is a system composed of a set of autonomous and heterogeneous agents situated in a shared environment, whose actions and interactions are governed by norms and sanctions related to such norms.

Definition 1. A NMAS is defined as a tuple

$$\text{NMAS} = \langle \mathcal{E}n, \mathcal{A}g, \mathcal{R}, \mathcal{A}c, \mathcal{N}, \mathcal{S} \rangle,$$

where:

- $\mathcal{E}n$ is the environment that may assume any of a finite set of discrete states.
- $\mathcal{A}g$ is the set of agents ag that can act alter the state of the environment or interact among themselves ($ag_i \in \mathcal{A}g \mid i \leq |\mathcal{A}g|$).
- $\mathcal{R}$ is the set of the domain application roles r that agents can play ($r_i \in \mathcal{R} \mid i \leq |\mathcal{R}|$).
- $\mathcal{A}c$ is the set of actions α agents can perform ($\alpha_i \in \mathcal{A}c \mid i \leq |\mathcal{A}c|$).
- $\mathcal{N}$ is the set of all norms n prescribing the expected agents' behaviors ($n_i \in \mathcal{N} \mid i \leq |\mathcal{N}|$).
- $\mathcal{S}$ is the set of all sanctions s prescribing possible reactions to norm violation or compliance ($s_i \in \mathcal{S} \mid i \leq |\mathcal{S}|$).

6.2.2 Actions and Events

Actions do not have any specific semantics in the model, meaning that the model is detached from the language used to represent actions. Nevertheless, it requires that actions are observable and agents are able to map from their language to actions and vice-versa. For practical purposes and simplicity in specifying the model, we will adopt the following action semantics in this thesis:

Definition 2. An Action α_i is defined as a first-order atomic formula of the form $\alpha(t_1, \ldots, t_j)$, in which the terms $t_1, \ldots, t_j$ represent extra attached data required for the action execution.

Example 1. This example specifies an action α_1 that depicts agent Alice supplying $20kWh$ of energy to agent Bob.

$$\alpha_1 = Supply(Alice, Bob, 20kWh)$$

Agents operate in a NMAS, whose environment $\mathcal{E}n$ has no specific semantics in the model, meaning that is detached from the language used to represent the environment and agents interactions. For practical purposes and simplicity in specifying the model, we will adopt that agents interact among themselves through the exchange of *events*[1]. Events represent agents' actions or interactions that take place during the execution of the NMAS.

Definition 3. An Event e_i is defined as a tuple

$$e_i = \langle \texttt{time}, \texttt{sender}, \texttt{receiver}, \texttt{data} \rangle,$$

where:

- `time` is a numeric value that indicates the global time at which the event was generated ($\texttt{time} \in \mathcal{T}$, where $\mathcal{T}$ is the domain of time).
- `sender` identifies the agent that originated the event ($\texttt{sender} \in \mathcal{A}g$).
- `receiver` identifies the recipient agent of the event ($\texttt{receiver} \in \mathcal{A}g$).
- `data` is the content of the event, i.e., what the event is about. Assuming that actions are represented as first-order atomic formula, we represent the event data as a conjunction of grounded atomic first-order formulas of the form $\phi_1 \wedge \ldots \wedge \phi_x$, in which each predicate is an action α_i and its terms are extra attached data about that action.

We assume that an agent can either observe events that have taken place in the environment, or explicitly receive them as a recipient.

Example 2. This example specifies an event sent at 10am by agent Alice to agent Charlie informing that Alice supplied $20kWh$ of energy to Bob.

$$e_1 = \langle 1000, Alice, Charlie, Supply(Alice, Bob, 20kWh) \rangle$$

6.2.3 Norms

In NMASs, actions and interactions (i.e., events data) are ruled by norms that prescribe the expected agents' behaviors.

[1] It is of our knowledge that base NMASs on the exchange of events may prevent agents the possibility to react in situations specifying no actions. However, the proposed model is abstract enough to allow it implementation using other approaches, for instance, state machines.

Definition 4. A Norm $n_i \in \mathcal{N}$ is defined as a tuple

$$n_i = \langle \texttt{status}, \texttt{conditions}, \texttt{issuer}, \texttt{content} \rangle$$

where:

- `status` is the state of the norm. Possible states are `active` or `inactive`.
- `conditions` is the set of contextual conditions that renders the norm applicable. For instance, it may define the role of the target agent to which the norm is addressed to or the environmental circumstances to which the norm applies.
- `issuer` identifies the agent that originally issued the norm.
- `content` represents the criteria prescribing the agents behaviors.

Example 3. This example specifies an active norm (n_1) issued by the *State* that obliges each supplying operation from A to B to be of at least $100kWh$. Additionally, the norm is only applicable to agents playing the role of *Producer* in the system.

$$n_1 = \langle active, role(A) = Producer, State, Supply(A \in \mathcal{A}g, B \in \mathcal{A}g, Q \geq 100kWh) \rangle$$

Note that A, B and Q are free variables which are unified respectively to the actual producer and buyer agent's name and the quantity of energy supplied.

Along with the ability of perceive events, agents can also interpret their content. In particular, they use the norm to (i) recognize that an event content matches with the prescribed norm, which implies that the performed actions are ruled by that norm, (ii) deduce that an event content violates or complies with the matched norm, and (iii) calculate the magnitude of the deviation between an event content and the norm prescription. Because these capacities strongly depend on the application domain, the model does not impose any specific way of implementing these operations in the norm. This task is left to the system developer that wants to use the model in a given application. The operations that should be implemented in a norm are:

- **Test-Condition.** The `test-conditions` operation checks whether a norm is applicable by testing its status and the truth value of the conditions in the norm. The operation `norm.test-conditions: n.conditions` $\rightarrow$ `{true,false}` takes as argument norm's applicable conditions `n.conditions` and returns `true` if it verifies that the condition has a true truth value, or `false` otherwise.
- **Match.** The `match` operation checks whether the data content of an event is ruled by the norm. The operation `norm.match: e.data` $\rightarrow$ `{true,false}` takes as argument the event content `e.data` and returns `true` if it verifies that the content is ruled by the norm, or `false` otherwise.

- **Comply.** The `comply` operation verifies whether the data content of an event complies or violates the criteria specified in the norm. The operation `norm.comply: e.data` $\rightarrow$ `{true,false}` takes as argument the event content and returns `true` if it is compliant to the norm prescription, or `false` otherwise.

- **Magnitude.** The `magnitude` operation assesses how much the event content deviates from the norm prescription. The operation `norm.magnitude: e.data` $\rightarrow$ `Magnitude` takes as argument the event content and returns the magnitude of the deviation between the norm prescription and the event content. The `Magnitude` semantics depends on the application domain and on the content that is being assessed, thus the model does not make any assumption about it either.

Analyzing the event e_1 in Example 2 and assuming that Alice plays the Producer role, we can assume that event e_1 matches the norm n_1 (by substituting the free variables, $A \leftarrow Alice$, $B \leftarrow Bob$ and $Q \leftarrow 20kWh$). However, its data content does not comply with the norm as it only provides $20kWh$ to agent Bob, while the minimum required by the State is $100kWh$. The magnitude of the deviation in this example is $80kWh$.

6.2.4 Sanctions

Actions matching the prescription of norms are subject to sanctions.

Definition 5. A Sanction $s_i \in \mathcal{S}$ is defined as a tuple

$$s_i = \langle \texttt{status}, \texttt{conditions}, \texttt{category}, \texttt{content} \rangle$$

where:

- `status` is the state of the sanction. Possible states are `active` or `inactive`.

- `conditions` is the set of contextual conditions that renders the sanction applicable. For instance, it may define the role of the target agent to which the sanction is addressed or the environmental circumstances to which the sanction applies.

- `category` is the classification of the sanction according to the dimensions of the typology detailed in Section 5.2. A category is defined as a tuple

  $\texttt{category} = \langle \texttt{purpose}, \texttt{issuer}, \texttt{locus}, \texttt{mode}, \texttt{polarity}, \texttt{discernability} \rangle$

  where possible values of each term are:

  - `purpose` = {`Punishment`, `Reward`, `Incapacitation`, `Guidance`, `Enablement`}.
  - `issuer` = {`Formal`, `Informal`}.
  - `locus` = {`Self-Directed`, `Other-Directed`}.

  - `mode` = {`Direct`, `Indirect`}.
  - `polarity` = {`Positive`, `Negative`}.
  - `discernability` = {`Obtrusive`, `Unobtrusive`}.

- `content` is the specification of the set of actions representing the sanction.

Agents are able to react to norm compliance and violations by sanctioning. This capability is strongly dependent on the application domain and current information to generate a sanction. Here we do not propose any specific way of implementing this operation and this task is left to the system developer that wants to use the sanction in a given application. The operations that should be implemented in a sanction are:

- **Test-Conditions.** The `test-conditions` operation checks whether a sanction is applicable by testing the truth value of the status and the conditions in it. The operation `sanction.test-conditions: s.conditions` → `{true,false}` takes as argument sanction's applicable conditions `s.conditions` and returns `true` if it verifies that the condition has a true truth value, or `false` otherwise.

- **Create.** The *create* operation creates actions from the sanction. It maps information representing, for instance, the agent's current situation, into the sanction to generate the actions. The operation `sanction.create: sanction-info` → `actions` takes as argument sanctioning information and returns `actions`.

Example 4. This example specifies two sanctions (s_1 and s_2). Sanction s_1 specifies a punishment sanction in which the supplier A is fined by twice the amount of its deviation magnitude. Sanction s_2 is a rewarding sanction in which the sanctioner spreads to its neighbors the reputation that agent A is a good supplier.

$$\begin{aligned} category_1 =& \langle Punishment, Formal, Direct, Negative, Obtrusive\rangle \\ s_1 =& \langle active, A \in \mathcal{A}g \wedge role(A) = Supplier, category_1, \\ & Fine(A, 2 \times Magnitude)\rangle \end{aligned}$$

$$\begin{aligned} category_2 =& \langle Reward, Informal, Indirect, Positive, Unobtrusive\rangle \\ s_2 =& \langle active, A \in \mathcal{A}g \wedge role(A) = Supplier, cat_2, \\ & Spread\_Reputation(A, Neighbors, Good\_Supplier)\rangle \end{aligned}$$

Note that A is a free variable which is unified to the actual supplier agent's name extracted from the event.

The action α_i created from the sanction s_1 assuming the event e_1 from Example 2 and the norm n_1 from Example 3 is

$$\alpha_i = Fine(Alice, 160)$$

On the basis of the above defined entities, we formalize in the sequence the repositories De Jure and De Facto that represent the passive entities of the sanctioning enforcement model.

6.2.5 De Jure Repository

The De Jure repository ($\mathcal{DJ}_{rep}$) stores all the known norms and sanctions of an agent as well as links between them. A link between a norm and a sanction implies that an agent can consider a sanction as a possible reaction to the compliance or violation of the norm it is associated with. These relationships can be many to many and they can change over time. The $\mathcal{DJ}_{rep}$ is defined as a tuple comprised of three data sets:

$$\mathcal{DJ}_{rep} = \langle \mathcal{NS}, \mathcal{SS}, \mathcal{LS} \rangle$$

where:

- $\mathcal{NS}$ (*Norm Set*) represents the set of norms that the agent knows ($\mathcal{NS} \subseteq \mathcal{N}$) stored in the $\mathcal{DJ}_{rep}$.
- $\mathcal{SS}$ (*Sanction Set*) represents the set of sanctions that the agent knows ($\mathcal{SS} \subseteq \mathcal{S}$) stored in the $\mathcal{DJ}_{rep}$.
- $\mathcal{LS}$ (*Link Set*) represents the set of all links between norms and sanctions ($\mathcal{NS} \times \mathcal{SS} \rightarrow \mathcal{LS}$) stored in the $\mathcal{DJ}_{rep}$. Each entity l in $\mathcal{LS}$ is defined as a tuple $l = \langle n, \mathcal{SS}_n \rangle$ where:
  - n is a norm ($n \in \mathcal{NS}$).
  - $\mathcal{SS}_n$ is a subset of sanctions in the Sanction Set potentially applicable to norm n' violations ($\mathcal{SS}_n \subseteq \mathcal{SS}$).

6.2.6 De Facto Repository

The De Facto repository ($\mathcal{DF}_{rep}$) stores data about the agent itself and other agents' sanctioning activities observed in the environment. This repository records the norm and the sanction applied due to a norm violation or compliance. Furthermore, it stores data about the efficacy of the applied sanction in promoting compliance. This information can then be used to assess the efficacy of different sanctions in achieving their purpose in specific contexts. The semantics of efficacy of a sanction is domain dependent, yet generally it means whether the sanction produced the expected behavior, i.e., norm compliance.

Some examples of information extracted from the data store in this repository are (i) the category of sanction more frequently applied as a reaction to a specific norm compliance or violation, and (ii) the most effective sanction in promoting compliance of a specific norm.

The $\mathcal{DF}_{rep}$ is defined as a tuple comprised of a single data set

$\mathcal{DF}_{rep} = \langle \mathcal{HS} \rangle$

where:

- $\mathcal{HS}$ (*Historical Set*) represents the set of historical information about applied and observed sanctions stored in the $\mathcal{DF}_{rep}$. Each entity h in $\mathcal{HS}$ is defined as a tuple

  $h = \langle \texttt{time}, \texttt{sanctioner}, \texttt{sanctionee}, \texttt{norm}, \texttt{sanction}, \texttt{complied}, \texttt{effective} \rangle$

  where:

  - `time` is a numeric value that indicates the global time at which the sanction was applied ($\texttt{time} \in \mathcal{T}$, where $\mathcal{T}$ is the domain of time).
  - `sanctioner` is the agent that applied the sanction ($\texttt{sanctioner} \in \mathcal{A}g$).
  - `sanctionee` is the target agent of the sanction ($\texttt{sanctionee} \in \mathcal{A}g$)
  - `norm` is the norm that triggered the application of the sanction ($\texttt{norm} \in \mathcal{NS}$).
  - `sanction` is the sanction applied to the `sanctionee` ($\texttt{sanction} \in \mathcal{SS}$).
  - `complied` is a flag that signals whether the sanction was applied due to the violation or compliance with the norm ($\texttt{complied} \in \{\texttt{true,false}\}$).
  - `efficacy` is a flag that signals whether the sanction was effective or not in promoting compliance ($\texttt{effective} \in \{\texttt{true,false}\}$).

Next, we formally specify the different active entities capabilities of the adaptive sanctioning enforcement model.

6.2.7 Detector Capability

The Detector checks whether the content of an event e is ruled or not by any norm n stored in the set of norms $\mathcal{NS}$ of the De Jure repository. If the event content matches with a specific norm, then this process transmits the set of matching norms to the Evaluator and Controller entities for processing.

The matching between an event e content and a norm n prescription is a `boolean` function defined in Equation 6.1.

$$\texttt{match(e,n)} = \begin{cases} true & if(n.Status = active) \wedge \\ & (\texttt{n.test-conditions}(n.Conditions) = true) \wedge \\ & (\texttt{n.match}(e.Data) = true) \\ false & otherwise \end{cases} \tag{6.1}$$

The matching function is then used in the `detect` function shown in Equation 6.2 that maps an event and a $\mathcal{NS}$ into a subset of norms whose prescriptions match to the event content. The `detect` function outputs a set of norms ($\mathcal{NS}_e$).

$$\texttt{detect} : e \times \mathcal{NS} \rightarrow \mathcal{NS}_e \tag{6.2}$$

where, $\mathcal{NS}_e \subseteq \mathcal{NS}$ is the set of norms that match with the event.

The `detect` function algorithm is illustrated in Pseudo-Algorithm 1.

Pseudo-Algorithm 1 Detect all the norms that match an event content.

Require: Event e
Require: Norm Set $\mathcal{NS}$
$\mathcal{NS}_e \leftarrow \emptyset$
for ns_i in $\mathcal{NS}$ **do**
  if $match(e, ns_i)$ = true **then**
    $\mathcal{NS}_e \leftarrow \mathcal{NS}_e \cup ns_i$
  end if
end for
return $\mathcal{NS}_e$

6.2.8 Evaluator Capability

The Evaluator receives from the Detector the set of norms that matches with the event content ($\mathcal{NS}_e$). It then obtains from the De Jure repository all the applicable sanctions associated to these norms (i.e., $\mathcal{LS}$) in order to evaluate the appropriate ones to apply, if any. The evaluation and selection of sanctions uses a set of decision factors. Those factors represent the contextual information that the Evaluator may use to determine the appropriate sanctions to apply, and are described in Section 6.3.1.

$$\texttt{evaluate} : \mathcal{NS}_e \times \mathcal{LS} \times Factors \rightarrow \mathcal{SS}_{n,e} \tag{6.3}$$

where, $\mathcal{SS}_{n,e} \subseteq \mathcal{SS}$ is the set of sanctions to apply.

Equation 6.3 represents an abstract specification of the `evaluate` function. An actual implementation of this function is proposed in Section 6.3.

6.2.9 Executor Capability

The Executor receives from the Evaluator a set of sanctions and executes them. The `execute` function maps sanctions received from the Evaluator to actions in the environment encapsulated in events.

$$\texttt{execute} : \mathcal{SS}_{n,e} \rightarrow \mathcal{A}_{n,e} \tag{6.4}$$

where, $\mathcal{A}_{n,e} \mid \forall \alpha_i \in \mathcal{A}_{n,e}, \alpha_i \in \mathcal{A}c$ is the set of actions to be applied due to the event e compliance or violation of norm n.

Equation 6.4 refers to the `execute` function that maps a set of sanctions to a set of actions.

6.2.10 Controller Capability

The Controller monitors the outcomes of applied sanctions, and stores and reviews the De Facto repository with them, as specified in Equation 6.5.

$$\texttt{control} : \mathcal{DF}_{rep} \times \mathcal{SS}_{n,e} \rightarrow \mathcal{DF}_{rep} \tag{6.5}$$

6.2.11 Legislator Role

The Legislator updates de jure norms and sanctions in the $\mathcal{DJ}_{rep}$ based on an assessment of De Jure and De Facto repositories.

$$\texttt{legislate} : \mathcal{DJ}_{rep} \times \mathcal{DF}_{rep} \rightarrow \mathcal{DJ}_{rep} \tag{6.6}$$

Equation 6.6 represents the mapping a $\mathcal{DJ}_{rep}$ and $\mathcal{DF}_{rep}$ into a new $\mathcal{DJ}_{rep}$. The updates could be motivated by reducing misalignment between de facto and de jure norms and sanctions. For instance, the Legislator could create a link between a norm n_i and a sanction s_i because it recognizes that sanction s_i is being frequently applied and effective in making agents to comply to norm n_i.

6.3 Sanctioning Evaluation Model

The sanctioning evaluation model consists of a decision process in which the agent uses a set of factors in order to determine whether to sanction and which type of sanction to apply expecting that it may increase compliant behaviors.

The importance of this decision has already been identified in social sciences in several empirical studies, such as Anderson, Chiricos and Waldo (1977), Jacob (1980), Hollinger and Clark (1982), Kean (1992), and more recently corroborated by laboratory experiments with human subjects, such as Masclet (2003), Noussair and Tucker (2005), Kube and Traxler (2011).

In computer science, Pasquier, Flores and Chaib-draa (2005) has identified the importance of such decision, although they have not proposed any model. Looking at the analyzed enforcement mechanisms in Chapter 4, this is a still a gap to be tackled (see Table 2).

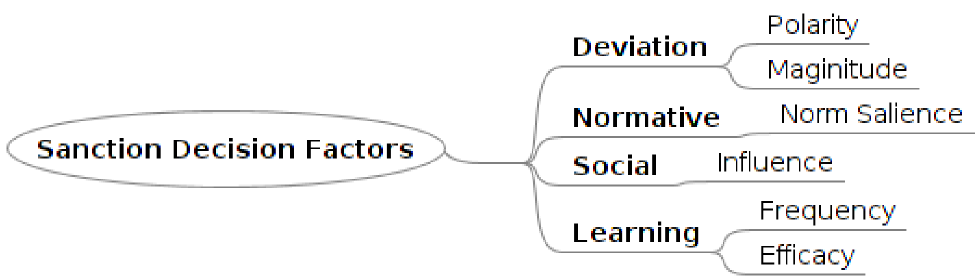
Hence, we propose a sanctioning evaluation model that enables agents to decide whether to sanction, and if so, decide to apply between a Formal and an Informal sanction (see Section 5.2.2). This model is based on a set of sanction decision factors taking into consideration social aspects claimed as important on humans decision (HORNE, 2009). We expect that this social aspect when integrated to the model may render it more suitable to interoperate with humans in STS.

6.3.1 Factors

The sanctioning evaluation process is based on a set of sanction decision factors as illustrated in Figure 19.

The factors are grouped in four types: (i) the *Deviation* factors relate to the action that triggered the sanction evaluation process and the possible application of sanctions, (ii) the *Normative* factors refer to normative aspects of the social group, (iii) the *Social* factors concern features about the interrelationship of the member of the social group, and (iv) the *Learning* factors refer to past behavior aspects of the members of the social group.

Figure 19 – Sanction decision factors.



In more detail, we propose to use the following decision factors:

- *Polarity*: indicates whether the performed action violates or complies with the norm.
- *Magnitude*: measures how much an action complies or violates a norm prescription. It is an objective measure extracted by comparing the actions performed and the expected behavior prescribed by the norm.
- *Norm Salience*: measures the importance of a norm within the Evaluator' social group in a given context (see Section 3.4.3). The higher the perceived salience of a norm,

the higher its impact on the agent's decision to comply with that norm, and to apply a sanction in those that comply or violate the norm (ANDRIGHETTO et al., 2013).

- *Social Influence*: measures how much an agent estimates it can indirectly influence others' behaviors through an informal sanction, in specific reputation, rather than resort to usual and more costly formal sanctions, e.g., material sanctions.

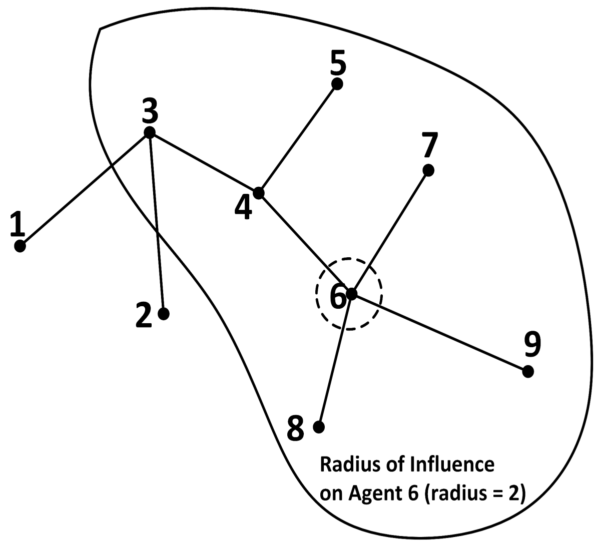


Figure 20 – Agent 1 evaluates the social influence it may have over Agent 6 considering a radius of influence equals 2.

Let us take as an example the social network presented in Figure 20. The social influence of Agent 1 on Agent 6 is an index that depends on previous experiences of Agent 1 with possible influencers of Agent 6. First, Agent 1 identifies the influencers of Agent 6 at a certain radius (Pseudo-Algorithm 2). The influencers of Agent 6 are those at a certain distance of it: if we consider a radius equal to 2, Agent 6' influencers would be Agents 3, 4, 5, 7, 8 and 9 (those inside the ellipse).

Agent 1 then sums up the estimates of the influence it would have on Agent 6 through each of the identified influencers (Pseudo-Algorithm 3). This is calculated as the proportion of positive interactions between Agent 1 and the influencer divided by the distance of the influencer to Agent 6 (line 9 in Pseudo-Algorithm 3). Finally, Agent 1 calculates its social influence on Agent 6 by multiplying the proportion of influencers to which it had any interaction and the normalized proportion of successful interactions (line 16 in Pseudo-Algorithm 3).

- *Frequency*: Number of times the norm was violated and complied with. The frequency is defined as a tuple

$$F = \langle f^{target}_{violate}, f^{target}_{comply}, f^{others}_{violate}, f^{others}_{comply} \rangle$$

Pseudo-Algorithm 2 Determines the influential agents distant a certain network distance radius from the target agent.

Require: Network $network$
Require: Radius $radius$
Require: Agent $target$

```
IA ← ∅
levels ← radius
nextAgents ← network.neighbors(target)
while nextAgents ≠ ∅ do
    levels ← levels − 1
    curAgents ← nextAgents
    nextAgents ← ∅
    for all curAgent in curAgents do
        if (IA ∩ curAgent) = ∅ then
            IA ← {IA ∪ curAgent}
            if levels ≥ 0 then
                nextAgents ← {nextAgents ∪ network.neighbors(curAgent)}
            end if
        end if
    end for
end while
return IA
```

where, $f_y^x \mid x \in \{target, others\} \wedge y \in \{violate, comply\}$ are the number of times that, respectively, the target agent or others violated and complied with the norm.

- *Efficacy*: Number of times that after applied the sanction that sanctioned agent subsequent action was a compliant behavior.

6.3.2 Evaluation Process

The evaluation decision process uses the factors described in the foregoing section in order to determine which sanction to apply. Figure 21 illustrates a decision-tree diagram indicating the main decisions to be made by the process and the factors influencing its decision.

The first decision to be taken is whether to sanction or not someone that performed an action ruled by a norm. This decision is made stochastically based on a *Sanction Probability* (`sanctionProb`) calculated using the factors:

- The Polarity (`polarity`) indicates whether the action has complied (i.e., Positive) or violated (i.e., Negative) the norm. It is used to calculate the Frequency coefficient

Pseudo-Algorithm 3 Calculate the social influence index of an agent in a network and considering a neighborhood radius.

Require: Network $network$
Require: Radius $radius$
Require: Target $target$
$\mathcal{IA} \leftarrow \texttt{influence}(network, radius, target)$
$totalSum \leftarrow 0$
$totalInt \leftarrow 0$
$numAgents \leftarrow 0$
for all $agent$ in $\mathcal{IA}$ **do**
  $pInt \leftarrow \texttt{positiveInteractions}(source, agent)$
  $nInt \leftarrow \texttt{negativeInteractions}(source, agent)$
  if $(pInt + nInt) \geq 0$ **then**
    $totalSum \leftarrow sum + \left(\frac{pInt}{\texttt{network.distance}(agent, target)}\right)$
    $totalInt \leftarrow totalInt + (pInt + nInt)$
    $numNodes \leftarrow numNodes + 1$
  end if
end for
$sii \leftarrow 0$
if $(\mathcal{IA} \neq \emptyset)$ and $(totalInt \geq 0)$ **then**
  $sii \leftarrow \left(\frac{numNodes}{\mid \mathcal{IA} \mid}\right) \times \left(\frac{totalSum}{totalInt}\right)$
end if
return sii

$freq_x$ according to Equation 6.7.

$$\texttt{freq}_x = \begin{cases} \frac{\texttt{nInt}}{\texttt{nInt+pInt}} & if \texttt{polarity} = \texttt{Negative} \\ \frac{\texttt{pInt}}{\texttt{nInt+pInt}} & if \texttt{polarity} = \texttt{Positive} \end{cases} \tag{6.7}$$

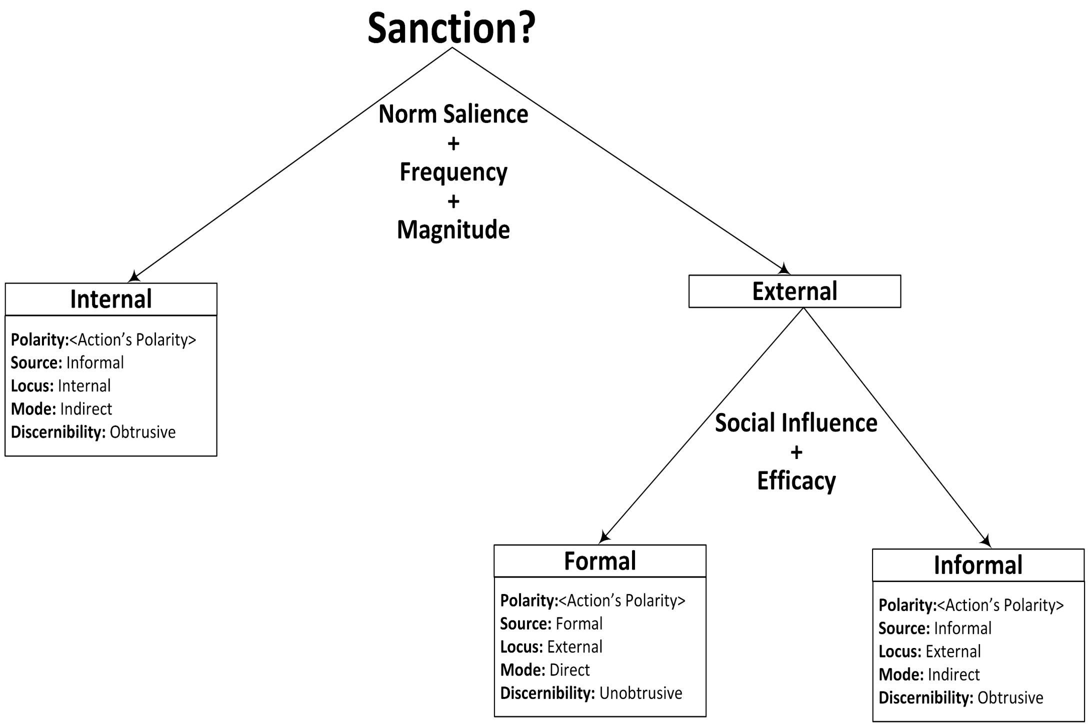
where, `nInt` is the number of negative interactions, and `pInt` is the number of positive interactions.

- The Frequency (`frequency`) corresponds to the number of compliant and violation actions observed or performed. Instead of using its actual value, we transform it in order to increase the probability to sanction as the frequency of the same actions increases. The hyperbolic tangent function (HASKELL, 1895) has this characteristics, which we apply here to transform the Frequency coefficient according to Equation 6.8.

$$\texttt{frequency} = \frac{1 - e^{(-2 \times \texttt{freq}_x)}}{1 + e^{(-2 \times \texttt{freq}_x)}} \tag{6.8}$$

- The Norm Salience (`salience`) measures subjectively the importance other agents in the social group care about the norm. It is a normalized value, ranging in the

Figure 21 – Evaluator decision process.



interval $[0, 1]$. Low values of norm salience indicates the norm is not important in the social group, while high values indicates it is important and other agents care about complying or violating it. Thus, higher Norm Salience values should increase the probability of sanctioning.

- The Magnitude (`magnitude`) measures the percentage deviation to norm prescription and is also represented by a normalized value in the domain $[0, 1]$.

The Sanction Probability is calculated as

$$\texttt{sanctionProb} = \frac{\texttt{magnitude} + \texttt{salience} + \texttt{frequency}}{3} \tag{6.9}$$

Pseudo-Algorithm 4 shows the decision between applying an Internal or an External sanction.

Pseudo-Algorithm 4 Decide between Internal and External sanction.

Require: Sanction Probability `sanctionProb`

$s \leftarrow \emptyset$
if $rand(0, 1) <$ `sanctionProb` **then**
    $s \leftarrow$ `Internal`
else
    $s \leftarrow$ `External`
end if
return s

If the Internal sanction branch is chosen, the agent should select sanctions of that type for apply. Otherwise, there is another decision to be taken, whether it is more appropriate to apply a Formal or Informal sanction. This decision is based on the *Social Influence* and *Efficacy* factors.

The Social Influence (`influence`) is calculated as described in Section 6.3.1. The Efficacy (`efficacy`) refers to the proportion of times the sanction after being applied makes the agent to cooperate in the next interaction. The Efficacy is measured to each category of sanction.

Pseudo-Algorithm 5 shows the decision between applying a Formal or an Informal sanction.

Pseudo-Algorithm 5 Decide between a Formal and an Informal sanction.

Require: Social Influence `influence`
Require: Efficacy Formal `influence-threshold`
Require: Efficacy Formal $\texttt{efficacy}_f$
Require: Efficacy Informal $\texttt{efficacy}_i$

1: $s \leftarrow \emptyset$
2: **if** $(\texttt{efficacy}_i > \texttt{efficacy}_f)$ or $(\texttt{influence} > \texttt{influence-threshold})$ **then**
3: $s \leftarrow$ `Informal`
4: **else**
5: $s \leftarrow$ `Formal`
6: **end if**
7: **return** s

6.4 Application Requirements

The proposed model intends to be applied on a large range of concrete settings; however, those settings need to fulfill a minimum set of conditions in order to take a better advantage of the proposed model. The unordered list of conditions are:

1. The agents must interact with each other and with the environment over time.

2. The agents' actions and interactions must be prescribed by a set of standards representing the correct behaviors expected from others, i.e., a behaviors' referential. In particular, these correct expected behaviors are prescribed through the concept of norms.

3. The agents must have a set of different types of sanctions available for application in case of the detection of an action that complies with or violates one or more of the norms.

4. The agents must have the possibility to gather information about others' behaviors and sanctions.

5. The agents must have some interdependence among themselves in order to generate, if not an explicit, at least an implicit social network. This social network is used to determine the possible social influence an agent may have on others in its social group.

6.5 Discussion

This chapter describes our adaptive sanctioning enforcement model that is composed of a conceptual enforcement process model and its formalization and a sanctioning evaluation model. The former is a generic process intended to guide the development of future enforcement models as it specifies the main features and components necessary for an enforcement mechanism. The latter is one possible sanctioning decision model that can be created based on the different categories of sanctions presented in the typology described in Chapter 5.

The sanctioning evaluation model proposed is tailored to choose between Formal and Informal sanctions in a network of connected agents. It makes possible measuring the influence an agent may have on another, i.e., the social influence index. Other proposals may use different factors and decision processes.

We present next a case study where this model is applied.

Part III

Case Study

7 Smart Grid Case Study

In this chapter, we present a case study in the SG domain. Modeled according to the ABM approach, it consists of an energy trading scenario, where agents interact and use the adaptive sanctioning enforcement model proposed in Chapter 6. Several experiments are conducted for evaluating the model in promoting agents' compliance with their energy supplying commitments. In Section 7.1, we briefly describe the features and advantages of using the ABM approach as an evaluation methodology. The description of the SG energy trading model, comprised of the environment's normative structure, the agents, and their dynamics is presented in Section 7.2. Finally, we describe the experiments carried out and their results in Section 7.3, whose analyses and discussion are presented in Section 7.4.

7.1 Agent-Based Modeling

The experimental methodology used for analyzing the adaptive sanctioning enforcement model is based on the ABM approach. This approach is used for building the SG energy trading simulation scenario in which experiments aiming to evaluate the proposed enforcement model are performed.

ABM is a powerful simulation modeling technique that has been used in the study of complex adaptive systems (BONABEAU, 2002). In particular, it has become popular in simulating human systems due to its capability of (i) representing individual and heterogeneous entities (i.e., agents as human individuals or institutions), (ii) representing multiple scales of analysis ranging from agents' actions (i.e., micro-level) to social level (i.e., macro-level), and (iii) capturing the emergence of structures resulting from the nonlinear interactions of these individual agents.

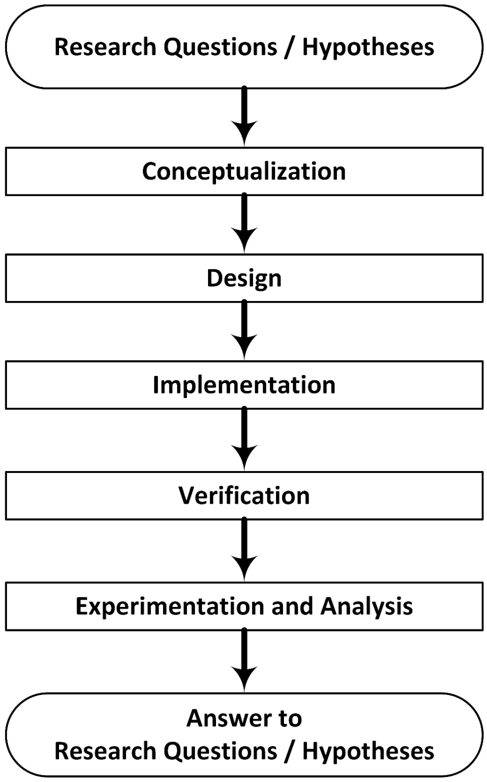
These capabilities have also made ABM one of the most popular approaches for analyzing STSs (NIKOLIC; GHORBANI, 2011), which is not a surprise as STSs involve the interrelationship between humans and artificial agents (see Section 2.1).

Gilbert (2007) defines ABM as "a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment." ABM basically consists of creating a simplified representation (i.e., a simulation model) of the target system or the phenomenon to be studied that serves to express how the target operates. This model can then be used to evaluate how different initial conditions and policies affect the model's outcomes.

Our methodology benefits from the ABM due to the fact that the latter enables the execution of simulation-based experiments, thus disregarding the need for a real SG energy trading system. This simulative approach enables the possibility of evaluating the performance of different policies at a reduced cost. Moreover, it isolates the system from external noise making sure that result differences among policies are due exclusively to the policies themselves.

Figure 22 depicts the phases of the methodology applied in this thesis, based on the ABM approach.

Figure 22 – Phases of the methodology based on the ABM approach.



Conte et al. (2001) argue that "(social) analysis should start with the problem rather than the model, technique or theory." Thus the first methodological phase corresponds to the definition of clear *Research Questions* and *Hypotheses* to be checked using the forthcoming model.

Once the aim of the research is defined, the *Conceptualization* phase consists of determining and scoping the system for modeling. Conceptualization is an abstract view of some selected part of the world that are of interest for some particular purpose, i.e., the target system or phenomenon. It corresponds to decide what the system entails, what are its boundaries, what it is composed of and how its entities interrelates. Additionally, we specify the output metrics that will help to answer the posed research questions and to validate (or not) the experimental hypotheses.

The *Design* phase consists of classifying and structuring the entities identified in the Conceptualization phase in terms of a software model. In ABM, agents are the basic active units of the model. They are recognized by their boundaries, behaviors and ability to interact with the environment or among themselves.

Completed the specification, the model is actually coded as a computer program in the *Implementation* phase. The implementation can be realized by using only a general-purpose programming language like C, C++ and Java, or supported by an agent-based simulator framework and toolkit like NetLogo (WILENSKY, 1999), Repast Symphony (NORTH et al., 2013) and Mason (LUKE et al., 2005). The correctness of the transformation from the conceptual model to the computer program is checked in the *Verification* phase. Its main task is to ensure that the computer program developed in the Implementation phase completely satisfies the conceptual model specified in the Design phase.

In our case, the preceding phases describe the steps taken for building the model on top of which the sanctioning enforcement model evaluation takes place. The *Experimentation and Analysis* phase refers to the execution of experimental settings under different initial conditions and configurations (i.e., policies), and evaluate the sanctioning enforcement model's efficacy in promoting norm compliance. The statistical hypothesis testing (BOSLAUGH; WATTERS, 2008) is used to comparatively evaluate the statistical significance of the results obtained via different policies. Particularly, we adopt a non-parametric hypothesis testing known as Wilcoxon Rank Sum Test (also known as Mann-Whitney Test) (HOLLANDER; WOLFE, 1973, p. 68–75) due to the fact that our data cannot be assumed normally distributed under the Shapiro-Wilk test (SHAPIRO; WILK, 1965).

In the next sections, we detail the application of this methodology in building and evaluating the proposed adaptive sanctioning enforcement model.

7.2 Simulation Model

In this section, we describe the SG energy trading simulation model[1] used as a case study for analyzing the efficacy of the proposed adaptive sanctioning enforcement model according to the methodology introduced in the preceding chapters.

7.2.1 Objectives

This case study evaluates the impact of different sanctioning policies on the level of compliance and enforcement costs in a SG. Specifically, it evaluates the impact of a more flexible sanctioning enforcement model that enables the use of different categories of sanctions as deterrence. We use the proposed sanctioning evaluation model (Chapter 6

1 Available for download at <https://github.com/gnardin/smartgrid>. See instructions for installation in Appendix A.

to evaluate *mono-type* and *multi-type* sanctioning policies in the SG renewable energy trading scenario. The mono-type policy means that a single type of sanction is available to agents, while the multi-type allows agents to choose among various available types of sanction. We hypothesize that compared to mono-type sanctioning policies, multi-type policies would (i) increase the level of norm compliance, (ii) decrease the enforcement costs, and (iii) decrease the use of non-renewable energy.

Thus the elaborated research questions are:

1. What is the effect of a mono-type sanctioning policies on the level of norm compliance in comparison to a multi-type sanctioning policy?
2. What is the effect of a mono-type sanctioning policies on the enforcement costs in comparison to a multi-type sanctioning policy?
3. What is the effect of a mono-type sanctioning policies on the use of non-renewable energy in comparison to a multi-type sanctioning policy?

Compared to mono-type sanctioning policies, we hypothesize that

H_{LC} a multi-type sanctioning policy increases the level of compliance,

H_{EC} a multi-type sanctioning policy decreases the enforcement costs, and

H_{NR} a multi-type sanctioning policy decreases the the use of non-renewable energy.

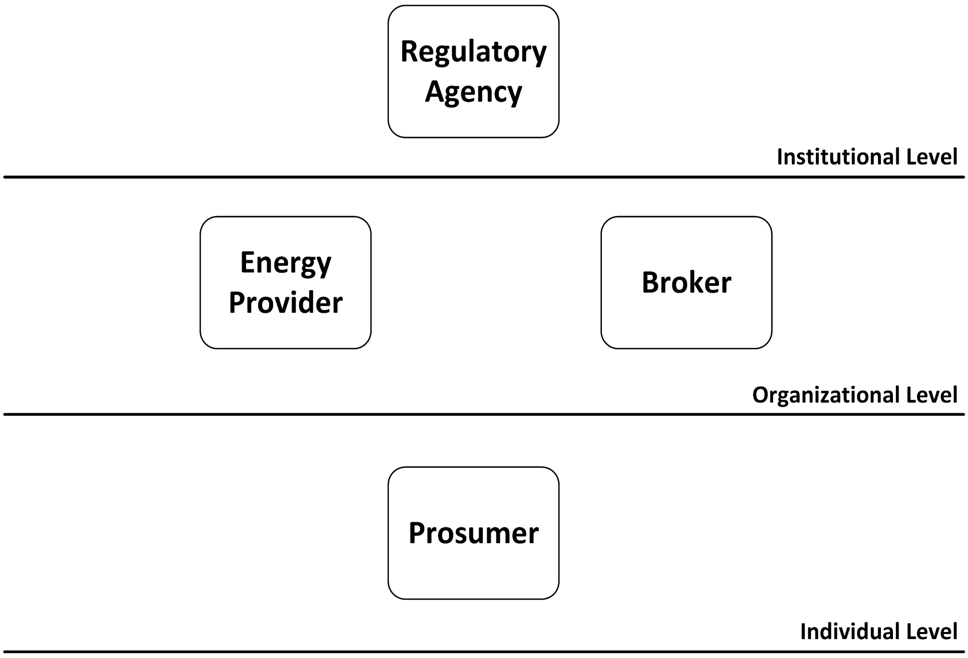
7.2.2 Model Description

This simulation model represents an energy trading scenario in a SG environment. It was inspired by the Motivational Scenario described in Chapter 2, even though it does not exactly reflect all the entities and functionalities introduced there.

Figure 23 illustrates the normative SG environment, which is structured in three distinct social levels: the *Individual Level*, the *Organizational Level* and the *Institutional Level*. Each level is populated with different types of agents: *Prosumer*, *Broker*, *Energy Provider* and *Regulatory Agency*.

These levels represent a social hierarchy in which agents at lower levels are subject to the norms prescribed by agents at upper levels. Agents can interact with other agents located at the same level (i.e., intra-level interaction) as well as at another levels (i.e., inter-level interaction). They are not restricted to interact with agents in their adjacent levels, yet they can interact bypassing levels, e.g., the Regulatory Agency in the Institutional Level can directly communicate with Prosumers at the Individual level and vice-versa.

Figure 23 – Simulation normative SG environment structured in three hierarchical levels and their respective types of agents.



The Regulatory Agency formally governs the interactions among Prosumers, the Broker and the Energy Provider. As part of its responsibility, the Regulatory Agency also (i) regulates the energy trading system, (ii) receives reports from Prosumers about contracts violations, and (iii) enforces regulatory requirements through the imposition of formal sanctions (i.e., fines and suspensions) to violators. Its set of attributes is listed in Table 7.

Table 7 – Regulatory Agency's agent attributes.

Attributes	**Description**
`reportsToPunish`	Minimum number of reports necessary for begin considering whether to punish a violator.
`probPunishing`	Probability of punishing, assuming the minimum number of reports has been reached.
`punishment`	Material cost inflicted on a violator.
`reportsToSuspend`	Minimum number of reports necessary for considering whether to suspend a violator.
`probSuspending`	Probability of suspending, assuming the minimum number of reports has been reached.
`periodSuspension`	The period a violator will be suspended from trading energy.

The only prescribed norm issued by the Regulatory Agency in the SG energy trading model states that a *seller Prosumer is obliged to supply the contractually agreed quantity of energy to the buyer Prosumer being it subject to sanctions*.

The Energy Provider[2], or simply Provider, is a power company whose energy generation is based on carbon-based fuels. Thus it generates a stable and guaranteed quantity of energy to fulfill its consumers' needs as its energy generation does not depend on the vagaries of the weather. The Provider can also buy any quantity of energy from Prosumers, which renders it responsible for balancing the energy supply and demand in the system.

The Energy Provider is an agent characterized by the set of attributes listed in Table 8.

Table 8 – Energy Provider's agent attributes.

Attributes	Description
`sellingPrice`	Price paid per kWh to sell energy to Prosumers.
`buyingPrice`	Price paid per kWh to buy energy from Prosumers.

Prosumers are agents representing households characterized by the set of attributes listed in Table 9 and more detailed described in Section 7.2.3. They can consume and generate small quantities of energy. Their energy generation is usually based on weather-dependent renewable energy sources, like solar panels and wind turbines.

Table 9 – Prosumer's agent attributes.

Attributes	Description
`selfInt`	Prosumer's greediness.
`minConsume`	Minimum quantity of energy consumed.
`maxConsume`	Maximum quantity of energy consumed.
`minGenerate`	Minimum quantity of energy generated.
`maxGenerate`	Maximum quantity of energy generated.
`consumeVar`	Variation between the estimation and the actual consumption.
`generateVar`	Variation between the estimation and the actual generation.
`energyPrice`	Price of kWh of energy to sell.

Prosumer's energy consumption and generation are quite unpredictable (i.e., stochastic) and can only be forecast. The consumption forecast, however, is more accurate than the generation forecast as the former is influenced mostly by the Prosumer's pattern of behavior, while the latter relies on less controllable factors and is subject to the vagaries of the weather.

Because Prosumers' consumption and generation of energy are not always balanced (i.e., consumption $\neq$ generation), they need to buy or sell energy depending, respectively, on whether they have estimated to generate less or more than they will consume. If a Prosumer estimates to produce more energy than he consumes, he may trade (i.e., sell) the

[2] Even though in reality we may have several Energy Providers available, this model considers a single Energy Provider to the whole system as its main role is to balance the demand and supply of energy.

surplus, otherwise he needs to buy the lacking quantity. Prosumers may trade energy with other Prosumers, or with the Energy Provider.

Trading energy with other Prosumers, however, is always economically more advantageous to the Prosumers as the Provider trades energy practicing higher prices. That is, the Provider buys energy for a lower price and sells it at a higher price than the average market price. This characteristic is introduced in the model for promoting the generation and the trade of renewable energy among Prosumers.

Prosumers trade energy through the Broker. Prosumers estimating to generate a surplus of energy may offer it for selling to the Broker, while those needing to buy energy send a buying demand request to the Broker. When offering energy, the Prosumer may provide a list of Prosumers whom energy cannot be sold to; and, when demanding energy, the Prosumer may provide an ordered list of preferred suppliers. The Broker receives these offers and demands, and matches them in a way that better fits the imposed constraints and available resources. To each matched offer and demand, the Broker creates a contractual commitment between the parties (i.e., seller and buyer Prosumers).

The Broker's assignment algorithm used to match offers and demands is a variation of the Gale-Shapley algorithm (GALE; SHAPLEY, 1962) as illustrated in Pseudo-Algorithm 6.

Because Prosumers trade the estimated surplus of energy, they may offer more than they actually generate. Eventually, this may cause the violation of the contractual commitment established. We assume that Prosumers are not bad intentioned in the sense that they do not explicitly plan to harm others (i.e., not supplying the committed quantity of energy) to take clear advantages from the situation. However, due to their risk seeking level and the stochasticity of the energy generation, they rationally would tend to over-estimate the quantity of energy generated in order to trade as much energy as possible, even if it ends up generating less than what was initially estimated and offered.

In the event of violation, Prosumers that have not received the expected quantity of energy buy the difference from the Provider, thus paying a higher price. Additionally, the affected Prosumer (i.e., the buyer) may react by sanctioning the violator Prosumer (i.e., the seller). The affected Prosumer has a set of options to sanction the violator:

- it may inflict a material cost on the violator[3],
- it may report[4] the violator to the Regulatory Agency, or
- it may spread a bad reputation about the violator to other agents.

[3] This type of sanction is very unlikely in a real trading system, yet we included it in order to support actions of sanctioning enforcement models that we compare with ours sanctioning model proposal.

[4] We assume that Prosumers do not cheat when reporting, meaning that all the denunciations are true and reflect a real violation of a contract between two parties.

Pseudo-Algorithm 6 Broker's assignment algorithm used to match offers and demands.

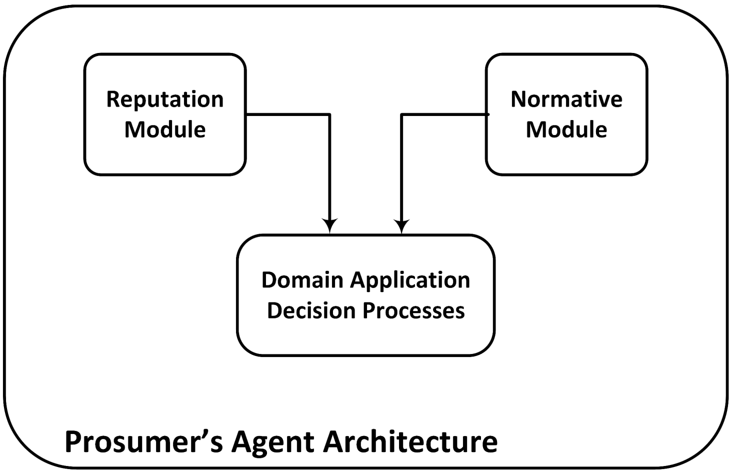
```
Require: Demands demands
Require: Offers offers
assigned ← ∅
FD ← demands
while FD ≠ ∅ do
  for demand in FD do
    prefProsumers ← demand.getPrefProsumers()
    assign ← false
    while (!assign) and (prefProsumers ≠ ∅) do
      prefProsumer ← prefProsumers.poll()
      offer ← prefProsumer.getOffer()
      if (offer.getExcluded() ∉ demand.getProsumer()) and
      (offer.getQty() ≥ demand.getQty()) then
        if offer ∉ assigned then
          assigned ← assigned ∪ {offer,demand}
          FD ← FD \ demand
          assign ← true
        else
          oldDemand ← assigned.getDemand(offer)
          if demand.getQty > oldDemand.getQty() then
            assigned.replace(offer,oldDemand,demand)
            FD ← (FD \ demand) ∪ oldDemand
            assign ← true
          end if
        end if
      end if
    end while
  end for
end while
return assigned
```

The decision to sanction and which sanction to apply is defined by the sanctioning enforcement model attached to the Normative Module of the Prosumer. For instance, the model proposed in Chapter 6 takes into account the strength of the norm (i.e., norm salience), the magnitude of the violation (i.e., difference between the quantity of energy sold and supplied) and the social influence of the affected Prosumer on the Prosumers violator neighbors in order to decide whether to sanction the violator, and if so, which sanction to apply.

7.2.3 Prosumer Agent Architecture

The Prosumer's architecture (Figure 24) is endowed with a *Reputation Module* and a *Normative Module* that enables Prosumers take reputation and normative concepts into account in their *Domain Application Decision Processes*.

Figure 24 – Prosumer agent architecture.



The Reputation Module, on one hand, computes and records the reputation scores of other Prosumers with respect to their skill as energy suppliers. The Reputation Module is based on the Repage model (CONTE; PAOLUCCI, 2002), thus it distinguishes between Prosumer's *image* and *reputation* (See Section 4.3.4.1). Image corresponds to the proportion of all successful experiences an evaluator Prosumer had with the evaluated Prosumer as energy supplier. It is calculated as shown in Equation 7.1.

$$image_{ij} = \frac{sucInt_{ij}}{totalInt_{ij}} \tag{7.1}$$

where, $image_{ij}$ is the image Prosumer i has about Prosumer j, $sucInt_{ij}$ refers to the number of successful interactions in which Prosumer j supplied the agreed quantity of energy to Prosumer i, and $totalInt_{ij}$ refers to the total number of interactions between them.

Reputation corresponds to a shared evaluation of Prosumers as energy suppliers, thus depends on information sharing. Prosumer i updates its reputation about Prosumer j based on the reputation evaluation received from Prosumer k according to Equation 7.2.

$$reputation_{ij} = \frac{reputation_{ij} + (image_{ik} * reputation_{kj})}{2} \tag{7.2}$$

where, $reputation_{ij}$ is the reputation Prosumer i has about Prosumer j, $image_{ik}$ is the image Prosumer i has about Prosumer k, and $reputation_{kj}$ is the reputation that Prosumer i received from Prosumer k about Prosumer j.

Equation 7.2 thus defines that the reputation updating is the arithmetic mean between the Prosumer i reputation of Prosumer j and the reputation shared by Prosumer k about Prosumer j normalized by the image Prosumer i has about Prosumer k.

The reputation score of a Prosumer ($score_{ij}$) is a combination of both image and reputation values as illustrated in Equation 7.3.

$$score_{ij} = imageW * image_{ij} + reputationW * reputation_{ij} \tag{7.3}$$

where, $imageW$ and $reputationW$ refers respectively to the weight given to the image and reputation values, where $imageW + reputationW = 1$.

The Normative Module, on the other hand, is responsible for handling normative information in the model and corresponds to the EMIL-A normative architecture (see Section 3.4.3). Its main feature is the ability to extract normative information from the social environment and to dynamically update its salience. The norm salience measures how important a norm is within the agent' social group in a given context.

Next, we describe the dynamics of the simulation model in a sequence of steps.

7.2.4 Simulation Dynamics

In the initialization stage of the simulation, the Regulatory Agency, the Energy Provider, the Broker, and a set of Prosumers (see Section 7.2.3) are instantiated. The Prosumers' energy price (`energyPrice` attribute) is randomly set with a value in between a minimum (`minPrice` parameter) and a maximum (`maxPrice` parameter) defined as simulation configuration parameters.

The Prosumers are then arranged in a network configuration in which each Prosumer is represented as a node of the network. The possible network configurations available are: (i) *Complete* – all Prosumers are connected to all other Prosumers, (ii) *Lattice* – each Prosumer is connected to Prosumers in a Von Neumann neighborhood (i.e., the four nearest orthogonal neighbor agents) in the square lattice, and (iii) *Scalefree* – Prosumers are connected following a power law distribution (BARABÁSI; ALBERT, 1999). The distribution of Prosumers in this network configuration represents their proximity (i.e., distance), yet it does not limit them to trade energy only to the Prosumers they are connected to.

Once completed the initialization stage, the agents interact for several rounds, following the steps illustrated in Figure 25.

Each round begins with Prosumers estimating the quantity of energy that they will generate and consume (`Forecast Consume and Generate`, see Figure 25). These quantities vary among Prosumers and they are bounded to the values set in the attributes `minConsume`, `maxConsume`, `minGenerate` and `maxGenerate` described in Table 9. The estimated quantity of energy to be consumed and generated are calculated according to Equations 7.4 and 7.5.

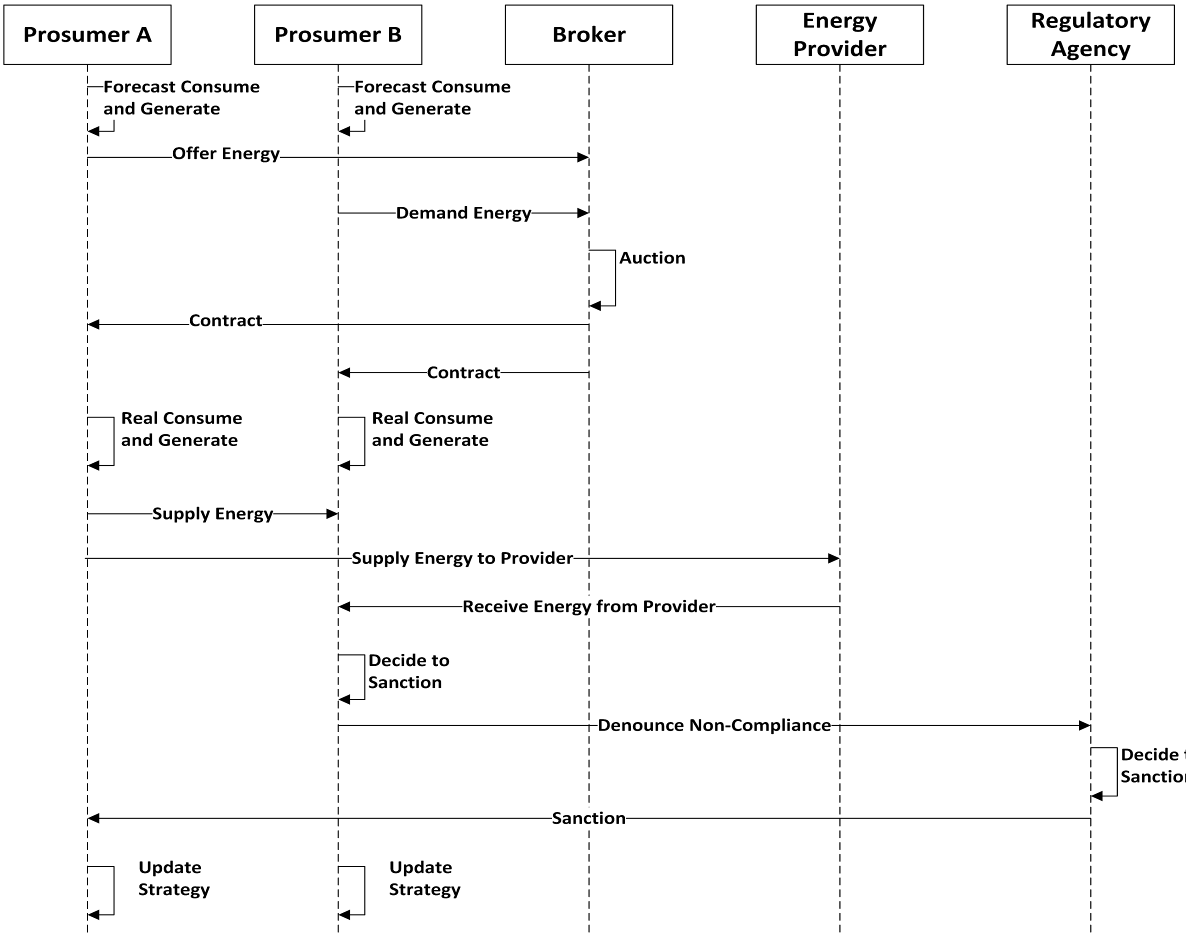
$$conE = \texttt{minConsume} + ((\texttt{maxConsume} - \texttt{minConsume}) \times rand(0,1)) \quad (7.4)$$

$$genE = \texttt{minGenerate} + ((\texttt{maxGenerate} - \texttt{minGenerate}) \times rand(0,1)) \quad (7.5)$$

where $rand(0,1)$ is a random generator that returns a real number between 0 and 1.

Once estimated the quantity of energy each Prosumer expects to consume and generate, those with surplus of energy ($generate > consume$) define the quantity they will

Figure 25 – Sequence diagram of the agents' interaction.



offer for sale to the Broker. To determine the quantity to offer, the Prosumer i first define the extremes minimum and maximum quantity of energy it will have available according to Equations 7.6 and 7.7.

$$minE_i = (genE_i \times genAcc_i) - (conE_i \times (1 + (1 - conAcc_i))) \quad (7.6)$$

$$maxE_i = (genE_i \times (1 + (1 - genAcc_i))) - (conE_i \times conAcc_i) \quad (7.7)$$

where, $genAcc_i$ and $conAcc_i$ are respectively the generation and the consumption accuracy value calculated from previous rounds. It is updated every round after the agent comes to know its actual consumption and generation of energy (see Equations 7.13 and 7.14).

The Prosumer i calculates the quantity to offer according to Equation 7.8.

$$offer_i = minE_i + ((maxE_i - minE_i) \times strategy_i) \quad (7.8)$$

where, $strategy_i$ represents the Prosumer i's dynamic risk seeking level, which is calculated based on three components: its greediness ($\texttt{selfInt}_i$), its view about its own reputation value ($reputation_{ii}$) and the importance of the supplying norm in the social group (Sal_i^{supply}). Equation 7.9 shows the formula used to calculate the strategy value of Prosumer i.

$$strategy_i = \frac{(IW \times \texttt{selfInt}_i) + (RW \times reputation_{ii}) + (NW \times (1 - Sal_i^{supply}))}{IW + RW + NW} \quad (7.9)$$

where, IW, RW and NW represent the weight give to each of the terms of the formula.

Each Prosumer with a surplus of energy sends a selling offer to the Broker (`Offer Energy`, see Figure 25). In the offer it informs the maximum quantity of energy to sell and also the Prosumers it would like not to sell the energy to (i.e., ostracize list).

Next, Prosumers with lack of energy ($generate < consume$) send a buying demand to the Broker (`Demand Energy`, see Figure 25). The demand is composed of the maximum quantity of energy it would like to buy and an ordered list of the Prosumers from whom it would like to buy energy (it is retrieved from the `demand` by the function `demand.getPrefProsumers()` in Pseudo-Algorithm 6 at line 5). Prosumers are ordered in ascending order according to their distance and reputation score as shown in Equation 7.10.

$$pref_{ij} = \left(DW \times \frac{dist_{ij}}{maxDist_i}\right) + (RSW \times (1 - score_{ij})) \tag{7.10}$$

where, DW and RSW are the weight given to the distance and to the reputation score of the offering Prosumer. $dist_{ij}$ is the distance in number of hops of the network between Prosumers i and j, $maxDist_i$ is the distance in number of hops to the farthest Prosumer of Prosumer i, and $score_{ij}$ is the reputation score Prosumer i has about Prosumer j (see Equation 7.3).

The Broker receives the offers and the demands and executes the auction (`Auction`, see Figure 25) among them. The auction is performed according to the Pseudo-Algorithm 6.

The assigned contracts are them informed to the buying and seller Prosumers (`Contract`, see Figure 25) and they come to know the real quantity of energy consumed and generated (`Real Consume and Generate`, see Figure 25) calculated according to Equations 7.11 and 7.12.

$$conR = conE \times rand(1 - \texttt{consumeVar}, 1 + \texttt{consumeVar}) \tag{7.11}$$

$$genR = genE \times rand(1 - \texttt{generateVar}, 1 + \texttt{generateVar}) \tag{7.12}$$

where $rand$ is a random generator that returns a real number between the two parameters. `consumeVar` and `generateVar` are respectively the attributes defining the variability of the consumption and generation of energy described in Table 9.

Furthermore, the consume and generate accuracy are updated according to the Equations 7.13 and 7.14.

$$conAcc = \frac{conAcc + \left(1 - \left(\frac{|conE - conR|}{max(conE, conR)}\right)\right)}{2} \tag{7.13}$$

$$genAcc = \frac{genAcc + \left(1 - \left(\frac{|genE - genR|}{max(genE, genR)}\right)\right)}{2} \tag{7.14}$$

Seller Prosumers with a contract supply their exceeding quantity of energy to the buyer Prosumers (`Supply Energy`, see Figure 25). Due to the stochasticity in the consumption and generation, the seller may not be able to generate sufficient energy for consumption and to supply to the buyer, and the buyer also may not need all the previously demanded energy.

After supplying and receiving energy, the Prosumers make a balance and identify whether they lack or have excess of energy. In both cases, the Prosumers trade energy with the Provider (`Supply Energy to Provider` and `Receive Energy from Provider`, see Figure 25). Even though the Provider has unlimited capacity to supply and receive energy, in reality a negotiation would occur between the parties (i.e., Prosumers and Provider); however, we have simplified it by making the Provider accept to sell and buy any amount of energy supplied or demanded by Prosumers without any negotiation.

Those Prosumers that do not have their contract fulfilled may decide to sanction the violator Prosumer (`Decide to Sanction`, see Figure 25). The decision refers to which sanction to apply, among the following available ones:

S1 Report the violation to the Regulatory Agency,

S2 Spread the negatively updated reputation score to other Prosumers,

S3 Ostracize the Prosumer.

Sanction **S1** is considered a formal sanction as it depends on an authority evaluation that will actually apply a sanction to the violator. Sanctions **S2** and **S3**, however, are informal sanctions as they can be applied directly by the Prosumer.

The decision of which sanction to apply follows the adaptive sanctioning enforcement model described in Chapter 6, in particular the sanctioning evaluation model described in Section 6.3.

Once decided which sanction to apply, the Prosumer acts. In case of reporting, the Regulatory Agency receives the violation report from the Prosumer (`Report Non-Compliance`, see Figure 25). The Regulatory Agency then decides whether or not to apply a formal sanction to the violator (`Sanction`, see Figure 25). The Regulatory Agency decision follows the Pseudo-Algorithm 7, that uses the attributes defined in Table 7.

Finally, the Prosumers update their strategies based on their actions, sanctions received and the information they have observed about the others agents performing in the environment (`Update Strategy`, see Figure 25). They basically update the image and reputation about other Prosumers (see Equations 7.1 and 7.2), the norm salience (see Section 3.4.3) and the greediness (`selfInt`) attribute value.

Pseudo-Algorithm 7 Regulatory Agency decision to sanction.

```
Require: Historic Violator numReports
Require: Violator prosumerId
Require: Magnitude magnitude sanction ← ∅ numReports ← numReports + 1
if numReports > reportsToSuspend then
    if rand(0,1) < probSuspending then
        sanction ← suspend(prosumerId,periodSuspension)
        numReports ← 0
    end if
end if
if numReports > reportsToPunish then
    if rand(0,1) < probPunishing then
        sanction ← punish(prosumerId,magnitude × punishment)
    end if
end if
return sanction
```

The greediness is updated based on the Prosumer's performance. If it sold energy and fulfilled the contract, the greediness is increased in proportion to what was not sold to another Prosumer divided by the actual quantity of energy in excess it had. Otherwise, it did not fulfill the contract, it reduces the greediness by the difference of what was supplied and what was demanded and the total sanction received for not fulfilling the contract divided by the demanded plus the total sanction received. Equation 7.15 illustrates the greediness updating.

$$update = \begin{cases} \text{fulfilled} & \texttt{selfInt} \leftarrow \texttt{selfInt} + \left(\frac{\texttt{actual}-\texttt{consumed}}{\texttt{actual}}\right) \\ \text{not fulfilled} & \texttt{selfInt} \leftarrow \texttt{selfInt} + \left(\frac{\texttt{supplied}-\texttt{demanded}-\texttt{sanctions}}{\texttt{demanded}+\texttt{sanctions}}\right) \end{cases} \quad (7.15)$$

Next, we describe some experiments carried out using the SG energy trading simulation model.

7.3 Experiments

In this section, we analyze the effect of different sanctioning enforcement models and settings on the trading dynamics and Prosumers behaviors in the SG energy trading model. They are evaluated in a set of experiments with a specific goal as shown in Table 10.

All these experiments are run with 100 Prosumers, whose input parameters values are shown in Table 11. The Provider's input parameters values are shown in Table 12.

The analyses of the experiments are based on a set of output metrics described in Table 13, whose values are calculated as the average all simulation replications results.

All the experiments were executed in a machine with processor Intel Core i7-3632QM 2.20 GHz with 8 GB RAM running Linux Ubuntu 14.04.01. The analyses were

Table 10 – List of Experiments.

Experiment	Description
1	Simulation Replication and Length
2	Baseline
3	Types of Sanctions
4	Social Influence Levels
5	Topologies

Table 11 – Prosumers' input parameters values.

Parameter	Value
`network`	Scalefree
`selfInt`	1.0
`minConsume`	100 kWh
`maxConsume`	700 kWh
`minGenerate`	200 kWh
`maxGenerate`	500 kWh
`consumerVar`	0%
`generateVar`	50%
`minPrice`	\$ 15
`maxPrice`	\$ 25

Table 12 – Provider's input parameters values.

Parameter	Value
`sellingPrice`	\$ 30
`buyingPrice`	\$ 10

Table 13 – Simulation output metrics.

Metric	Description
`levelCompliance`	Level of compliance
`numCompliances`	Number of compliances
`numViolations`	Number of violations
`numFines`	Number of fines inflicted
`numReputation`	Number of reputation spreading activity
`numOstracized`	Number of ostracized Prosumers
`providerSell`	Quantity of energy sold by the Provider
`providerBuy`	Quantity of energy bought by the Provider

carried out using R Statistics v3.0.2 (R Core Team, 2014) and the graphics generated using ggplot2 (WICKHAM, 2009).

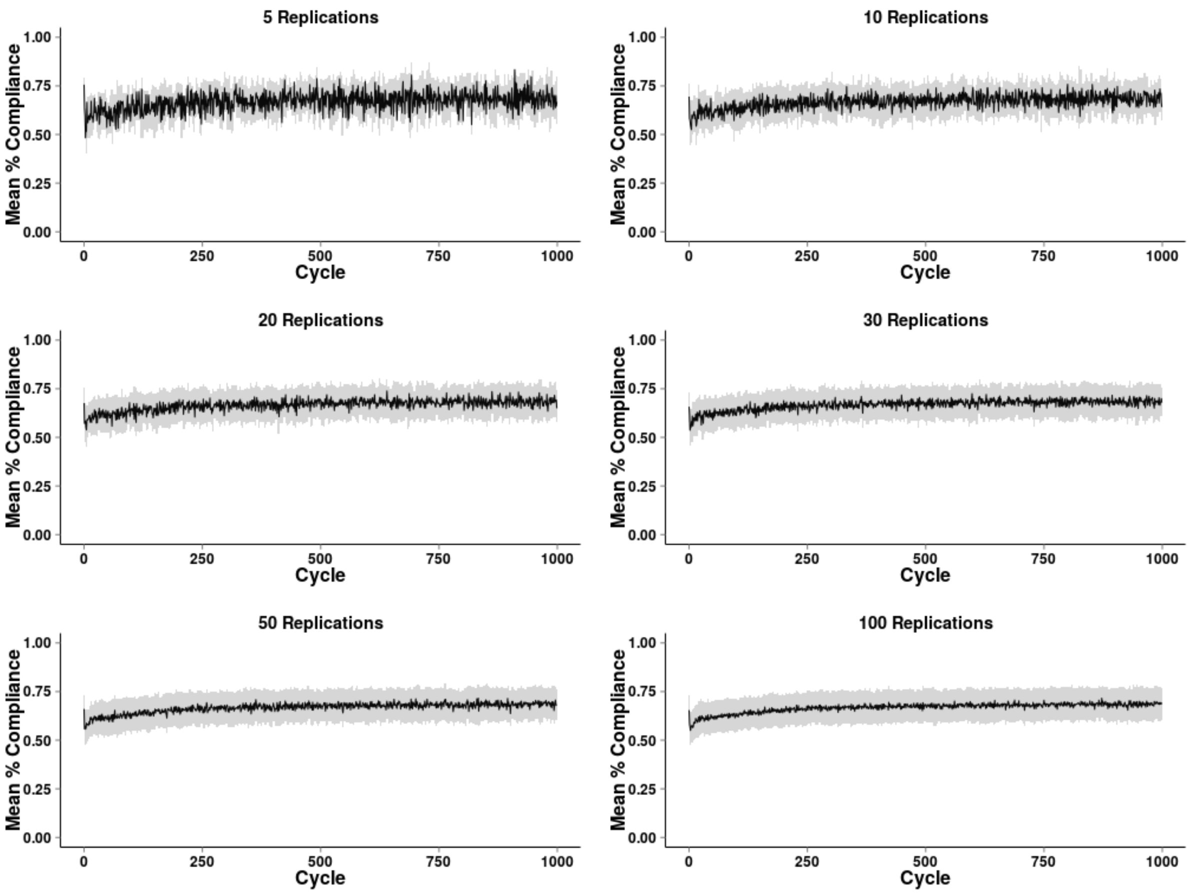
7.3.1 Experiment 1: Simulation Replications and Length

This experiment determines (i) the number of replications needed per simulation setting, and (ii) the moment (i.e., the round) at which the system is assumed stable.

Figure 26 plots the levels of compliance output metric for 5, 10, 20, 30, 50 and 100 replications for 1000 rounds.

The adequate number of replications can be determined by estimating the experimental error variance. As suggested by Lorscheid, Heine and Meyer (2012), the *coefficient*

Figure 26 – Plot the level of compliance' output metric for 5, 10, 20, 30, 50 and 100 replications with a duration of 1000 rounds. The black line represents the mean of the level of compliance and the gray shade indicates the standard deviation.



of variation (c_v) is a prominent measure for analyzing the accuracy of the experimental error variance as it is a dimensionless and normalized measure. The coefficient of variation is calculated according to Equation 7.16.

$$c_v = \frac{s}{\mu} \tag{7.16}$$

where, s is the standard deviation and μ the arithmetic mean of a set of values.

The procedure to determine the adequate number of replications for a simulation requires, first, the calculation of the coefficient to a relatively low number of replications. Then, if increasing iteratively the number of replications and comparing the new calculated coefficient to the preceding one reach a situation in which the difference does not change, meaning that increasing the number of replications does not impact the accuracy of the variance. Hence, the last number of replications in which a change was noticed can be assumed as the minimum number of replications for the simulation setting.

We adopt the coefficient of variance to analyze the variance accuracy of our simulation model. In particular, we analyze the coefficient for the variation accuracy of the level of compliance (`levelCompliance`) and number of violations (`numViolations`) output metrics. These metrics are chosen because they represent the main aspects we are trying to control with our sanctioning enforcement model, i.e., increase the level of compliance and reduce the number of violations. Table 14 shows the results obtained for 5, 10, 20, 30, 50 and 100 replications.

Table 14 – Coefficient of variance (c_v) for 5, 10, 20, 30, 50 and 100 replications to the output metrics `levelCompliance` and `numViolations`.

Replications	Coefficient of Variance (c_v)	
	`levelCompliance`	`numViolations`
5	0.06	0.17
10	0.05	0.13
20	0.04	0.12
30	0.03	0.11
50	0.03	0.11
100	0.03	0.11

Analyzing Table 14 c_v values, we can assume that increasing the number of replications to more than 30 does not actually reduce the variance for both output metrics. Hence, we adopt 30 number of replications in all the experiments presented in this thesis.

Once the number of replications of a simulation is defined, there is the need to identify the number of rounds required for the simulation outputs to stabilize. We use the approach proposed by Chli et al. (2003) in which stability refers to the convergence of a particular system metric to an equilibrium distribution. They view an agent-based system as a stochastic process, in particular a Markov process, with a countable set of states I whose state at time n is the random variable X_n. This stochastic process x_1, x_2, x_3, $\ldots$ is stable, if the probability distribution of x_m becomes independent of the time index m for large m.

This stability can be verified by testing whether two consecutive sets of values of the system's metric has the same distribution. Chli et al. (2003) propose the use of the statistical hypothesis testing as a method to check the distribution convergence.

We have applied this method and we have used the Wilcoxon Rank Sum Test to check the stability of the level of compliance output metric comparing different consecutive sets of values as shown in Table 15.

Table 15 – Stability analysis.

Set 1	**Set 2**	p-**value**
(0,200]	(200,400]	4.778×10^{-41}
(200,400]	(400,600]	8.894×10^{-13}
(400,600]	(600,800]	1.060×10^{-4}
(600,800]	(800,1000]	1.096×10^{-1}

Assuming an $\alpha = 0.05$ and a set of length of 200 values, we can infer that the simulation results begin to stabilize when comparing the sets of values (600,800] and (800,1000] (p-value $> \alpha$ or $0.1096 > 0.05$). We can thus conclude that the system's metric stabilizes before round 1000. For the sake of precaution, however, we adopt 1000 rounds as the number of rounds we will use in all the experiments in this thesis. Furthermore, all the analysis will be based on the average value of the output metrics after its stabilization, accordingly the average values are calculated from round 600 to 1000.

7.3.2 Experiment 2: Baseline

This experiment determines the baseline values of the output metrics (see Table 13) disregarding sanctions. The Prosumer's and Regulatory Agency input attributes values are shown in Tables 16.

Table 16 – Prosumer's and Regulatory Agency parameters values.

Attribute	Value
Prosumer	
`network`	Scalefree
`normActivateNumMsg`	2
`normActivateNumAction`	10
`normActivateSalThreshold`	0.5
`noemActive`	5 (True) 95 (False)
`normSalience`	0.5
`IW`	1
`NW`	0
`RW`	0
`DW`	1
`RSW`	0
`imageValue`	1
`reputationValue`	1
`imageWeight`	0.7
`ostracizeThreshold`	0
`influenceRadius`	1
`influenceThreshold`	100%
Regulatory Agency	
`reportsToPunish`	0
`probPunishing`	0%
`punishment`	0
`reportsToSuspend`	0
`probSuspending`	0%
`periodSuspension`	0

The results obtained in the Baseline experiment are shown in Table 17.

Table 17 – Experiment 2: Baseline results.

Output Metric	Value
`levelCompliance`	61.19%
`numCompliances`	21.54
`numViolations`	13.62
`numFines`	0
`numReputation`	0
`numOstracized`	0
`providerSell`	2986.06 kWh
`providerBuy`	2875.60 kWh

These results indicate that the level of compliance in the sanctionless simulation model is around 61.19% without any mechanism of enforcement. The next experiments will analyze different sanctioning enforcement configurations in order to identify those that improve the compliance with a reduced cost.

7.3.3 Experiment 3: Types of Sanctions

This experiment compares all the possible combinations of sanctions using the adaptive sanctioning enforcement model. These possible combinations, or policies, are shown in Table 18.

Table 18 – Experiment 3: Combination of Types of Sanctions.

Policies	Description
Base	No sanction.
Formal	Prosumers can use only Formal sanctions (i.e., Report).
Informal	Prosumers can use only Informal sanctions (i.e., Reputation spreading).
Hybrid	Prosumers can choose to use between Formal and Informal sanctions (i.e., choose between Report or Reputation spreading).

The configuration attributes values that change with respect to the Baseline values in Table 16 are shown in Table 19.

Table 20 shows the results obtained in this experiment.

Comparing the levels of compliance (`levelCompliance`) obtained for each policy, we conclude that the Formal policy is the most successful as it maintains a compliance of 71.94%. The main cause of such success is the direct and immediate impact of the Formal sanctions in the gain of the Prosumers. The Informal sanction, however, may take a while to have an effect on the violator, what may not be easily detectable in a first moment.

Table 19 – Prosumer's and Regulatory Agency parameters values.

Attribute	Formal	Informal	Hybrid
Prosumer			
network	Scalefree	Scalefree	Scalefree
IW	1	1	1
NW	1	1	1
RW	0	1	1
DW	0.5	0.5	0.5
RSW	0.5	0.5	0.5
ostracizeThreshold	0	0.5	0.5
influenceRadius	1	1	1
influenceThreshold	100%	50%	50%
Regulatory Agency			
reportsToPunish	0	0	0
probPunishing	100%	0%	100%
punishment	3000	0	3000

Table 20 – Experiment 3: Types of Sanctions results.

Metric	Base	Formal	Informal	Hybrid
levelCompliance	61.19%	71.94%	66.26%	68.40%
numCompliances	21.54	23.05	23.25	23.40
numViolations	13.62	8.98	11.81	10.77
numFines	0	6.72	0	1.16
numReputation	0	0	16.09	13.67
numOstracized	0	0	30.95	29.11
providerSell	2986.06 kWh	2156.43 kWh	2652.95 kWh	2472.95 kWh
providerBuy	2875.60 kWh	3357.06 kWh	3125.63 kWh	3228.12 kWh

Nonetheless, if we look at the average number of punishments (numFines) inflicted to achieve this level of compliance, we can note that compared to the Hybrid policy the use of punishment is extremely high. Remember that punishment in this model represents material punishments that usually incurs a cost also to the sanctioneer. Hence, although maintaining a higher level of compliance of about 3.5% compared to the Hybrid policy, the Prosumers in the Formal policy need to use almost 6 times more punishments. Making a parallel to the human societies, we can interpret it as a characteristic of an extremely violent society, which only mechanism to be protected is paying the cost to punish.

The Hybrid policy can achieve a reasonable level of compliance without paying the cost of punishing by using other two mechanisms, the reputation spreading and ostracism. Look that the average number of ostracized Prosumers are relatively high, about 30% of the whole group. It has an effect which is less interaction among Prosumers and more trading of energy with the Provider (see providerSell and providerBuy).

7.3.4 Experiment 4: Social Influence Levels

This experiment checks the impact that different Social Influence Thresholds, i.e., the minimum level of influence for a Prosumer to choose to use the Informal sanction instead of the Formal sanction.

We use as a reference the input parameters values to the Hybrid policy in Table 19. Then, we create four different policies in which the only parameter that changed is the `influenceThreshold`. The values tested for this parameter are: 0%, 25%, 50%[5] and 75%. The results obtained in this experiment are shown in Table 21.

Table 21 – Experiment 4: Social Influence results.

Metric	**Social Influence Threshold**			
	0%	25%	50%	75%
`levelCompliance`	66.26%	66.94%	68.39%	69.83%
`numCompliances`	23.35	23.30	23.40	23.42
`numViolations`	11.81	11.47	10.77	10.08
`numFines`	0	0.48	1.16	3.13
`numReputation`	16.09	15.05	13.67	8.35
`numOstracized`	30.95	29.71	29.11	28.89
`providerSell`	2652.95 kWh	2586.57 kWh	2472.95 kWh	2346.51 kWh
`providerBuy`	3125.63 kWh	3166.33 kWh	3228.12 kWh	3285.86 kWh

The different thresholds to the social influence parameter seems to have a very moderate impact (5% approximately) on the level of compliance. As the threshold increases, however, the level of compliance increases because it is linked to the increase also of the number of punishments (Formal sanctions) inflicted.

7.3.5 Experiment 5: Topologies

This experiment checks the impact of different network topologies in the dynamic of the simulation.

We use as reference the input parameters value set to the Hybrid policy in Table 19. Then, we create three different policies in which we change the network topology. The topologies tested are: Complete, Lattice and Scalefree[6].

The results obtained in this experiment is shown in Table 22.

The experiment results in Table 22 evidence a particular characteristic between the Formal and Informal sanctions. Informal sanctions are usually more effective in small groups. We can observe that in the Lattice configuration (all agents have 4 neighbors), the level of compliance is almost as high as when only Formal sanction is used, however, the

[5] Note that the 50% is the value we have used to the Hybrid policy in Experiment 3.
[6] Note that the Scalefree is the value we have used to the Hybrid policy in Experiment 3.

Table 22 – Experiment 5: Topologies results.

Metric	Network Topology		
	Scalefree	Complete	Lattice
levelCompliance	68.39%	66.84%	70.14%
numCompliances	23.40	14.44	23.39
numViolations	10.77	7.14	9.93
numFines	1.16	5.73	0.66
numReputation	13.67	0.21	15.59
numOstracized	29.11	37.92	27.50
providerSell	2472.95 kWh	1602.83 kWh	2315.95 kWh
providerBuy	3228.12 kWh	1912.88 kWh	3297.08 kWh

number of punishments is very low (only 0.66). The Complete configuration, on the other hand, represents a huge social group (all agents have 100 neighbors) and since the use of Informal sanction in this model is conditioned to the influencer, an agent would need to be very influential in order to start using it. Furthermore, in the Complete configuration the number of ostracized agents is higher than any other configuration.

7.4 Discussion

This section answers the posed research questions and check the validity of the hypotheses presented in Section 7.2.1 based on the experimental results described in Section 7.3.

We hypothesize in Section 7.2.1 that a multi-type sanctioning policy (i.e., Formal and Informal sanctions available) compared to a mono-type sanctioning policy (i.e., only Formal or Informal) would

H_{LC} increase the level of compliance,

H_{NR} decrease the use of non-renewable energy.

To check the validity of the hypotheses H_{LC}, H_{EC} and H_{NR}, we use the statistical hypothesis testing as discussed in Section 7.1.

The validation (or not) of hypothesis H_{LC} requires the comparison of the values of the `levelCompliance` metric obtained using different policies in Experiment 3. The following statistical hypothesis testing are formulated:

Hypothesis A The value of the `levelCompliance` metric is higher in the Hybrid policy rather than in the Formal policy.

$Q^{\texttt{levelCompliance}}_{\texttt{Hybrid}} > Q^{\texttt{levelCompliance}}_{\texttt{Formal}}$

To validate Hypothesis A, we test:

$H0$: $Q^{\texttt{levelCompliance}}_{\texttt{Hybrid}} \leq Q^{\texttt{levelCompliance}}_{\texttt{Formal}}$

$H1$: $Q^{\texttt{levelCompliance}}_{\texttt{Hybrid}} > Q^{\texttt{levelCompliance}}_{\texttt{Formal}}$

Hypothesis B The value of the `levelCompliance` metric is higher in the Hybrid policy rather than in the Informal policy.

$Q^{\texttt{levelCompliance}}_{\texttt{Hybrid}} > Q^{\texttt{levelCompliance}}_{\texttt{Informal}}$

To validate Hypothesis B, we test:

$H0$: $Q^{\texttt{levelCompliance}}_{\texttt{Hybrid}} \leq Q^{\texttt{levelCompliance}}_{\texttt{Informal}}$

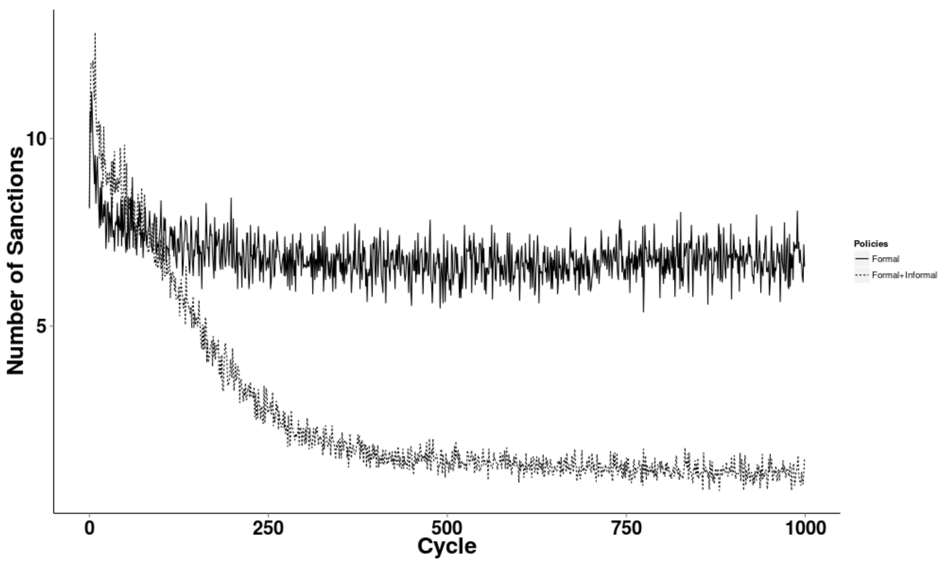
$H1$: $Q^{\texttt{levelCompliance}}_{\texttt{Hybrid}} > Q^{\texttt{levelCompliance}}_{\texttt{Informal}}$

Using the Wilcoxon Rank Sum Test, we obtain that Hypotheses A and B have a p-value of 1 and 2.2×10^{-16}, respectively. Assuming $\alpha = 0.05$, H0 is rejected to Hypothesis B, but not to Hypothesis A.

These results validate partially hypothesis H_{LC} as Hybrid policy has a lower level of compliance value than the Formal policy, but a higher level compliance value than the Informal policy.

We have noticed, however, that the number of formal sanctions (`numFines`) in the Hybrid policy reduces drastically when compared to the Formal policy, that without reducing too much the level of compliance. Figure 27 shows the dynamics of the number of formal sanctions inflicted when using the Formal and the Hybrid policy.

Figure 27 – Number of Punishment in the Formal and the Hybrid policies.



The validation (or not) of hypothesis H_{NR} requires the comparison of the values of the `providerSell` metric obtained using different policies in Experiment 3. The following statistical hypothesis testing are formulated:

Hypothesis C The value of the `providerSell` metric is lower in the Hybrid policy rather than in the Formal policy.

$Q^{\texttt{providerSell}}_{\texttt{Hybrid}} \leq Q^{\texttt{providerSell}}_{\texttt{Formal}}$

To validate Hypothesis C, we test:

$H0$: $Q^{\texttt{providerSell}}_{\texttt{Hybrid}} > Q^{\texttt{providerSell}}_{\texttt{Formal}}$

$H1$: $Q^{\texttt{providerSell}}_{\texttt{Hybrid}} \leq Q^{\texttt{providerSell}}_{\texttt{Formal}}$

Hypothesis C The value of the `levelCompliance` metric is lower in the Hybrid policy rather than in the Informal policy.

$Q^{\texttt{levelCompliance}}_{\texttt{Hybrid}} \leq Q^{\texttt{levelCompliance}}_{\texttt{Informal}}$

To validate Hypothesis C, we test:

$H0$: $Q^{\texttt{providerSell}}_{\texttt{Hybrid}} > Q^{\texttt{providerSell}}_{\texttt{Informal}}$

$H1$: $Q^{\texttt{providerSell}}_{\texttt{Hybrid}} \leq Q^{\texttt{providerSell}}_{\texttt{Informal}}$

Using the Wilcoxon Rank Sum Test, we obtain that Hypotheses C and D have a p-value of 1 and 2.2×10^{-16}, respectively. Assuming $\alpha = 0.05$, H0 is rejected to Hypothesis F, but not to Hypothesis E.

These results validate again partially hypothesis H_{NR} as the Hybrid policy has a higher non-renewable energy selling value than the Formal policy (i.e., uses more non-renewable energy), but it has a lower non-renewable energy selling value than the Informal policy, which indicates that it uses less non-renewable energy than the latter.

These results show that a multi-type policy improves partially the level of compliance and the use of non-renewable energy in comparison to a mono-type policy.

The Formal policy shows a great advantage on the level of compliance and use of non-renewable energy; however, it has a high cost as requires too many formal sanctions to maintain this level of compliance. Conversely, the Informal policy is less effective in promoting compliance and reduce the use of non-renewable energy compared to the Hybrid policy.

8 Conclusions and Future Works

The governance of systems, specially those involving human and artificial agents like STSs, are as essential as a challenge. These systems interrelate social and technical aspects that need to be tackled in an integrated fashion, which renders an effective governance a critical aspect for their success.

The governance requirements imposed by those systems are: (i) support for multiple categories of sanctions; (ii) potential association of multiple sanctions with a norm violation or compliance; (iii) adaption of the sanction content depending on the context; and (iv) decision about the most adequate sanction to apply depending on the context. We have established that existing enforcement models in NMASs are inadequate for dealing with these requirements.

We have addressed the above-mentioned gap by proposing, first, a typology of sanctions that reflects the interplay of relevant features of STSs. It provides a set of dimensions enabling the distinction of different categories of sanctions.

Second, we have developed an adaptive sanctioning enforcement model supported on a sanctioning enforcement process and a sanctioning evaluation model. The former details and formalizes the main components and capabilities that enable agents to specify, detect, evaluate, choose, apply and learn new sanctions depending on their current situation and goals. The latter is an evaluation decision model used to select among a variety of sanctions the most appropriate ones based on normative, social and learning decision factors. In particular, the evaluation model enables choosing basically between formal and informal categories of sanctions.

We demonstrate our contributions via a SG energy trading simulation model in which Prosumer agents endowed with the adaptive sanctioning enforcement model can trade energy among themselves. They may also sanction each other in the event of some supplier does not fulfill its contractual commitment.

Several experiments were carried out using this simulation model in order to validate the hypotheses posed in Section 7.2.1

H_{LC} a multi-type sanctioning policy increases the level of compliance compared to mono-type policy,

H_{EC} a multi-type sanctioning policy decreases the enforcement costs compared to mono-type policy,

H_{NR} a multi-type sanctioning policy decreases the use of non-renewable energy compared to a mono-type policy.

These results show that a multi-type policy improves partially the level of compliance and the use of non-renewable energy in comparison to a mono-type policy.

The policy that uses only formal sanctions shows a great advantage on the level of compliance and use of non-renewable energy; however, it has a high cost as it requires the application of too many sanctions to maintain the level of compliance. Conversely, the policy that uses only informal sanctions is less effective in promoting compliance and using non-renewable energy. The hybrid policy, which combines formal and informal sanctions enabling the agents to choose between them, although does not out-compete the formal policy present a reasonable level of compliance without using too much formal (possibly costly) sanctions.

The evaluation of those sanctioning policies were possible due only to the development of the proposed adaptive sanctioning enforcement model that enables the agents to choose among several categories of sanctions.

8.1 Future Works

Some of possible future directions in the research in sanctioning enforcement are:

- *Evaluate the model in a real* STS. Due to the unavailability of a real SG environment, we have evaluate the model only in a simulated environment. Nonetheless, it is of interest to understand how a system endowed with the developed model would perform in a real setting. The PowerMatching City (BLIEK et al., 2010) is a living lab Smart Grid environment in the Netherlands that represents a potential venue in which the model would be evaluated.

- *Empirical and experimental data*. The sanction literature review suggests that decisions of why and how individuals choose to sanction depends on several factors. While the literature provides several analysis of why individuals sanction, less is said about how they choose to sanction. We support that understanding how people choose a sanction would render the integration between humans and artificial agents more transparent and easier accepted by the former. Hence, this would be a topic of interest to psychologists and social scientists to investigate.

- *Complex normative environments*. The environment simulated in the case study consists of a single norm that the agents need to evaluate. It would be important to identify whether agents in a more complex normative environment would benefit differently from this model.

- *Recognition of sanctions*. All the norms and sanctions need to be known by the agent in order to the model to operate. Norm recognition modules are available in the literature, but the capacity of recognizing sanctions was not proposed by any work analyzed.
- STS *and regimentation enforcement approach*. As we developed a model based on the regulation enforcement approach, i.e., in which agents can violate the norms, we have not explored the regimentation enforcement approach in the context of STS. Hence, we have not been able to evaluate the real advantages of the regulation and regimentation approaches in governing a STS.

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Appendix

APPENDIX A – Installation Instructions

Instructions to download, compile and install the SG Energy Trading Simulation Model.

1. Software Pre-Requisites
   - Git
   - Maven
   - Oracle Java SE 8
2. Download project from GitHub.com, compile and install
   - $ git clone git@github.com:gnardin/smartgrid.git
   - $ cd smartgrid
   - $ mvn clean
   - $ mvn compile
   - $ mvn package
   - $ mvn install
3. Configure
   - Edit the file at smartgrid/src/main/resources/conf/smartgrid.xml and change parameters' value
4. Execute
   - $ mvn exec:exec -Pexec -Dexec.args="src/main/resources/conf/smartgrid.xml src/main/resources/conf/smartgrid.xsd"
   - The 'log' and 'output' directories is created under the smartgrid directory (if not changed the default values in the configuration smartgrid.xml file).
5. Analysis
   - There is a script located at the 'script' directory that you can execute using R Statistics software to summarize the results in the files created in the 'output' directory.