Web Intelligence and Agent Systems: An International Journal 9 (2011) 1–13
DOI 10.3233/WIA-2011-0224
IOS Press

Social control in a normative framework: An adaptive deterrence approach

Henrique Lopes Cardoso* and Eugénio Oliveira
LIACC / Departamento de Engenharia Informática, Faculdade de Engenharia, Universidade do Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal
E-mail: hlc@fe.up.pt, eco@fe.up.pt

Abstract. Normative environments are used to regulate multi-agent interactions, by providing means for monitoring and enforcing agents' compliance with their commitments. In business encounters, agents representing business entities make contracts including norms that prescribe what agents should do. Agent autonomy, however, gives agents the ability to decide whether to fulfill or violate their commitments. In particular, when the normative space is imperfect, contracts to which norms apply may be unbalanced, making it individually rational for agents to exploit potential flaws to their own advantage. In this paper we present and analyze an approach for exerting social control within a normative environment. An adaptive mechanism is proposed that enables a normative framework to change deterrence sanctions according to the behavior of an agent population, in order to preclude agents from exploiting potential normative flaws. The system tries to avoid institutional control beyond what is strictly necessary, seeking to maximize agent contracting activity while ensuring a certain commitment compliance level, when agents have unknown risk and social attitudes. We analyze how the adaptive deterrence sanctioning model responds to different agent populations, which are characterized by predominant risk tolerance or social awareness degrees. We show that risk-averse or socially concerned populations cause lesser deterrence sanctions to be imposed by the normative system.

Keywords: Norm, violation, sanction, deterrence, adaptation

1. Introduction

Multi-agent systems applied to B2B have been widely studied (e.g. [1,2]). Interaction infrastructures for autonomous agents representing real-world business entities (such as enterprises) have been developed (e.g. [3,4]), including negotiation and contracting facilities. Normative environments (e.g. [5–7]) are middleware that provide support for making agents' mutual commitments explicit. Those commitments are expressed as norms (behavior prescription rules), which can be assembled in contracts. Furthermore, when embedded in some notion of "institution", normative environments take an active role in checking agents' compliance with their commitments, and furthermore in enforcing such compliance. As such, electronic institutions [7,8] have been developed with norm monitoring and enforcement facilities in place, with the aim of establishing trust among participants in a norm-regulated relationship, giving contracts a binding force.

Another important facet of an electronic institution with a contracting emphasis is its ability to facilitate and assist contract establishment, by providing a normative framework [7] that specifies norms applicable to different contractual settings. Given that complete contract negotiation automation is not likely to be possible (both in terms of technological limitations and real-world acceptance), software agents may rely on background normative frameworks that fill-in the normative body of contracts. This feature is especially important when considering contrary-to-duty situations, which typically should not be likely to occur. A contract's normative structure will certainly reflect the coarse business workflow between the involved agents, but will probably include provisions for the most likely possible violations only. Further contingencies will often not be

* Corresponding author.

dealt with when establishing a contract, because it may be costly or even impossible to anticipate them.

Normative environments can provide trust by using different enforcement mechanisms. One such mechanism consists of making sure that norms are applied as defined in a contractual relationship. Some of those norms will state what agents should do when they violate some obligation (e.g.: when failing to deliver a promised good, an agent should return the payment received in advance with a 10% increase). These norms are known as contrary-to-duties. However, as mentioned above, in certain cases there will be no specified consequence. This is when other coercive approaches may be relevant, in situations where agents try to take advantage of their potential gain when violating norms (because they might be more self-interested than socially concerned).

In the literature (e.g. [9,10]) we find, among others, two basic kinds of sanctions that an institution may apply in order to incentive norm compliance (or, to put it another way, to discourage deviations). *Direct material sanctions* have an immediate effect, and consist of affecting the resources an agent has (e.g. by applying fines). *Indirect social sanctions*, such as changing an agent's reputation, may have an effect that extends through time. Depending on the domain and on the set of agents that inhabit the institutional environment, the effectiveness of such sanctions may be different: if agents are not able to take advantage of other agents' reputation information, material sanctions should be used instead.

There are two general policies used when applying (direct) sanctions, which concern their intended effects: (i) *deterrence* aims at punishing the violator so as to discourage future violations; (ii) *retribution* aims at compensating the addressee of the violation. Bringing these policies to the electronic institution realm, we see retribution sanctions as those specified in contractual norms, be they negotiated or inherited from a preexistent normative framework. In this case the institution, while monitoring norm compliance, acts as a mediator. As for deterrence sanctions, they will be applied by the institution itself, and may be used so as to maintain order (by motivating agents to comply) and consequently trust in the system. A similar distinction is made in [11], where *active sanctions* describe actions to be performed by the violator (and if he does so the violation will become extinguished) and *passive sanctions* describe actions that the norm enforcer is authorized to perform.

Deterrence has also been studied from a different perspective in political science [12], where theories are proposed for explaining international relations in tense periods such as the Cold War. In this case, deterrence is based on threats between different nations.

Economic approaches to law enforcement have suggested analyzing sanctions and their amplitude by taking into account their effects on parties' activities. Agents committing to norms that have associated deterrence sanctions enter risky activities, because they may unintentionally violate them. It has been argued [13] that under strict liability (where violators are always sanctioned) sanctions should equal harm done. An increase in the level of activity brings an increase in the expected harm; if damages equal harm, parties will have socially correct incentives to engage in risky activities (that is, to establish commitments). However, this conclusion relies on the additional assumption that parties are risk-neutral. If they are risk-averse, the optimal level of damages tends to be lower than harm. This comes from the fact that with risk-aversion, a sanction imposes a cost which does not exist under risk neutrality. As explained in [14], risk-aversion introduces costless deterrence and the policy-maker (an electronic institution in our case) should take that into account when choosing the optimal sanction.

The presence of social sanctions will also influence the behavior of agents concerning their commitments. Reputation-aware environments should have a lesser need for deterrence sanctions (see, for instance, [15]). Besides reducing agents' risk (see above), a reduction of deterrence mechanisms may be important for other reasons. On one hand, both the enforcement activities and the completion of direct sanctions may be costly, which asks for either lowering the resources used in those activities or eliminating sanctions in non-compensating cases. On the other hand, we can imagine (at least in theory) a computational system where these costs can be marginal: assuming that automatic norm monitoring is computationally inexpensive and that sanctions consist e.g. of fines that are debited from agents' accounts administered by the system. But in this case, higher fine levels require higher financial warranties from agents, which may once again decrease their level of activity: some agents may not meet such requirements, which will inhibit them from committing to certain normative relationships.

In this paper we seek to explore these issues inside an institutional environment, under the following assumptions:

- Strict liability: norm violation is always detected.
- Costless enforcement: monitoring and sanctioning have a negligible cost to the institution.

– Unknown agent population: concerning agents' risk tolerance and social awareness.

We envisage a normative framework that is able to adapt itself (by changing applicable sanctions) according to some measurement of success, which will have to manage the following conflicting goals: i) keep the normative framework as simple as possible, by avoiding over-constraining the environment; and ii) maximize trust on the institutional environment's use. These conflicting goals must be balanced well enough in order to encourage agents to increase their level of activity, when the agent population's risk tolerance is unknown beforehand. Obviously, we assume that agents' preferences regarding the kinds of sanctions we employ are known: agents prefer not to be fined.

In the following section we present an abstract model for contractual commitments and the adaptation approach that we take, based on adjusting deterrence sanctions. Section 3 describes a simulation environment, and specifies the adaptation approach by describing how it is implemented and tested. Section 4 provides an experimental evaluation of the adaptive deterrence model according to different settings, which comprise the normative structures that are used and the behavior of agents that are subject to them. Section 5 analyzes the adaptation of the system with respect to different agent populations, characterized by predominant risk tolerance or social awareness degrees. Section 6 concludes and puts this research in perspective with related work.

2. The model

In our approach we take the stance that agents are truly autonomous, and thus cannot be forced to fulfill their obligations. The institution may, however, impose certain fines as deterrence sanctions: those fines are assumed to be fully regimented (that is, agents cannot escape them, e.g. because they were required, upon entering the institution, to make a deposit that is in control of the institution). Sanctions other than fines could also be envisaged as deterrence measures.

We are mainly concerned with contracting scenarios, wherein agents make mutual commitments and create business expectations. Violations, even when handled by contractual norms, should be seen as exceptional situations. Hence, if a certain kind of violation becomes frequent, response should be taken through an increase of sanctions.

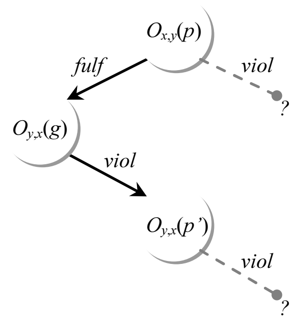

Fig. 1. Sample commitment tree.

2.1. Commitment trees

In order to obtain a tractable model for handling contractual commitments, we use a tree-based representation for interdependent obligations. This representation is useful for understanding the simulation model that we describe later on.

When establishing contracts, agents create a network of directed obligations, some of which are dependent on the fulfillment or violation of other obligations. For the sake of illustration, consider the following two-party contract: agent x will pay p currency units to agent y, after which y will deliver good g to x. In case y fails to deliver, he must return $p'=p+\delta$ to x. This sequence of commitments is illustrated in Fig. 1, in a tree-like structure – a *commitment tree*. Each node (i.e., each commitment) represents a directed obligation from a bearer b to a counterparty c to bring about a fact f – $O_{b,c}(f)$. Bringing about that fact is assumed to imply a cost to the obligation's bearer, and presumably produces some benefit to the counterparty. In the next section we will take this into account when providing a more formal account to the representation of nodes in the commitment tree. Each labeled directed edge in Fig. 1 indicates, in the child node pointed to, what follows when the obligation contained in the parent node is fulfilled (*fulf*) or violated (*viol*). In this simple example nothing is specified should agent x violate his commitment to pay p, or should agent y violate his commitment to return p'. On the other hand, returning p' is seen as a sanction applied to y if he violates his obligation to deliver g.

Typically, a *viol* child node includes a contrary-to-duty that remedies the failure of the bearer to fulfill his previous obligation, potentially allowing for the contract to be resumed. A *fulf* child node will usually define a complementary obligation where the bearer and counterparty roles are switched.

While this example shows a simple binary tree, one can imagine multi-party contracts with a potentially complex commitment tree structure. The tree will not be binary if each obligation fulfillment or violation may lead to more than one consequence. Also, if we consider that a norm can prescribe an obligation if two or more fulfillments or violations occur, we end-up with a *directed acyclic graph* instead of a tree, since each node may have more than one parent. However, this is not very common in the case of violations (which are our main concern here): each violation will typically be handled in isolation (as in the model of "reparation chains" in [16]).

The violation of an obligation with a prescribed sanction may simply denote a case where an agent preferred to incur the sanction for matters of conflicting goals (e.g. he had another more important contract, and could not stand for both). If such violation becomes frequent, however, this may denote a flaw in the normative system that agents are being able to exploit to their own advantage.

2.2. Adaptation

The importance of adaptation in a normative framework resides in the fact that contracts may be unfair in certain execution outcomes. If self-interested agents exploit such flaws to their own profit, action should be taken in order to discourage such behaviors.

In order to build a model that adapts the normative framework in a domain-independent way, we will concentrate on adding deterrence fines to the system (which are not violable), instead of changing the prescribed obligations in each violation situation. The normative framework's adaptation is based on associating, with each obligation, a fine that can be strengthened or weakened (see Fig. 2). With this approach, every obligation will have a (possibly null) fine to be imposed on the bearer in case of violation; this fine is added up to the violation consequence in the child node already in the tree, if there is one.

In order to correctly model appropriate responses to specific situations, we need to assess how often an obligation is used, and how often it is violated. Fines will be updated according to these measurements. The basic principle that we rely on is that the strength of a fine should be directly proportional to its application frequency. As such, fines should increase when they are applied often, and decrease when they are not used. A low level of fine usage indicates that obligations are being fulfilled or they are not being used as often as desired: in both cases fines should be decreased, since they either are not needed or are inhibiting activity. On the other hand, a high level of fine usage means that agents still prefer to go through the sanction, and as such it should be increased as a deterrence mechanism. In summary, this approach tries to make fines (a) strong enough to discourage deviation and (b) weak enough to avoid unnecessary or counterproductive institutional control.

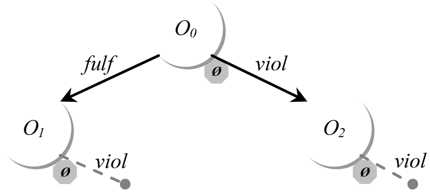

Fig. 2. Binary commitment tree[1] with null fines.

3. Simulation environment

Aiming at the development of a simulation prototype that allows us to test the adaptation model briefly described above, we designed the following experimental scenario.

A number of agents will be in the environment, and each will be given the opportunity to sign a contract, whose structure is defined by the number of enacting roles and by an underlying binary commitment tree (BCT from now on). In the BCT structure, contract roles are used as bearers or counterparties of obligations. Furthermore, each obligation has an associated cost (to be supported by a fulfilling bearer) and benefit (to be collected by the counterparty of a fulfilled obligation). Therefore, when an obligation is fulfilled, the agent enacting the bearer role bears the cost of fulfillment, while the agent enacting the counterparty role gets the benefit. Figure 3 summarizes the characterization of a node in a BCT.

When an agent decides to sign a contract, he will enact the corresponding commitment tree with a role assigned to him before contracting. We say that the *state* of a contract enactment is the commitment currently under appreciation. If the bearer of such a commitment is the agent that decided to contract, he will be asked for a play: either to fulfill or to violate the commitment. If the commitment's bearer is not the agent, the system will decide whether the com-

[1] From now on, we will only consider the case for *binary* commitment trees (this simplification does not limit the applicability of our approach, while it does make it easier to follow).

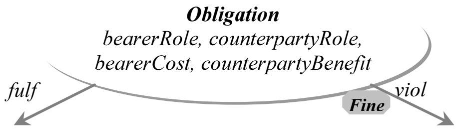

Fig. 3. A node in a BCT.

mitment will be fulfilled or not, according to a uniform strategy.

The current state will be updated according to the decision taken: if the choice is to fulfill, then the root commitment of the fulfillment sub-tree will become the current state; if the choice is to violate, then the root commitment of the violation sub-tree will become the current state. The contract terminates when the state becomes null (i.e. when no fulfillment/violation sub-tree exists upon a fulfill/violate decision).

3.1. Agent decision-making

Each agent has two distinct kinds of decisions to make. If he does not currently have an ongoing contract, he is given the opportunity to sign one. For that, a random role from the contract structure is selected and the agent is asked if he wants to contract with that role. Each agent is configured with a *risk tolerance* parameter $Rt \in [0; 1[$, which denotes his willingness to contract in the presence of violation fines. If $Rt = 0$, the agent will only decide to contract if he will be subject to no fines at all. On the other extreme, if $Rt \approx 1$, the agent will always risk to contract, regardless of any fines. An agent will decide to contract depending on the highest fine that is associated with commitments for the assigned role. In order to contract, the following relation should be true:

$$highestFine(role) \leq b * Rt / (1 - Rt) \tag{1}$$

where b is a slope parameter associated with the agent's budget.

We assume that agents always prefer to contract, regardless of commitment costs or benefits. A contract is presumably beneficial to all partners should they fulfill all their commitments. Having said this, we allow a contract to be unbalanced or incorrect from a safeness point of view, in the sense discussed in [2]. In our case, we consent that participating in the contract may in some cases be worse-off than not participating, depending on the behavior of contractual partners.

When an agent has an ongoing contract, whenever the contract's state is a commitment where he is the bearer he will decide whether to fulfill or to violate such a commitment. Depending on a so-called *in-contract strategy*, the agent will explore the contract's BCT in order to decide which option is best for him. Such strategies may vary from simply comparing the cost of fulfillment with the applicable fine in case of violation, to computing the path with the best outcome from the whole BCT. Some possible strategies will be presented in Section 4.

Agents are essentially expected utility maximizers. This means that, in principle, they will fulfill obligations only when the expected outcome from this choice is better than the expected outcome from violating (according to his in-contract strategy). We do however embed in our agents some notion of social welfare, which impels them to fulfill even when they do not have a strict advantage in doing so. While for now we do not consider the effect of reputation in future contracts, we allow in our model that agents are not all equally self-interested. For that we introduce a *social awareness* parameter $Sa \in [0; 1[$. If $Sa = 0$, the agent will violate whenever the outcome from this choice is better than the outcome from fulfilling. On the other extreme, if $Sa \approx 1$ the agent will always choose to fulfill. The agent will decide to fulfill an obligation O whenever the following relation is true:

$$violationOutcome(O) - fulfillmentOutcome(O) \leq b * Sa / (1 - Sa) \tag{2}$$

where b is as before. The violation/fulfillment outcomes are calculated by the in-contract strategy.

3.2. Fine update policy

In each simulation step, all agents running in the simulation will have a chance to play. After this, the contract structure will have a chance to adapt, that is, the fines associated to the BCT will be updated. Each fine is updated independently of all other fines.

In order to delineate a fine update policy, we first need to define the goal function that will be pursued. As mentioned before, fine updates should take into account how often they are applied. We define a threshold parameter $Th \in [0; 1]$ that roughly indicates the highest percentage of fines that the system should accept as normal. For instance, with a value $Th = 0.1$ we are saying that if more than 10% of the agents running in the simulation violate a given obligation the normative system will raise the fine in the next step – in this case, we say that 10% of the total number of agents is the number of *tolerated* violations. Furthermore, since not all agents will be in the same state at a given time point, we adjust the threshold according to the number of agents that did in fact make a decision concerning the fulfillment or violation of a specific obligation (because they were in that state). For instance, if with a group of 1000 agents we have 10 violations of a specific obligation in a simulation step, this may have a different response from the normative environment depending on the number of agents that went through that same obligation at that time step. If there were 10 play decisions taken on that obligation, this makes a 100% percentage of violations; if there were 100 plays, that percentage comes down to 10%. While in none of these cases we exceed 10% of the total number of agents (1000), it seems clear that the system should react in the former case.

The fine associated with each state will be increased if the number of violations exceeds the following tolerated violations function:

$$toleratedViolations = 2*Th*Nag/(1+e^{-(5/Nag)*x}) - Th*Nag \quad (3)$$

where *Nag* is the number of agents running in the simulation and *x* is the number of agents that were in this state. This is a sigmoid function with an upper bound set at *Th*Nag* (a percentage of the total number of agents). The steepness parameter is *5/Nag*, which makes the sigmoid curve approach the upper bound close to *Nag*, which is the ceiling for *x* (there can be no more than *Nag* agents at this state).

The fine will be decreased whenever the number of violations does not exceed the number of tolerated violations. Fines are increased heavier than they are decreased. We have set an increase step of 0.1 and a decrease step of 0.01. This fixed update policy determines the convergence rate for fines. Furthermore, fines will be applied rounded to the first decimal place, which gives a sense that it takes ten simulation steps (without exceeding the tolerated violations function) to decrease the fine value.

4. Experimental evaluation

In this section we provide, through a set of experiments, an evaluation of the adaptation model using the simulation environment described above.

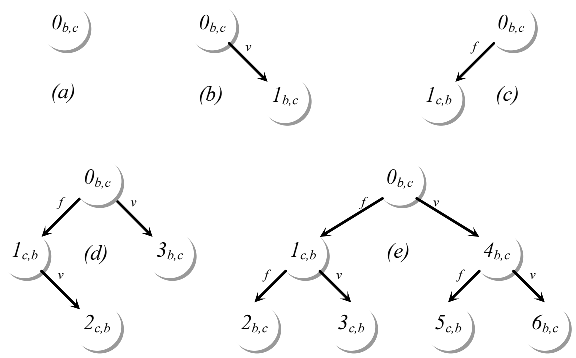

Fig. 4. Binary commitment trees[2]: each node $Id_{i,j}$ is an obligation, where *i* is the bearer and *j* is the counterparty.

4.1. Settings

What we want to study with the simulation scenario described in the preceding section is whether the normative framework is able to adapt and stabilize fine changes in a situation with a static agent population. Furthermore, the system should keep fines as low as possible, while still conforming to the goal function outlined above. This is because the system aims to avoid excessive control and through that maximize agents' contracting activity, which should be obtained with less risk exposure in an agent population with unknown risk tolerance.

If we change the agent population in the middle of the simulation, then we have a moving target setting, which is out of the scope of the experiments reported in this paper. However, since we lower fines whenever the tolerated violations are not exceeded, we believe that the system will quickly adapt in a moving target setting.

4.1.1. Contract structures

Since we are not concerned with the correctness of the contract to be signed, we may abstract away from the concrete meaning of the contract that is represented by a BCT. In other words, we may carry out experiments with a large number of arbitrary BCTs. Figure 4 shows some possibilities, all considering two roles only. For instance, (d) includes two complementary obligations 0 and 1, and their respective *contrary-to-duties* 3 and 2. We shall call obligation 1 the *to-duty* obligation of obligation 0.

We will present some experimental results based on some of these BCTs. In all cases, obligation costs

[2] For simplicity, fines are not shown; however, every node (including leaf nodes) should be seen as shown in Fig. 3.

were set at 10.0 and benefits at 12.0 (setting benefits higher than costs tries to give all partners some gain when the contract is well-balanced and is smoothly enacted). Also, fines were initialized at 0.0.

4.1.2. Agents

As noted before, we aim at testing the normative framework's adaptation when the agent population is unknown, concerning agents' risk tolerance and social awareness. For that reason, all agents in the system have a uniform random distribution concerning the risk-tolerance and social-awareness parameters. Also, for these parameters the slope value b was set to 10.0. This makes the right hand side of Eq. (1) reach 10.0 when a middle value of 0.5 is used for Rt. It also turns out to make 10.0 a ceiling for fines.

Several in-contract strategies can be devised, representing different reasoning abilities of agents when deciding whether to fulfill or violate an obligation. As explained in Section 3.1, the in-contract strategy will be used to compute the fulfillment and violation outcomes at a given state. We consider the following simple strategies, which may have different relevance depending on the BCT being used:

i. ***Local***: considers only local information with respect to the obligation being analyzed.
Fulfillment outcome (FO): – fulfillment cost
Violation outcome (VO): – fine

ii. ***LocalCtd***: considers the cost of fulfilling the contrary-to-duty obligation (if there is one); ignores possible entitlements in case of fulfillment
FO: – fulfillment cost
VO: – fine – contrary-to-duty cost

iii. ***LocalTd***: considers the benefit to gain from the to-duty obligation's fulfillment (if there is one); ignores possible normative sanctions in case of violation
FO: – fulfillment cost + to-duty benefit
VO: – fine

iv. ***LocalBoth***: a mixture of *LocalCtd* and *LocalTd*
FO: – fulfillment cost + to-duty benefit
VO: – fine – contrary-to-duty cost

v. ***FulfillmentBalance***: considers the balance (net gain) obtained if the contract is enacted without any violations
FO: net gain if every participant fulfills the contract
VO: – fine

vi. ***DoubleFulfillmentBalance***: considers two possible balances, one as in *FulfillmentBalance* and another by assuming that there will be no further violations from the contrary-to-duty obligation onwards (in this case the agent is fined)
FO: net gain if every participant fulfills the contract
VO: net gain if every participant fulfills the contract from the contrary-to-duty obligation onwards – fine

vii. ***BestPathCompliantPartners***: explores the whole BCT in order to find the best net gain for every possible path, assuming that *contract partners will always fulfill*
FO: best net gain from the fulfillment subtree – fulfillment cost
VO: best net gain from the violation subtree – fine

viii. ***BestPathMinimax***: explores the whole BCT in order to find the best net gain for every possible path, considering that *contract partners will use the same strategy*
FO: best net gain from the fulfillment subtree – fulfillment cost
VO: best net gain from the violation subtree – fine

Strategies iii through vii assume that partners will always fulfill their obligations. Analyzing these strategies together with the BCTs depicted in Fig. 4, we can see that, for instance, *FulfillmentBalance* will only make sense in tree (e), since in all other BCTs the same outcome can be achieved with less computationally demanding strategies.

Strategy viii is a *minimax* strategy: the agent will maximize his own expected utility while assuming that the other agent will do the same. For instance, considering BCT (d) at Fig. 4 with no fines, the agent will choose to violate on every obligation. While this seems obvious for obligations 1, 2 and 3 (there is no personal benefit in fulfilling), in obligation 0 the agent chooses to violate because he assumes that the counterparty will violate on 1 and 2, bringing him no benefit that can compensate the cost of fulfilling on 0. This strategy seems counterintuitive with the very decision of establishing a contract. However, for the sake of testing the adaptation capabilities of the normative framework, this agent decision practice is bearable.

4.2. Experiments and results

In all experiments a uniform strategy "always fulfill" was used by the system for commitments whose bearer is not a simulation agent. The violation

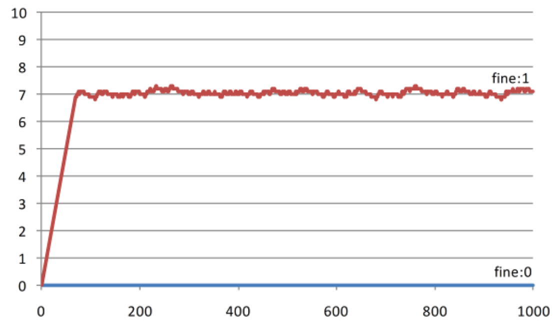

Fig. 5. Fine evolution for BCT (c) and *LocalTD*.

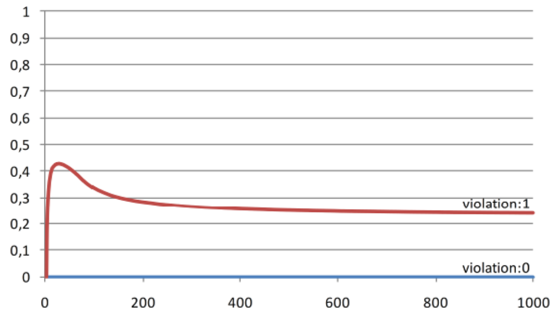

Fig. 6. Violation cumulative average (%) for BCT (c) and *LocalTD.*

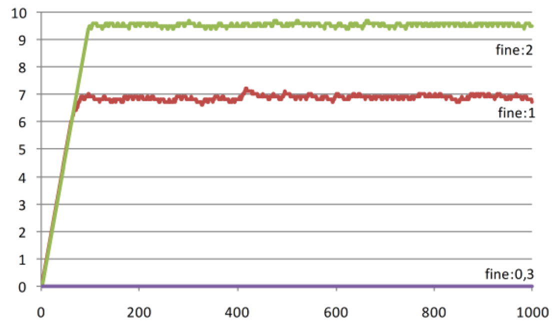

Fig. 7. Fine evolution for BCT (d) and *LocalTD*.

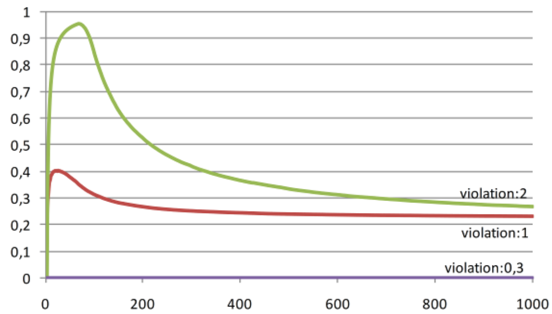

Fig. 8. Violation cum. average (%) for BCT (d) and *LocalTD*.

threshold parameter *Th* was set to 0.1. Each simulation was run with 10000 agents and 1000 time steps.

Figures 5–14 present the evolution of fines and their effect on agents' in-contract behavior for some possible combinations of BCTs and in-contract strategies.

In BCT (c) a *LocalTD* strategy (Fig. 5) is able to grab the benefit achieved from obligation 1 when fulfilling obligation 0. Only the violation of obligation 1 is tempting, and thus the system adapted the corresponding fine. The concrete value obtained for this fine is correlated with the values defined for the obligation cost and benefit, together with the strategy used by agents when deciding on fulfilling the obligation. Figure 6 shows the relative cumulative average of violations with these settings. We can observe a decrease on the number of violations for obligation 1 as a consequence of the fine increase, which ceases when the number of violations is below the tolerated violations threshold (see Section 3.2).

In BCT (d) the *LocalTD* strategy (Fig. 7) impels agents to fulfill obligation 0. Agents that are more socially concerned will tend to fulfill obligation 1 with lower fines than other agents, hence the difference between fines 1 and 2. Figure 8 shows the corresponding relative cumulative average of violations. The effect of fines on agents' behavior is clearly visible.

In the same scenario, *BestPathMinimax* (Fig. 9) gives agents the ability of evaluating every possible outcome with rational plays for both contractual partners – an agent will maximize his own expected utility while assuming that the other agent will do the same. For BCT (d) this means that each agent playing in state 0 initially violates because he sees his partner preferring to violate obligation 1 (and 2), therefore giving him no benefit. However, when fines 2 and 3 are high enough, fines 0 and 1 are no longer necessary. Figure 10 shows the evolution of violations for this case. There are no violations for obligations 0 and 1 (their averages tend to 0 in the figure) since before time step 400 (fines applied in these states become nil).

As for BCT (e), unlike the previous two contractual structures, this one is not profitable (with the complete fulfillment execution 0-1-2) for the agent playing at state 0, if we consider the values set for every obligation's cost (10.0) and benefit (12.0). The *DoubleFulfillmentBalance* strategy (Fig. 11) is able to detect the better path 0-4-5, causing a reaction of the normative system with a raise of fine 0. Without

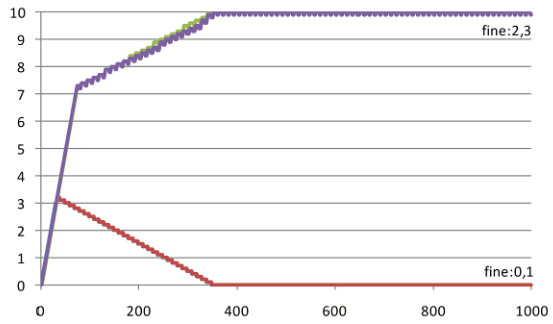

Fig. 9. Fine evolution for BCT (d) and *BestPathMinimax.*

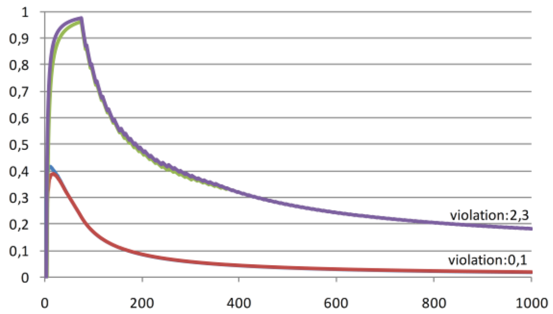

Fig. 10. Viol. cum. avg. (%) for BCT (d) and *BestPathMinimax.*

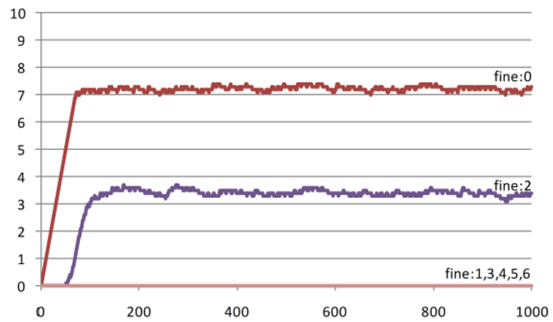

Fig. 11. Fine evolution for BCT (e) and *DoubleFulfillmentBalance.*

this escape, violating obligation 2 is a means of taking some profit out of the game, bringing a raise of fine 2. Figure 12 shows the evolution of violations for this case. The delayed raise on the number of violations for obligation 2 is clearly visible.

The *BestPathMinimax* strategy in this scenario (Fig. 13) makes up the most complex setting we have experimented. Starting at state 0, the best path when playing with a similar agent is initially to violate all obligations (including contrary-to-duties), bringing an outcome of 0. This is because the agent assumes that his partner will maximize his own profit, there-

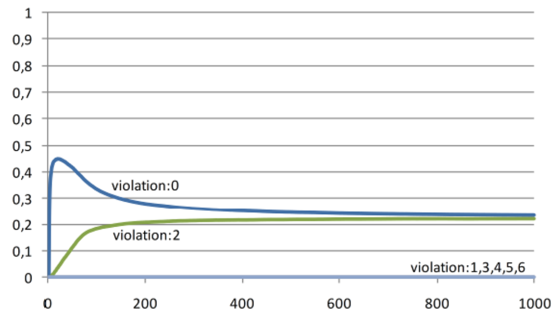

Fig. 12. Violation cumulative average (%) for BCT (e) and *DoubleFulfillmentBalance.*

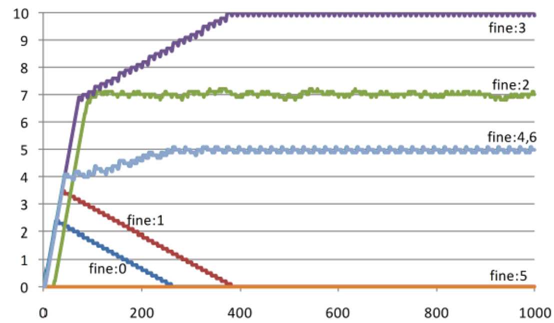

Fig. 13. Fine evolution for BCT (e) and *BestPathMinimax.*

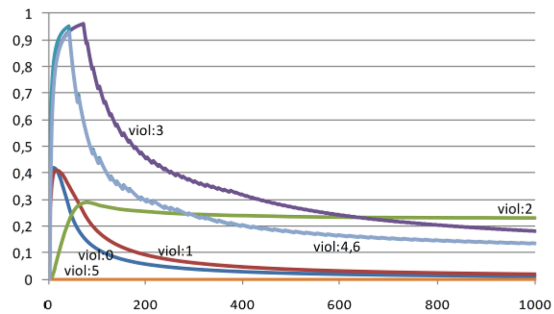

Fig. 14. Viol. cum. avg. (%) for BCT (e) and *BestPathMinimax.*

fore preferring to violate at states 1 and 5. Fines at obligations 0 and 1 become ineffective as soon as fines associated with contrary-to-duties are high enough. Figure 14 shows the corresponding evolution of violations.

The system is able to adjust deterrence sanction values to the behavior of an agent population with any combination of BCTs and in-contract strategies, stabilizing fines after a period of time. We should emphasize that the system continuously tries to lower fines, which is observable by the slight fluctuations

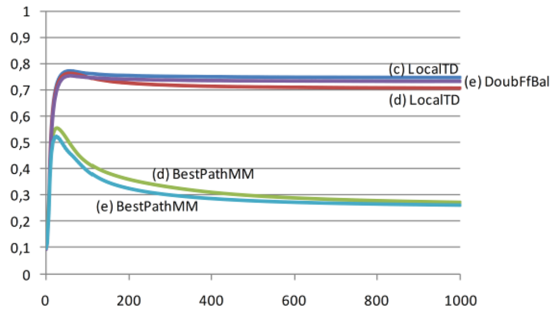

Fig. 15. Contract cumulative average (%) for the five settings.

of fines towards the end of curves in Figs 5, 7, 9, 11 and 13. Therefore, system imposed fine levels are the lowest that keep violations below the tolerated violations function.

Besides affecting the number of violations (that is, agents' in-contract behavior), the adaptation of fines also affects contractual activity. Figure 15 shows the relative cumulative average of contracts in each of the described settings. While analyzing this graph, it is clear that when agents use the *BestPathMinimax* strategy they pose further demands on the system when trying to force agents to comply. In other words, agents use more information and therefore the adaptive mechanism must increase the level of sanctions in order to prevent excessive violation levels. As a consequence, agents that are more risk-averse tend to lower their level of activity, which explains why the number of contracts in these cases is lower.

We should also note that in these scenarios, where agent populations have no bias regarding social awareness or risk tolerance, the potentially harmful effect of fine adaptation in contractual activity is marginal for the remaining in-contract strategies.

5. Addressing different agent populations

In this section we analyze the adaptation of the system when handling different agent populations, in which risk tolerance and social awareness distributions are concerned. For that, a set of experiments were conducted using BCT (d) (see Fig. 4). The *BestPathMinimax* strategy was used by all simulation agents. The reader may want to observe Fig. 9 again in order to recall the system's behavior when addressing a uniform distribution of agents (concerning risk-tolerance and social-awareness).

5.1. *Risk tolerance*

With this first group of experiments we aimed at observing the behavior of the deterrence sanction adaptation model when facing agent populations with different risk tolerance distributions. In a population that tends to be more risk-averse, higher fines should tend to decrease. In these experiments we used beta distributions centered at different risk tolerance values, in order to represent populations having a predominance of agents with specific risk tolerances. For each beta distribution, we set $\alpha=1+(c*p-c)$ and $\beta=p-(c*p-c)$, where c is the center value and p is a peak factor that we have set to 100.

Figures 16–19 show fine evolutions for different risk tolerance center values. As expected, higher fines tend to decrease with lower risk tolerance values. This is due to the fact that, when deciding whether to contract or not, agents compare their risk tolerance with the highest applicable fine.

Another interesting observation is that while the highest fines tend to decrease, the system tries to compensate this potentially lower ability to ascertain the desired level of compliance by increasing other sanctions. More specifically, since fines 3 and 2 are lowered, they lose their effect on decisions taken at states 0 and 1, respectively. As a consequence, fines in these states are raised.

This outcome turns out to be an important emergent property of the normative system: the ability to grasp interdependencies between fines applied to different nodes in the BCT, without being preprogrammed to do so (the fine update policy adapts fines in an independent way). Furthermore, such interdependencies are caused by the in-contract strategy used by agents; if agents do not take into account possible "future" fines when making a decision (as with strategies *i* to *vi* introduced in Section 4), then the system behavior will not pointlessly make a connection between fines.

5.2. *Social awareness*

With this second group of experiments we aimed at observing the behavior of the deterrence sanction adaptation model when facing agent populations with different social awareness distributions. In a population that tends to be more socially concerned, fines should tend to decrease. Selfish agents will only fulfill if it is in their own interest, while a higher social awareness impels agents to fulfill even when they do not benefit directly from that option.

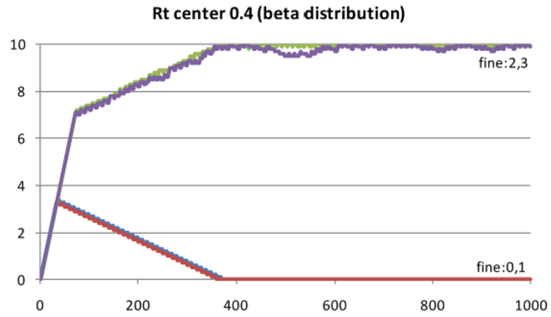

Fig. 16. Fine evolution for BCT (d) and *BestPathMinimax*, with a beta distribution of risk tolerance centered at 0.4 and a uniform distribution of social awareness.

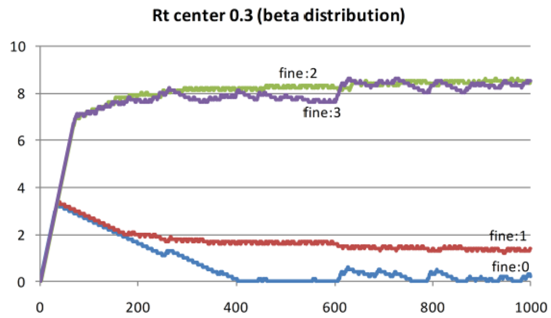

Fig. 17. Fine evolution for BCT (d) and *BestPathMinimax*, with a beta distribution of risk tolerance centered at 0.3 and a uniform distribution of social awareness.

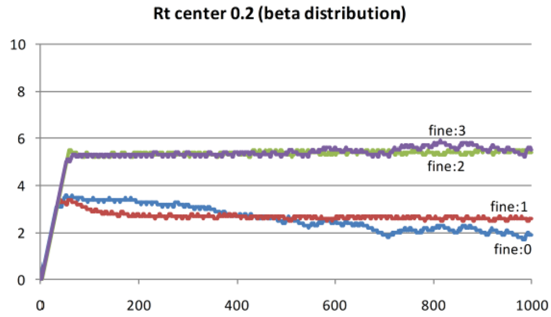

Fig. 18. Fine evolution for BCT (d) and *BestPathMinimax*, with a beta distribution of risk tolerance centered at 0.2 and a uniform distribution of social awareness.

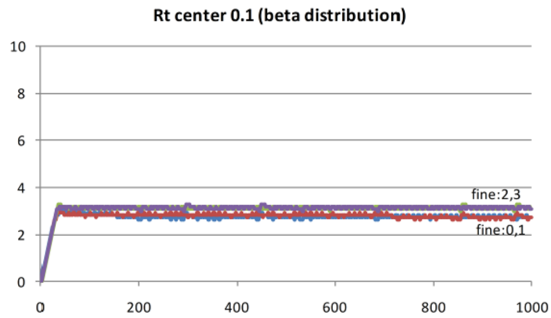

Fig. 19. Fine evolution for BCT (d) and *BestPathMinimax*, with a beta distribution of risk tolerance centered at 0.1 and a uniform distribution of social awareness.

Figures 20–21 show fine evolutions for different social awareness center values (using beta distributions as before). As expected, fines tend to increase with lower social awareness values. By doing so, the system tries to discourage commitment violations. The dependency mentioned before between fines is also visible here: fines 3 and 2 tend to absorb the effects of fines 0 and 1 sooner for higher social awareness values, and the system is able to find these intricacies.

5.3. Combining risk tolerance and social awareness

By adjusting both parameters when setting up an agent population, we get a combination of the effects identified above. Figure 22 shows what happens when we set both risk tolerance and social awareness to beta distributions centered at 0.1. In this case, since highest fines are limited by a low risk tolerance, the system raises fines 0 and 1 as much as it can, in order to try to force a population of mostly self-interested and risk-averse agents to contract and also comply with contractual commitments.

We should add that in these extreme and unlikely conditions the normative system is not successful: the obtained fine levels are insufficient to force compliance, and at the same time too demanding to motivate contractual activity. This means that the few agents that do contract (which nevertheless are in essence risk-averse) will violate their commitments (because they are also too self-interested).

6. Conclusions and related work

Embedding adaptive enforcement mechanisms in normative frameworks is important in open environments. Adapting deterrence levels to the behavior of an agent population is important when the normative space has imperfections that make contracts to which norms apply unfair, opening the possibility for self-interested agents to exploit their potential advantage.

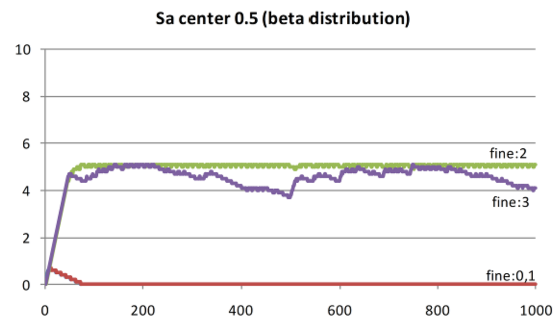

Fig. 20. Fine evolution for BCT (d) and *BestPathMinimax*, with a uniform distribution of risk tolerance and a beta distribution of social awareness centered at 0.5.

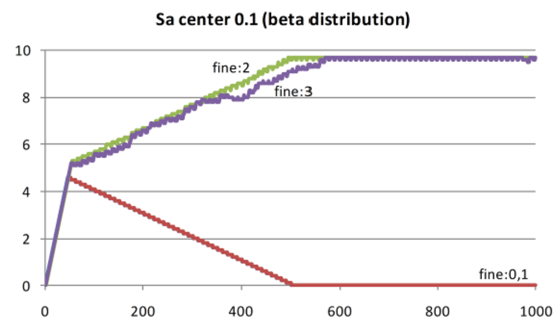

Fig. 21. Fine evolution for BCT (d) and *BestPathMinimax*, with a uniform distribution of risk tolerance and a beta distribution of social awareness centered at 0.1.

In this paper we have presented a simple model for the adaptation of deterrence sanctions used in a normative framework. We have shown that it is feasible to adapt deterrence levels to the behavior of an agent population: under uniform random distributions the system is able to adapt by appropriately raising and stabilizing fine values.

We have built an abstraction for contractual commitments by modeling their corresponding obligations in a binary commitment tree structure. In such a tree we are able to include both "to-duty" complementary obligations and contrary-to-duty retribution sanctions. This abstract representation allows us to consider contracts of arbitrary complexity.

We have studied how the adaptive deterrence sanction model, while trying to "maintain order", responds when facing different agent populations. Such populations were characterized by a predominant level of risk tolerance and social awareness. The parameterization of agents with different social attitudes is common in computational models for social interactions. Agents range from selfish to respectful

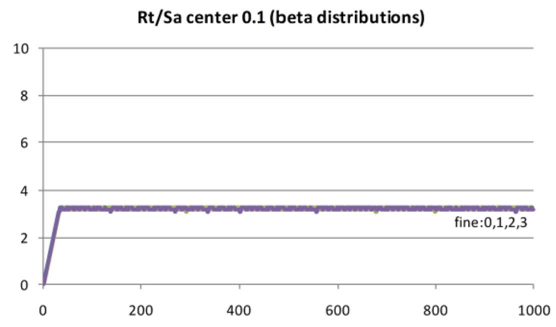

Fig. 22. Fine evolution for BCT (d) and *BestPathMinimax*, with beta distributions of risk tolerance and social awareness centered at 0.1.

[6]. Respectful agents are those that internalize norms and fulfill obligations simply because they are obligations [17], irrelevant of there being associated sanctions in case of violation. Our social awareness parameter tries to take this heterogeneity of social attitudes into account. Configuring agents with different risk attitudes was inspired by the economic theory on deterrence sanctions [13], stating that agents incur a risk when making contracts that are subject to deterrence sanctions.

Our experimental evaluations show that imposed fines tend to be lower when agents are more risk-averse or more socially concerned. We also observed that when a combination of sanctions is able to drive agents to comply with their commitments, the adaptive mechanism is able to pursue such a combination when constraints limit some options – such constraints are rooted in the agent population (namely in the predominant risk tolerance), and are implicitly captured in the fine update policy. This ability is an interesting emergent property of the system.

Influencing agent decision making regarding social commitments is generally conceived as social control [17], and is usually focused on enforcement, sanctions and reputation. A different perspective has been taken in [18], where some agents in the system are directly controlled by the system's designer. Making such agents play specific strategies will lower the payoff of joint activities when uncontrolled agents play selfishly, therefore making them choose to fulfill. This seems unrealistic in contracting scenarios. Yet, the authors have made a theoretical analysis in scenarios where uncontrolled agents are expected utility maximizers and when they are reinforcement learners. Such scenarios can be tested in our simulation model as well.

Dynamic properties of normative systems have been studied from different perspectives. In [19] norms are seen as patterns of behavior that may emerge bottom-up from agent interactions. In our case, however, the normative system is external to the agents, and we seek to adapt it to a specific agent population in order to pursue an overall system goal.

Sanction-based self-adaptation of institutional normative environments is also studied in [20], with two significant differences to our approach. First, their adaptation model is based on the definition of domain-dependent transition functions, stating what specific change should be made in a specific norm when some goal specification is not met. Second, their model does not assume strict liability: agents are able to violate norms while not being detected.

In this paper we have not considered the influence of reputation on agent's contractual behavior. It has been argued [15] that in the presence of reputation mechanisms there is a lesser need for deterrence policies. We believe that positive reputation updates triggered by the normative environment may be an incentive for agents to fulfill their commitments.

Acknowledgments

The first author is supported by FCT (Fundação para a Ciência e a Tecnologia), Portugal, under grant SFRH/BD/29773/2006.

References

[1] M.B. Blake, Agent-oriented approaches to B2B interoperability, *The Knowledge Engineering Review* **16**(4) (2001), 383–388.

[2] N. Desai, N.C. Narendra and M.P. Singh, Checking correctness of business contracts via commitments, in: *Proc. of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems (IFAAMAS)*, Estoril, Portugal, 2008.

[3] M. Sallé, Electronic contract framework for contractual agents, in: *Advances in Artificial Intelligence: 15th Conference of the Canadian Society for Computational Studies of Intelligence*, R. Cohen and B. Spencer, eds, Springer, 2002, pp. 349–353.

[4] H. Lopes Cardoso and E. Oliveira, Electronic institutions for B2B: Dynamic normative environments, *Artificial Intelligence and Law* **16**(1) (2008), 107–128.

[5] J.L. Arcos, et al., Environment engineering for multiagent systems, *Engineering Applications of Artificial Intelligence* **18**(2) (2005), 191–204.

[6] G. Boella and L. van der Torre, A game-theoretic approach to normative multi-agent systems. in: *Normative Multi-agent Systems*, Schloss Dagstuhl, 2007.

[7] H. Lopes Cardoso and E. Oliveira, A context-based institutional normative environment, in: *Coordination, Organizations, Institutions, and Norms in Agent Systems IV*, J. Hubner, et al., eds, Springer, 2009, pp. 140–155.

[8] A. García-Camino, et al., Norm-oriented programming of electronic institutions: A rule-based approach, in: *Coordination, Organizations, Institutions, and Norms in Agent Systems II*, P. Noriega, et al., eds, Springer, 2007, pp. 177–193.

[9] P. Pasquier, R.A. Flores and B. Chaib-Draa, Modelling flexible social commitments and their enforcement, in: *Engineering Societies in the Agents World V*, M.-P. Gleizes, A. Omicini and F. Zambonelli, eds, Springer, Toulouse, France, 2005, pp. 139–151.

[10] D. Grossi, H. Aldewereld and F. Dignum, Ubi lex, ibi poena: Designing norm enforcement in e-institutions, in: *Coordination, Organizations, Institutions, and Norms in Agent Systems II*, P. Noriega, et al., eds, Springer, 2007, pp. 101–114.

[11] N. Fornara and M. Colombetti. Specifying and enforcing norms in artificial institutions, in: *7th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2008)*, Estoril, Portugal, 2008.

[12] F.C. Zagare and D.M. Kilgour, *Perfect Deterrence*, Cambridge University Press, 2000.

[13] A.M. Polinsky and S. Shavell, Punitive damages, in: *The New Palgrave Dictionary of Economics and the Law*, P. Newman, ed., Stockton Press, New York, 1998, pp. 192–198.

[14] N. Garoupa, The theory of optimal law enforcement, *Journal of Economic Surveys* **11**(3) (1997), 267–295.

[15] M. Luck, et al., Trust and norms for interaction, in: *Proc. of the IEEE SMC 2004 International Conference on Systems, Man & Cybernetics*, IEEE, The Hague, The Netherlands, 2004, pp. 1944–1949.

[16] G. Governatori and A. Rotolo, Logic of violations: A gentzen system for reasoning with contrary-to-duty obligations, *Australasian Journal of Logic* **4** (2006), 193–215.

[17] C. Castelfranchi, Engineering social order, in: *Engineering Societies in the Agents World*, A. Omicini, R. Tolksdorf, and F. Zambonelli, eds, Springer, Berlin, Germany, 2000, pp. 1–18.

[18] R.I. Brafman and M. Tennenholtz, On partially controlled multi-agent systems, *Artificial Intelligence Research* **4** (1996), 477–507.

[19] S. Sen and S. Airiau, Emergence of norms through social learning, in: *20th International Joint Conference on Artificial Intelligence*, Hyderabad, India, 2007.

[20] J. Campos, et al., Formalising situatedness and adaptation in electronic institutions, in: *Coordination, Organizations, Institutions, and Norms in Agent Systems IV*, J. Hubner, et al., eds, Springer, 2009, pp. 126–139.