Reasoning About Norms under Uncertainty in Dynamic Environments

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Abstract

The behaviour of norm-autonomous agents is determined by their goals and the norms that are explicitly represented inside their minds. Thus, they require mechanisms for acquiring and accepting norms, determining when norms are relevant to their case, and making decisions about norm compliance. Up until now the existing proposals on norm-autonomous agents assume that agents interact within a deterministic environment that is certainly perceived. In practice, agents interact by means of sensors and actuators under uncertainty with non-deterministic and dynamic environments. Therefore, the existing proposals are unsuitable or, even, useless to be applied when agents have a physical presence in some real-world environment. In response to this problem we have developed the n-BDI architecture. In this paper, we propose a multi -context graded BDI architecture (called n-BDI) that models norm-autonomous agents able to deal with uncertainty in dynamic environments. The n-BDI architecture has been experimentally evaluated and the results are shown in this paper.

Keywords: Norms, Uncertainty, Graded BDI agents

1. Introduction

The first approaches on norms inside the multi-agent system (MAS) field assumed that agents have a physical presence in closed and relatively static environments where agents cooperate to achieve a common objective. For this reason, these first proposals were focused on hard-coding norms on agents. Later, the interest switched from such closed systems to open and dynamic systems in which heterogeneous and autonomous agents coexist. Norm-programmed agents are unsuitable for these systems because of two main reasons [21]: the circumstances might change, which makes the programmed norms obsolete; and agents may interact with agents that follow different norms. In this situation, explicit representations of norms can support appropriate, more flexible, reasoning.

Thus, there was a shift from norm-programmed agents into norm-autonomous agents.

In [16] a *norm-autonomous agent* is defined as an agent whose behaviour is influenced by norms that are *explicitly represented* inside its mind. Agents with an explicit representation of norms are able to participate in different societies (in which different norms may apply), to communicate norms and to reason about them [33]. *Norm-autonomous* agents require capabilities for *acquiring* norms; i.e., agents should be capable of recognising the norms that are *in force* in their environment [4]. Moreover, agents can have motivations to *accept* these recognised norms [33]. For example, a norm can be rejected when the majority of agents in the MAS do not consider it as important. Besides that, norm-autonomous agents need to be endowed with capabilities for determining whether a norm concerns their case and it is *relevant* [31]. Once the recognised norm has been accepted and considered as relevant, then agents must decide whether or not to conform to it. This decision about obeying or violating a norm is known as *norm compliance* decision [33].

Up until now, the majority of the existing proposals on norm-autonomous agents, such as [10] and [4], assume that agents interact within a deterministic environment that certainly perceived. As a consequence, they propose rigid and static procedures, such as utility functions, for reasoning about norms. Thus, these proposals assume that it is possible to define off-line which the best decision in all circumstances is. It entails a limitation on the agent capacities for adapting to new societies or to the environmental changes. The development of dynamic mechanisms for allowing agents to reason about norms according to current circumstances has received little attention [33]. Moreover, these proposals assume that agents are situated within an environment that can be perceived by agents with complete precision. In practice, agents interact by means of sensors and actuators under uncertainty with a non-deterministic environment. Therefore, the existing solutions are unsuitable to be applied in real applications. To address this problem, we propose here to endow norm-autonomous agents with declarative and flexible procedures for reasoning about norms under uncertainty within dynamic environments.

Specifically, in this paper we propose a new architecture for norm-autonomous agents. This architecture, named as n-BDI, is an expansion of a multi-context graded BDI architecture [12] with explicit normative notions. Thus, our agents have a more precise representation of the uncertainty and the norms that regulate this environment. Moreover, agents use declarative procedures that adapt to different personality traits depending on the cognitive elements present in the agent theory. Thereby, our agents are able to achieve a better adaptation to dynamic environments. To demonstrate this we will use them a fire-rescue case study. Specifically, we seek to determine whether the fact that our agents have an explicit representation of the uncertainty and that they use expressive and flexible rules to reason about norms allow them to achieve a better adaptation to the environment.

This article is organized as follows: in the next section we introduce the fire rescue case study and the basic notions used in this paper. In Section 3 we propose the n-BDI architecture. Sections 4 and 5 describe the two main components of the n-BDI architecture. Section 6 describes how n-BDI agents make decisions about norm compliance. Section 7 contains the evaluation of the n-BDI architecture. We make a review of related work in Section 8. Finally, Section 9 contains conclusions of this paper.

2. Background

2.1. Case Study

As aforementioned, we will use in this paper a fire-rescue case study to: (i) illustrate how a n-BDI agent reasons about norms under uncertainty within a dynamic environment; and (ii) evaluate if our agents achieve better results in such kind of situations. In the fire-rescue case study we consider two different types of persons: a fireman[1] and victims that must be rescued. Victims are located in a building in flames. Since they are not endowed with flame-proof clothes they wait until they are rescued by a fireman who leads victims to the door of the building. The fireman dies when there is not any path that allows him to reach the door. There are norms that define general patterns that firemen must follow when dealing with fire threats. Specifically, we assume the existence of a norm that obliges firemen to abort the fire-rescue operation when it is taking too much risk. This is a simple scenario controlled by a single norm that becomes relevant under circumstances that are uncertain (i.e., a risky situation). Moreover, the fireman cannot be sure of the repercussions of violating or obeying the norm. Finally, the environment (i.e., the building design and the position of victims) may change from fire-rescue to fire-rescue. Thus, decision making procedures that allow firemen to make decisions in unforeseen fire-rescue scenarios are required.

2.2. Multi-context Graded BDI Architecture

A norm-autonomous agent is defined in this paper as a practical reasoning agent [14] whose actions are directed towards its internal goals and the norms that regulate its environment. Specifically, this paper focuses on how a norm-autonomous agent reasons about norms under uncertainty within dynamic environments. To make such kind of decisions a norm-autonomous agent considers its current circumstances; i.e., the beliefs about the world in which the agent is placed; and its objectives or the situations that the agent wants to accomplish or bring about; i.e., the agent desires. For these reasons, in this paper we endow BDI agents with capabilities for considering norms in their decisions. The feature that distinguishes norm-autonomous BDI agents from classic BDI agents is the availability of an explicit representation of norms and instances and the capabilities for reasoning about them. It serves this purpose well to address different mental attitudes in a modular way, and for that reason we rely on multi-context systems for the formalisation of those attitudes [26, 9].

[1]For simplicity, we assume that only one fireman participates in the fire-rescue operation.

The main intuition beyond multi-context systems is that reasoning is usually performed on a subset of the global knowledge base. Each one of these subsets is a context. Informally, a context contains a partial theory of the world which encodes the agent's perspective about this part of the world. Let be I a set of indexes, a multi-context system is defined by a set of interconnected contexts $\langle\{C_i\}_{i\in I}, \Delta\rangle$. Each context has inference routines used to reason about it [25]. Formally, each context $c_i \in \{C_i\}_{i\in I}$ is a tuple $\langle Li, A_i, \Delta_i\rangle$, where L_i, A_i and Δ_i are the language, axioms and inference rules defining the logic of each context, respectively. Moreover, the reasoning in one context may affect reasoning in other contexts. Specifically, Δ is the set of bridge rules between the contexts; i.e., inference rules whose premises and conclusions belong to different contexts:

$$\frac{C_1 : A_1, ..., C_q : A_q}{C_j : A}$$

meaning that if for all $k \in \{1, ..., q\}$ A_k is deduced in context C_k, then A is inferred in C_j. Thus, the top of any bridge rule is the precondition (i.e., the formulas that must hold to apply the bridge rule) and the bottom of the bridge rule is the postcondition (i.e., the formula that is generated within a context).

Because we want our agents to contend with uncertainty, we will assume graded logics. As a consequence, in this article we endow multi-context graded BDI agents, proposed by Casali et al. in [12], with capabilities for considering explicit normative notions in their decisions. As proposed by Casali et al., a multi-context graded BDI agent has *mental* contexts to characterise graded beliefs (BC), intentions (IC), and desires (DC). All these contexts contain weighted expressions that represent the degree of certainty, desirability, or intentionality of mental attitudes:

- *Belief Context (BC).* It is formed by expressions belonging to the BC-Logic, which was defined by Casali et al. in [12]. The language $\mathcal{L}_{\mathcal{BC}}$ is defined over a classical propositional language $\mathcal{L}_{\mathcal{P}}$ (built from a countable set of propositional variables with connectives $\rightarrow$ and $\neg$) which is expanded with a fuzzy modal operator $\mathcal{B}$. Thus, the BC contains logic propositions such as $(\mathcal{B}\ \gamma, \rho)$; where $\mathcal{B}\ \gamma$ represents a belief about proposition $\gamma \in \mathcal{L}_{\mathcal{P}}$, and $\rho \in [0, 1]$ represents the certainty degree associated to this belief. The logical connective $\rightarrow$ is used to represent explanation relationships between propositions. Thus, $(\mathcal{B}\ \alpha \rightarrow \beta, \rho)$ represents that the agent believes that α explains β, with a certainty degree ρ; i.e., the agent believes the probability α causes β is ρ.

- *Desire Context (DC).* In the original proposal of Casali et al. [12] a many value modal logic to represent and reason about agent bipolar preferences (i.e., positive and negative desires) is defined. For the purpose of this article, we just require a single fuzzy modal operator $\mathcal{D}$ for representing desires. Thus, the DC contains logic propositions such as $(\mathcal{D}\ \gamma, \rho)$; where $\mathcal{D}\ \gamma$ represents a desire about proposition $\gamma \in \mathcal{L}_{\mathcal{P}}$, and $\rho \in [0, 1]$ represents the desirability degree. Thus, negative desires are represented using the negation connective $\neg$ (i.e., $(\mathcal{D}\ \neg\gamma, \rho)$). Degrees of desires allow setting different levels of preference or rejection.

- *Intention Context (IC).* It is formed by expressions belonging to the IC-Logic [12]. Thus, it is formed by graded intentions that are denoted by $(\mathcal{I}\gamma, \rho)$, where $\rho \in [0, 1]$ may be considered as the truth degree of the expression *"γ is intended through the best plan to reach γ"*. Thus, the intentionality degree of a proposition γ must be the consequence of finding a best feasible plan that permits a state of the world where γ holds to be achieved.

The logic of mental contexts is a mixture of first-order modal logic [44], which is employed to represent those propositions that are believed, desired, or intended; and Rational Pavelka Logic (RPL) [39] to represent the probability of propositions. Therefore, the axioms and rules are built by considering axioms of first-order predicate logic and axioms of RPL[2]. Deduction rules for each context are Modus Ponens and Necessitation for the mental modalities $\mathcal{B}, \mathcal{D}, \mathcal{I}$. For a complete description of these contexts see [12].

In the proposed case study, the theory of the fireman agent is formed by:

- *Graded beliefs* that represent its beliefs about environment in which it is situated: e.g., its perceptions. For example, it has beliefs about the fire condition or the victims that are situated in its surroundings. Moreover, the fireman knows explanation relationships between beliefs. These relationships allow the firemen agent to represent the potential consequences of actions or states. For example, the fireman agent knows its survival probability if it aborts the rescue. It also knows the probability of saving one more victim if it continues with the rescue.

- *Graded desires* that represent the agent preferences; i.e., its intrinsic goals. The fireman has desires that represent how much it wants to protect its own life and how much it wants to preserve victims' life..

- *Graded Intentions* that represent the deliberative state of the agent. Specifically, the fireman knows plans for aborting the rescue and plans for carrying on the rescue. Thus, the fireman agent can generate intentions on-line to abort the rescue and to continue with the rescue depending on its circumstances (i.e., its beliefs and desires).

Let us suppose that there is a fireman working in a specific building ($gateHouse$). Table 1 shows an example of the fireman beliefs, desires and intentions (see rows corresponding to contexts BC, DC and IC) at a given moment of the rescue. Specifically, the fireman agent believes that the situation is somehow risky —$(\mathcal{B}\ risky(gateHouse), 0.5)$. It also believes that it has 50% probability

[2]RPL is an extension of Lukasiewicz's infinitely-valued logic by expanding its language with rational truth-constants to explicitly reason about degrees of truth [29].

of survival if it aborts the rescue —($\mathcal{B}$ $abort(gateHouse) \rightarrow survive(self), 0.5$). Since the closest victim is quite far from the fireman position, it believes that it has low probabilities of saving one more victim if it continues with the rescue —($\mathcal{B}$ $\neg abort(gateHouse) \rightarrow survive(victims), 0.25$). The rest of beliefs can be ignored at this moment. This fireman considers equally important the lives of the victims and its own life; i.e., it desires the survival of victims and itself with the highest desirability —($\mathcal{D}$ $survive(victims), 1$) and ($\mathcal{D}$ $survive(self), 1$). Finally, it has an intention to continue with the rescue —($\mathcal{I}$ $continue(gateHouse), 1$).

Context	**Content**
BC	($\mathcal{B}$ $risky(gateHouse), 0.5$) ($\mathcal{B}$ $abort(gateHouse) \rightarrow survive(self), 0.5$) ($\mathcal{B}$ $\neg abort(gateHouse) \rightarrow survive(victims), 0.25$) ($\mathcal{B}$ $play(self, fireman), 1$) ($\mathcal{B}$ $inform(expert_1, norm(n_{fireAbortion}) \wedge salience(0.75)), 1$) ($\mathcal{B}$ $inform(expert_2, norm(n_{fireAbortion}) \wedge salience(0.2)), 1$) ($\mathcal{B}$ $inform(expert_3, norm(n_{fireAbortion}) \wedge salience(0.8)), 1$)
DC	($\mathcal{D}$ $survive(victims), 1$), ($\mathcal{D}$ $survive(self), 1$)
IC	($\mathcal{I}$ $continue(gateHouse), 1$)
NAC	$normOpinion(n_{fireAbortion}, expert_1, 0.75)$, $normOpinion(n_{fireAbortion}, expert_2, 0.2)$, $normOpinion(n_{fireAbortion}, expert_3, 0.8)$, $norm(n_{fireAbortion}, 0.64)$
NRC	$instance(i_{fireAbortion}, 0.32)$

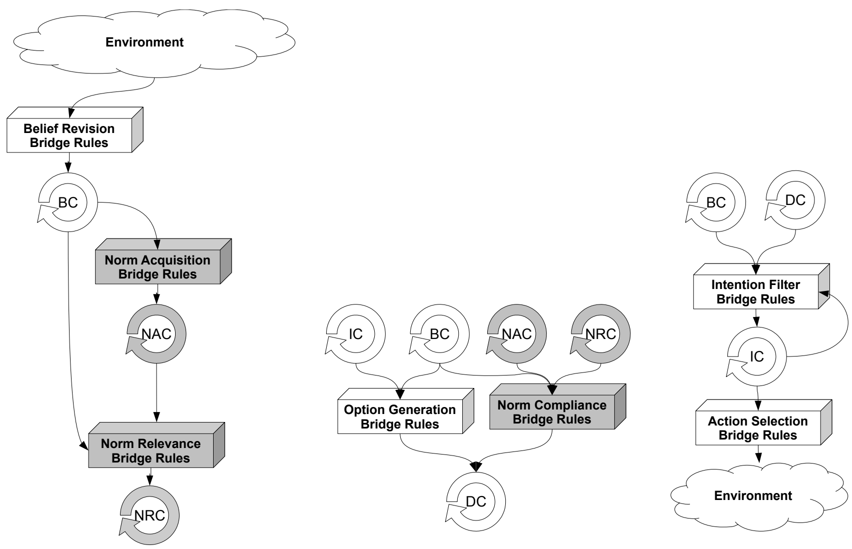
Table 1: Theory of the fireman agent (using the n-BDI architecture)

The reasoning process in a multi-context graded BDI agent is mainly performed by bridge rules that connect mental contexts. Thus, the information flows from perception to action via bridge rules that define how the information that is represented inside several contexts is combined for inferring new information in other contexts. The reasoning process can be summarised into three different phases. In the first one, the agent perceptions are used for updating the agent knowledge. In the second phase, desires are updated. In the third phase, the agent makes a decision about the next action to be performed.

Phase 1. Perception. The agent perceives the environment and translates this perception into new formulae that are inserted in those contexts that are responsible for representing the agent environment. The perception process is illustrated in Figure 1(a) (see the white circle and the white box). This image shows how the different contexts (i.e., circles) are connected by means of bridge rules (i.e., boxes). Specifically, the *belief revision* bridge rules change beliefs to take into account new pieces of information.

Phase 2. Deliberation. In this phase desires that represent the motivations of agents are updated (see the white circles and the white box of Figure 1(b)). Specifically, the *option generation* bridge rules determine the options available to the agent (its desires) on the basis of its current beliefs about its environment and its current intentions.

Phase 3. Decision Making. The *intention filter* bridge rules determine the agents intentions on the basis of its current beliefs, desires, and intentions. Finally, the *action selection* bridge rules determine an action to perform on the basis of current intentions. An overview of the decision making phase is illustrated in Figure 1(c).



(a) Perception (b) Deliberation (c) Decision Making

Figure 1: Reasoning phases in a multi-context BDI agent and in a n-BDI Agent. The contexts that contain the cognitive elements defined by Casali et al. in [12] (i.e., the contexts BC, DC, IC) are represented as white circles. Similarly, the bridge rules defined by Casali et al. in [12] are represented as white boxes, where: the input links represent the precondition of the bridge rules, and the output links represent the postcondition of the bridge rules. The normative contexts and the normative bridge rules, that we propose in this paper, are represented as grey circles and boxes.

This article is not aimed at providing an exhaustive description of how the multi-context graded BDI agent reasons. Therefore, only those aspects that are relevant to the normative extensions that we propose have been described. For a complete description of the logic of the contexts and the bridge rules defined by Casali et al. see [12][3].

[3]Note that the logic proposed in [12] has not been created for building agents endowed with normative reasoning capabilities. Therefore, this logic does not deal with norms.

2.3. Normative Definitions

Norms help to define control, coordination and cooperation mechanisms that attempt to: (i) promote behaviours that are satisfactory to the organization, i.e., actions that contribute to the achievement of global goals; and (ii) avoid harmful actions, i.e., actions that prompt the system to be unsatisfactory or unstable. Norms have been studied from different perspectives such as philosophy [49], sociology [43], law [1], etc. MAS research has given different meanings to the norm concept. For example, it has been employed as a synonym of obligation and authorization [20], social law [35], social commitment [46] and other kinds of rules imposed by societies or authorities. The purpose of this paper is not to propose, compare or improve existing normative definitions, but to make use of these definitions for proposing an information model, knowledge representation and inference mechanism to allow agents to reason about norms under uncertainty within dynamic environments. The aim of this section is to provide the reader with the basic normative notions used in this paper.

In this paper we consider *norms* as formal statements that define patterns of behaviours by means of *deontic modalities* (i.e., *obligations* and *prohibitions*). Specifically, our proposal is based on the notion of norm as a general rule of behaviour that defines under which circumstances a pattern of behaviour becomes relevant and must be instantiated. This notion of norm has been widely used by the existing literature ([31], [33] and [38]).

To express norms in a general form, we make use of a first-order predicate language $\mathcal{L}$ that is built by extending the classical propositional language $\mathcal{L}_{\mathcal{P}}$ with an infinite set of variables. In addition, the alphabet contains predicate, constant and function symbols. Variables are implicitly universally quantified[4]. In this article variables are written as any sequence of alphanumeric characters beginning with a capital letter. Let us also assume the standard notion of substitution of variables; i.e., a substitution σ is a finite and possibly empty set of pairs Y/y where Y is a variable and y is a term [23]. The predicate, constant and function symbols are written as any sequence of alphanumeric characters beginning with a lower case letter. Specifically, there are constant symbols that identify roles and agents. Thus, $\mathcal{R}$ and $\mathcal{A}$ are the sets containing all role and agent identifiers, respectively. For the purpose of this paper it is necessary to know that the relationship between agents and roles is formally represented by a binary predicate (*play*). Specifically, the expression $play(a, r)$ describes the fact that the agent identified by $a \in \mathcal{A}$ enacts the role identified by $r \in \mathcal{R}$.

2.3.1. Norm Definition

Given the informal definition of norm and the logic preliminaries given above, a norm is formally defined as:

Definition 1 (Norm). A norm (n) is defined as a tuple $n = \langle D, C, T, A, E, S, R \rangle$, where:

[4]Note that the appropriate use of Skolem functions [36] allows all existential quantifiers to be removed without loss of expressivity.

- $D \in \{\mathcal{O}, \mathcal{F}\}$ is the deontic modality of the norm, determining if the norm is an obligation ($\mathcal{O}$) or prohibition ($\mathcal{F}$);
- C is a wff of $\mathcal{L}$ that represents the norm condition, i.e., it denotes the goal or action that is controlled by the norm;
- $T \in \mathcal{R}$ is the target of the norm; i.e., the role to which the norm is addressed;
- A is a wff of $\mathcal{L}$ that describes the activation condition;
- E is a wff of $\mathcal{L}$ that describes the expiration condition;
- S is a wff of $\mathcal{L}$ that describes the sanction that will be applied to the target agents if the norm is not fulfilled;
- R is a wff of $\mathcal{L}$ that describes the reward that will be provided to the target agents if the norm is fulfilled.

We assume a "closed legal system" [41], which is a normative system where everything is considered are permitted by default. Therefore, only obligation and prohibition norms are considered by our proposal. These norms define exceptions to this default permission rule[5].

For example, the norm that obliges firemen to abort the fire-rescue when the situation becomes too risky is formally defined as:

$$\langle \mathcal{O}, abort(R), fireman, risky(R), fireExtinguished(R), -, - \rangle \qquad (n_{fireAbortion})$$

We have assumed that once a rescue R is consider as a risky situation, then the norm is active. The norm expires when the fire has been extinguished. This norm determines when firemen are obliged to abort a rescue and, as a consequence, this norm allows fireman to create intentions to abort the rescue.

2.3.2. Instance Definition

Once the activation conditions of a norm hold it becomes relevant and several instances, according to the possible groundings of the activation condition, must be created. Thus, *instances* are unconditional expressions that bind a particular agent to an obligation or prohibition. Formally an instance is defined as:

Definition 2 (Instance). Given a norm $n = \langle D, C, T, A, E, S, R \rangle$ and a theory $\Gamma \subseteq \mathcal{L}_{\mathcal{P}}$, an instance of n is the tuple $i = \langle D, C', AgentID, A', E', S', R' \rangle$ where:

- $\Gamma \vdash \sigma(A)$ where σ is a substitution of variables in A such that $\sigma(A)$ is a logical consequence of Γ and $\sigma(A), \sigma(E), \sigma(C), \sigma(S), \sigma(R)$ are grounded;

[5] Note that we might have used permission norms to create exceptions to the application of more general obligation and prohibition norms. However, the resolution of exceptions among norms is beyond the scope of this paper and has been addressed by other works such as [31].

- $A' = \sigma(A)$, $E' = \sigma(E)$, $C' = \sigma(C)$, $S' = \sigma(S)$ and $R' = \sigma(R)$;
- $AgentID \in \mathcal{A}$ is an agent identifier that corresponds to the agent affected by the norm, which is playing the target role T.

When a norm is instantiated it must be grounded. In order to ensure that all instances have no free variables, in any norm $\langle D, C, T, A, E, S, R\rangle$ the variables that occur in E, C, S, R must be contained in A (i.e., $v_A \supseteq v_E \cup v_C \cup v_S \cup v_R$). We denote v_X as the set of variables occurring in any formula X.

Remember, that the fireman believes that the rescue is risky (see the first belief in Table 1). In this case, the norm that obliges firemen to abort the fire-rescue is instantiated as follows:

$$\begin{aligned}&\langle \mathcal{O}, abort(gateHouse), self, risky(gateHouse),\\ &\quad fireExtinguished(gateHouse), -, -\rangle\end{aligned} \qquad (i_{fireAbortion})$$

Any agent identifies itself by the $self$ constant.This instance states that the fireman is obliged to abort the operation rescue that it is carrying out in the $gateHouse$ building until the fire has been extinguished.

In this section, the basic notions used in this article have been provided. In the next sections we propose the normative extensions made to the multi-context graded BDI architecture and we explain how these extensions allow the development of norm-autonomous agents capable of reasoning about norms under uncertainty within dynamic environments.

3. Normative Multi-context Graded BDI Architecture

As mentioned in the introduction of this paper, there is a need for norm-autonomous agents that are capable of reasoning about norms under uncertainty within dynamic environments. To address this need, in this paper we propose the *Normative Multi-context Graded BDI Architecture* (or n-BDI for short) [18], which is formed by: *mental* contexts, which have been described in the previous section; and *normative* contexts for allowing agents to acquire and maintain norms (NAC), and to consider instances created out of relevant norms in their decision making processes (NRC).

3.1. Normative Contexts

To endow multi-context graded BDI agents with contexts for representing and reasoning about normative notions, we have considered the work of Sripada et al. [47] as a reference. In this work Sripada et al. analyse the psychological architecture subserving norms. In particular, this architecture is formed by two closely linked innate mechanisms: one responsible for norm acquisition, and the other maintains a database of those instances that have been created out of relevant norms.

To allow agents to have an explicit representation of norms and instances and to consider them in their reasoning process, additional contexts are needed.

We have decided to represent norms and instances separately in two dedicated contexts due to two main reasons. Firstly, we consider that representing norms and instances independently of other mental attitudes allows us to explain the norm reasoning with more clarity: i.e., we are able to define explicitly the relationships among norms, instances and the other contexts. Secondly, the explicit distinction between instances and norms allows us to illustrate the differences between them; i.e., they have a different definition, semantics and dynamics and are considered in different steps of the reasoning process. Specifically, the two normative contexts are:

- *Norm Acquisition Context (NAC).* It maintains a norm base that contains all norms which are *in force* at a given moment.
- *Norm Relevance Context (NRC).* This is the component responsible for maintaining the instances that have been created out of relevant norms at a specific moment.

3.2. Reasoning Process in a n-BDI Agent

The reasoning process in a n-BDI agent is mainly performed by bridge rules that connect mental and normative contexts. As multi-context graded BDI agents, n-BDI agents also carry out a reasoning process in three different phases. Specifically, in n-BDI agents the perception and deliberation phases have been extended with new bridge rules:

Phase 1. Perception. The new bridge rules that we add to the perception process are represented by the grey elements of Figure 1(a):

- *Norm Acquisition Bridge Rules.* These bridge rules are responsible for inferring the norms that are *in force* in the agent environment.
- *Norm Relevance Bridge Rules.* These bridge rules create instances out of the norms are relevant (i.e., are pertinent) to the current situation.

Phase 2. Deliberation. The new bridge rules that we add to the deliberation process are represented by the grey elements of Figure 1(b):

- *Norm Compliance Bridge Rules.* The norm compliance bridge rules determine the instances that the n-BDI agent wants to obey. Then, the obeyed instances are propagated to the agent's desires.

As previously mentioned, the n-BDI architecture has been formalised as a multi-context system, which allows different logics to be used in different contexts. In the following sections, the logics used by normative logics are defined as well as the bridge rules that define the relationship between normative contexts and mental contexts.

4. Norm Acquisition Context (NAC)

According to Conte et al. [16], the problem of acquiring norms[6] entails the evaluation of candidate norms against several criteria. For example, a norm must be rejected if the agent that issues the norm is a non-recognised authority and, as a consequence, the majority of agents do not consider this norm important.

In our proposal, the *Norm Acquisition Context* (NAC) allows agents to maintain a norm base that contains current norms; i.e., the legislation that is *in force* at a given moment. Specifically, the NAC receives information from the environment, determines whether that information is relevant to norms that regulate the agent's environment and updates, accordingly, the existing set of norms (i.e., adding the new norms and deleting the obsolete ones).

For example, the fireman agent must be capable of participating in fire-rescue operations in different regions and countries. Each region or country has its own fire-rescue norms. Moreover, fire-rescue norms are occasionally modified. For example, the fire-rescue strategy can be modified according to the features of the fire that is being fought. For these reasons the fireman must be endowed with mechanisms that allow it to update the set of norms that regulate fire-rescue operations. Moreover, the fact that the fireman agent is capable of acquiring norms on-line implies a greater flexibility and a reduced load at the level of the agents' knowledge bases [16].

Norm Acquisition. Computational models of norm acquisition receive the agent perceptions and identify the set of norms that control the agent environment. Perceptions which are relevant to the norm recognition may be classified into: (i) *explicit normative perceptions,* which correspond to those messages exchanged by agents in which norms are explicitly communicated; and (ii) *implicit normative perceptions*, which correspond to the observation of actions performed by agents.

n-BDI agents consider only *explicit normative information* (i.e., those messages exchanged by agents in which norms are explicitly communicated) as the only source of information for inferring norms. Specifically, n-BDI agents are informed by expert agents (or *experts* for short) about the current norms. Experts provide information about the creation (*issuance*) and elimination (*abolition*) of norms that regulate their environment. Besides that, the set of current norms may change both explicitly, by means of the addition, deletion or modification of the existing norms; and implicitly by introducing new norms which are not specifically meant to modify previous norms, but which change in fact the system because they are incompatible with such existing norms and prevail over

[6]Note that the norm acquisition process have been also called norm recognition process. For example, Campenní et al. in [11] refer to this process by using the term norm recognition. Within the MAS and psychological field the term acquisition norm has been widely used, e.g., both Conte et al. and Sripada et al. refer to it in [17] and [47], respectively. Given that our proposal highly is inspired by these two works, we have adopted the term norm acquisition in this article.

them [28]. However, this is a complex issue which is out of the scope of this article[7]. For simplicity, we do not consider here incompatibility relationships among norms.

Norm Acceptance. The term *norm salience* was defined by Campennì et al. in [11] as "the degree of activity and importance of a norm within a social group and a given context". As psychological [15, 5] and behavioural economics [6, 50] studies have pointed out, norm acceptance is strongly influenced by the norm salience. Therefore, n-BDI agents should be aware of salience of norms in order to make appropriate decisions about which norms to accept. For this reason, n-BDI agents represent norms together with their salience.

All fire-rescue norms are not equally important. Thus, the fireman agent needs to represent and consider the salience of fire-rescue norms to decide which norms are less important and can be violated if necessary. Moreover, the relative importance among these norms is a social factor that changes from one region to other. Finally, there are specific moments (e.g., summer) or facts (e.g., when the population is shaken by a fire that has made a great impact) that may affect the importance that the society gives to fire-rescue norms.

The salience of norms can vary depending on social and individual factors. The estimation of the norm salience is not trivial and it is beyond the scope of this article. Thus, we have assumed that the norm salience is estimated by experts which provide this information to n-BDI agents.

Since the identification of norms and the determination of their salience is a complex problem, it seems appropriate that n-BDI agents consider the information sent by multiple experts, since multiple experts can provide more information than a single expert.

4.1. NAC Language

4.1.1. Syntax

The NAC contains the set of *in force* norms making use of two normative predicates: the *opinion* predicate, which is used for representing the salience that each expert assigns to a norm; and the *norm* predicate, which is used for representing the salience that the n-BDI agent assigns to a norm. Thus, the NAC is formed by expressions such as $norm(n, \rho)$, where n is a norm and $\rho \in [0, 1]$ is a real value that represents the salience of this norm. The NAC also contains expressions such as $opinion(n, j, \rho)$ where n is a norm, j identifies the expert that has provided the opinion and $\rho \in [0, 1]$ is the salience value that expert j has expressed for norm n. These two types of expressions are closely related. In particular, the opinions provided by experts are used by n-BDI agents to estimate the salience of norms.

[7] Proposals presented at the *Formal Models of Norm Change* (http://www.cs.uu.nl/events/normchange2/) are good examples of proposals which provide a formal analysis of all kinds of dynamic aspects involved in systems of norms.

4.1.2. Semantics

We define the semantics of the NAC language using operational semantics[8] [40]. Specifically, the operational semantics of the NAC is given by a set of rules that define a transition relationships between configurations $\langle Opinion, Norm \rangle$ of the NAC where:

- $Opinion$ is a set of norm opinions, where each opinion is an expression such as $opinion(n, j, \rho)$ that represents the salience (ρ) that an expert j assigns to a norm n.
- $Norm$ is a set of $norm(n, \rho)$ expressions that represent the salience (ρ) that the agent assigns to a norm n.

In the general case, in the agent's initial configuration both $Opinion$ and $Norm$ are empty. The operational rules for the NAC language formalise the transitions between possible configurations of the NAC as follows:

$$\frac{preCond}{Conf \rightarrow Conf'}$$

where the top of the rule — represented by the expression $preCond$ — is a boolean expression that represents the precondition of the rule, and the bottom of the rule — represented by the expression $Conf \rightarrow Conf'$— defines the transitions between configurations: i.e., how the initial configuration — represented by the expression $Conf$— changes once the rule is applied —represented by the expression $Conf'$.

Norm Opinion Operational Rules. The inference process of the NAC starts when a new norm opinion is generated. When an expert provides its first opinion about a norm, then the opinion is directly inserted into the NAC according to the following operational rule:

$$\frac{opinion(n,j,\rho) \in f_{\Delta}(\Gamma_{BC}, \Gamma_{DC}, \Gamma_{IC}, \Gamma_{NAC}, \Gamma_{NRC}) \wedge \nexists \rho' : opinion(n,j,\rho') \in Opinion}{\begin{array}{c}\langle Opinion, Norm \rangle \longrightarrow \langle Opinion', Norm \rangle \\ Opinion' = Opinion \cup \{opinion(n,j,\rho)\}\end{array}} \quad \text{(a)}$$

where f_{Δ} is a function that returns the set of formulas that are inferred by the bridge rules (Δ) according to the information present in the contexts of a n-BDI agent (i.e., in the $\Gamma_{BC}, \Gamma_{DC}, \Gamma_{IC}, \Gamma_{NAC}$ and Γ_{NRC}).

Later, when an expert provides a subsequent opinion about the same norm, the norm opinion set is updated according to the following operational rule:

[8]Operational semantics has been widely used for specifying norm semantics in MAS[2, 48]. Moreover, operational semantics describes how the logic statements are used by sequences of computational steps, which has facilitated us the use of a functional programming language to implement our architecture and perform experiments to assess empirically our proposal.

$$\frac{opinion(n,j,\rho) \in f_{\Delta}(\Gamma_{BC},\Gamma_{DC},\Gamma_{IC},\Gamma_{NAC},\Gamma_{NRC}) \ \wedge \exists \rho' : opinion(n,j,\rho') \in Opinion}{\begin{array}{c}\langle Opinion, Norm\rangle \longrightarrow \langle Opinion', Norm\rangle \\ Opinion' = Opinion \setminus \{opinion(n,j,\rho')\} \cup \ \{opinion(n,j,\rho)\}\end{array}} \tag{a*}$$

Norm Operational Rules. There are also operational rules that define the process by which the inferred norms are inserted inside the NAC. If a norm is inferred for the first time, then it is inserted into the NAC as indicated by the following operational rule:

$$\frac{norm(n,\rho) \in f_{\Delta}(\Gamma_{BC},\Gamma_{DC},\Gamma_{IC},\Gamma_{NAC},\Gamma_{NRC}) \wedge \ \nexists \rho' : norm(n,\rho') \in Norm}{\begin{array}{c}\langle Opinion, Norm\rangle \longrightarrow \langle Opinion, Norm'\rangle \\ Norm' = Norm \cup \{norm(n,\rho)\}\end{array}} \tag{b}$$

Later, when the same norm is deduced again, then the norm set is updated according to the following operational rule:

$$\frac{norm(n,\rho) \in f_{\Delta}(\Gamma_{BC},\Gamma_{DC},\Gamma_{IC},\Gamma_{NAC},\Gamma_{NRC}) \ \wedge \exists \rho' : norm(n,\rho') \in Norm}{\begin{array}{c}\langle Opinion, Norm\rangle \longrightarrow \langle Opinion, Norm'\rangle \\ Norm' = Norm \setminus \{norm(n,\rho')\} \cup \{norm(n,\rho)\}\end{array}} \tag{b*}$$

Both the syntax and the operational rules of the NAC have been explained in this section. Next, we describe the norm acquisition bridge rules that infer the opinions and the norms that trigger the execution of these operational rules.

4.2. Norm Acquisition Bridge Rules

The process by which n-BDI agents update the norms and their salience is performed by a set of bridge rules that are applied any time the agent receives a message that informs about a change in the normative system (i.e., the set of norms that are *in force*). Therefore, these bridge rules (named as norm acquisition bridge rules in Figure 1(a)) relate the belief context (BC) —in which received messages are inserted— to the NAC — which contains the mental representation of norms. Specifically, two norm acquisition bridge rules are applied by n-BDI agents: (i) norm opinion, and (ii) salience aggregation bridge rules.

4.2.1. Norm Opinion Bridge Rule

Communication related to the information about norms is considered by the *norm opinion* bridge rule for generating norm opinion expressions. Specifically, we define this rule as follows:

$$\frac{BC : (\mathcal{B}\ inform(J, norm(\langle D,C,T,A,E,S,R\rangle) \wedge salience(\rho)), \rho_{BC}) \wedge \rho_{BC} \geq \delta_{Validity}}{NAC : opinion(\langle D,C,T,A,E,S,R\rangle, J, \rho)}$$

If an agent is informed by another agent (the expert) J about the existence of a norm — represented by the expression $norm(\langle D,C,T,A,E,S,R\rangle) \wedge salience(\rho)$

—, then this information must be employed for generating a new norm opinion. ρ is the salience that the expert assigns to the norm and ρ_{BC} is the validity of the message. The validity of messages is determined in terms of their integrity, i.e., it can be calculated depending on several factors such as the security of the channel through it has been received, the possibility of identifying the provenance of the message, etc. Determining the validity of messages is beyond the scope of this paper. For simplicity, we define that only those messages whose validity is higher or equal to a validity threshold — represented by the expression $\delta_{Validity}$ — are taken into account by the norm opinion bridge rule.

If the expert has not informed previously about this norm, Rule (a) is executed and a new opinion is inserted inside the NAC. Later, the expert might change the norm salience. In this case, the opinion that is stored in the NAC is updated as indicated by Rule (a*).

An expert considers that a norm has been abolished when it believes that the norm is not important anymore. Thus, experts inform n-BDI agents about the deletion of norms by sending messages in which they indicate that the salience of the abolished norm is 0.

For example, the fireman is informed by three experts[9] ($expert_1, expert_2$ and $expert_3$) that have different opinions about the salience of the rescue abortion norm (see the last three beliefs in Table 1). These messages have the maximum reliability and are considered by the *norm opinion* bridge rule. This bridge rule is applied for each one of the experts and, as a consequence, three norm opinion expressions are inserted inside the NAC (see the first three expressions in row NAC of Table 1).

4.2.2. Salience Aggregation Bridge Rule

As previously stated, opinions from experts are considered for determining the salience that n-BDI agents assign to norms. Specifically, we propose that all opinions sent by different experts about the same norm are combined by the salience aggregation bridge rule as follows:

$$\frac{\begin{array}{c} NAC : opinion(\langle D, C, T, A, E, S, R\rangle, J_1, \rho_1) \\ ... \\ NAC : opinion(\langle D, C, T, A, E, S, R\rangle, J_K, \rho_K) \end{array}}{NAC : norm(\langle D, C, T, A, E, S, R\rangle, f_{Aggregation}(\{\rho_1, ..., \rho_K\}))}$$

This bridge rule will be executed any time an opinion changes. The $f_{Aggregation}$ function aggregates opinions of experts by using a robust aggregation operator that reduces the impact of outlier experts. Specifically, all opinions are combined using the *Robust Linear Opinion Pool* (R-LOP) technique proposed by García et al. in [24] . Specifically, the R-LOP measures the conflict level introduced

[9]For example, these three experts can be its instructior in the fire department, its boss at the fire station and the leader of its fire brigade. Each one of these experts may have their own view about the importance of the norm and therefore they provide the agent with three different opinions.

by every expert by taking into account the similarity between its opinion and expertise level, and the other experts. The calculation of the expertise levels is beyond the scope of this paper. Thus, we assume that agents consider that all experts have the same expertise level. In this case the R-LOP technique is applied as follows.

Given a set of K elements $\Psi = \{\psi_1, ..., \psi_K\}$, where each $\psi_1 \in [0, 1]$; the similarity between one of the elements in Ψ and the other elements is defined as:

$$Sim_i(\Psi) = Sim(\psi_i, \Psi \setminus \{\psi_i\}) = 1 - \frac{1}{K-1} \sum_{j=1, j\neq i}^{K} |\psi_i - \psi_k|$$

Let us consider that there are K independent experts that express their opinion about salience of a given norm. Let $\mathcal{O} = \{\rho_1, ..., \rho_K\}$, where each $\rho_j \in [0, 1]$, represents the salience values given by the different experts about the same norm. An expert who disagrees with the majority of other experts is assumed to be conflicting (i.e., it is an "outlier" expert). Based on this, the reliability of each expert j is calculated as follows:

$$Reliability_j = Sim_j(\mathcal{O})$$

Basically, the reliability of an expert represents to what extent this expert can be trusted because it behaves well as a norm expert.

The aggregated salience is obtained by the $f_{Aggregation}$ function as the weighted average of the salience values, with the weights being the reliability levels determined as before:

Definition 3 (Aggregation Function). Given a set $\mathcal{O} = \{\rho_1, ..., \rho_K\}$, where each $\rho_j \in [0, 1]$ represents the set of salience values given by the different experts about the same norm; the aggregated salience is a real function defined as follows:

$$f_{Aggregation}(\mathcal{O}) = \frac{\sum\limits_{j=1}^{K} o_j \times Reliability_j}{\sum\limits_{j=1}^{K} Reliability_j}$$

According to the norm opinions that the fireman agent knows (see the first three expressions in row NAC of Table 1), the set of opinions is $\mathcal{O} = \{0.75, 0.2, 0.8\}$. The similarities between each one of the salience values in $\mathcal{O}$ and the other two values is $Sim(O) = \{0.7, 0.425, 0.675\}$. According to these similarities, the second expert is the least reliable and its opinion must be less considered. As a consequence, the combined salience is more influenced by the other two experts and takes 0.64[10]. Thus, the salience aggregation bridge rule generates the last expression in row NAC of Table 1.

[10] $f_{Aggregation}(\{0.75, 0.2, 0.8\}) = \frac{(0.75\times0.7)+(0.2\times0.425)+(0.8\times0.675)}{0.7+0.425+0.675} = 0.64$

5. Norm Relevance Context (NRC)

The *Norm Relevance Context* (NRC) is the component responsible for maintaining the instances that have been created out of relevant norms. Thus, the NAC recognises all norms that are *in force*, whereas the NRC only contains those instances which are active according to the current situation.

For example, fire-rescue norms are general norms that are not always active. Some of them, such as the $n_{fireAbortion}$ norm, only come into effect under specific circumstances; e.g., in risky situations. What is considered as a risky situation is ambiguous. Therefore, there are norms that come into effect under uncertain circumstances. As a result, the fireman agent needs to be able to detect the activation and expiration conditions on the basis of uncertain beliefs. This section illustrates how n-BDI agents manage the activation and expiration of norms under uncertainty.

5.1. NRC Language

5.1.1. Syntax

The NRC contains information about instances using the *instance* predicate. Thus, it contains expressions such as: $instance(i, \rho)$ where i is an instance and $\rho \in [0, 1]$ is a real value that represents the relevance degree of the instance (i.e., the degree in which the instance is pertinent to the current circumstances of the agent).

5.1.2. Semantics

Again, we define the operational semantics of the NRC language by a set of operational rules that define a transition relationship between configurations $\langle Instance \rangle$ of the NRC where:

- $Instance$ is a set of instances, where each instance is an expression such as $instance(i, \rho)$ where i is an instance and ρ is the certainty degree of the instance.

In the general case, an agent's initial configuration is $\langle Instance \rangle$ where $Instance$ is empty.

Instance Operational Rules. The reasoning cycle starts when a new instance is generated (the process by which instances are inferred in the NRC by *norm relevance* bridge rules is described below in Section 5.2). Since this is the first time that an instance is deduced, it is inserted into the NRC according to the following operational rule:

$$\frac{instance(i, \rho) \in f_{\Delta}(\Gamma_{BC}, \Gamma_{DC}, \Gamma_{IC}, \Gamma_{NAC}, \Gamma_{NRC}) \wedge \nexists \rho' : instance(i, \rho') \in Instance}{\begin{array}{c}\langle Instance \rangle \longrightarrow \langle Instance' \rangle \\ Instance' = Instance \cup \{instance(i, \rho)\}\end{array}} \quad \text{(c)}$$

When an instance that already belongs to the NRC is deduced again, then the instance set is updated according to the following operational rule:

$$\frac{instance(i,\rho) \in f_{\Delta}(\Gamma_{BC}, \Gamma_{DC}, \Gamma_{IC}, \Gamma_{NAC}, \Gamma_{NRC}) \ \wedge \exists \rho' : instance(i,\rho') \in Instance}{\begin{array}{c}\langle Instance \rangle \longrightarrow \langle Instance' \rangle \\ Instance' = Instance \setminus \{instance(i,\rho')\} \cup \{instance(i,\rho)\}\end{array}} \quad \text{(c*)}$$

The language that allows instances to be represented in the NRC has been explained in this section. Next, we describe the bridge rules that infer instances inside the NRC causing the execution of the NRC operational rules.

5.2. Norm Relevance Bridge Rules

As stated before, norms are not always active. Thus, instances are created inside the agents' mind when the agent has beliefs that sustain the activation of norms. Similarly, norms also include an expiration condition that defines the validity period or deadline of instances. Thus, agents must believe that a given instance has expired in order to delete its mental representation. As illustrated by Figure 1(a), norm relevance bridge rules relate the agent beliefs (BC) and the mental representation of norms (NAC) to infer instances (NRC). Specifically, two norm relevance bridge rules are executed by n-BDI agents: (i) instance activation and (ii) instance expiration bridge rules.

5.2.1. Instance Activation Bridge Rules

When the agent knows a norm and it believes that there is an agent, which can be itself, under the influence of this norm (i.e., there is an agent that enacts the target role of the norm) and the norm is relevant to the current situation; then a new instance must be created. To model this reasoning process we define the *norm relevance* bridge rule as follows:

$$\frac{\begin{array}{c}NAC : norm(\langle D, C, T, A, E, S, R \rangle, \rho_{NAC}), \\ BC : (\mathcal{B}\,\sigma(A), \rho_{\sigma(A)}), BC : (\mathcal{B}\,play(AgentID, T), \rho_T)\end{array}}{NRC : instance(\langle D, \sigma(C), AgentID, \sigma(A), \sigma(E), \sigma(S), \sigma(R) \rangle, f_{Relevance}(\rho_{NAC}, \rho_{\sigma(A)}, \rho_T))}$$

If an agent considers that a norm — represented by the expression $\langle D, C, T, A, E, S, R \rangle$ — is currently active — i.e., there is a substitution σ such as the expression $(\mathcal{B}\,\sigma(A), \rho_{\sigma(A)})$ is deduced in BC; where $\sigma(A)$ denotes the result of applying σ to A, and $\rho_{\sigma(A)}$ is a real number within the $[0,1]$ interval representing the certainty about this belief — and the agent knows that there is an agent — represented by the expression $AgentID$ — that it is under the influence of the norm — i.e., the expression $(\mathcal{B}\,play(AgentID, T), \rho_T)$ is deduced in BC; where $play(AgentID, T)$ denotes fact that $AgentID$ is playing role T, and ρ_T is a real number within the $[0,1]$ interval representing the certainty about this belief—, then a new instance is generated[11].

[11] Note that n-BDI agents create instances that affect them and also instances that affect other agents. It allows n-BDI agents to be aware of which norms affect other agents, which can be useful for predicting and evaluating the behaviour of their interaction partners. However, this predicting and evaluating feature is beyond the scope of this article.

Therefore, agents should believe simultaneously that a given norm is active and that an agent is under its influence to create an instance that binds this particular agent to the norm. [12].

$f_{Relevance}$ is defined as a numerical fusion operator[13] that can be given different definitions depending on the properties that are required in each concrete application. In particular, the relevance degree assigned by the $f_{Relevance}$ function is a combination among the salience of the norm — represented by the expression ρ_{NAC} —, the certainty about the activation of the norm — represented by the expression $\rho_{\sigma(A)}$ — and the certainty about the fact that the agent is affected by the norm — represented by the expression ρ_T. In this article, we assume that the conditions that are necessary to create an instance (i.e., the existence of an important norm and the two beliefs) are independent (e.g., the consideration of a norm as important does not imply that the activation condition of this norm holds). Given that the intersection or join certainty about independent events is the product among the event certainties, we define the combination among the uncertain values that cause the instantiation of a norm as follows:

$$f_{Relevance}(\rho_{NAC}, \rho_{\sigma(A)}, \rho_T) = \rho_{NAC} \times \rho_{\sigma(A)} \times \rho_T$$

According to the information in Table 1, the fireman is completely sure about being acting as a fireman (see the the fourth belief in row BC). Moreover, it considers that it participates in a risky rescue with a 50% of probability (see the first belief in row BC). Therefore, the *instance activation* bridge rule is applied as follows[14]:

$$\frac{\begin{array}{c} NAC : norm(\langle \mathcal{O}, abort(R), fireman, risky(R), fireExtingished(R), -, -\rangle, 0.64), \\ BC : (\mathcal{B}\ risky(gateHouse), 0.5), BC : (\mathcal{B}\, play(self, fireman), 1) \end{array}}{\begin{array}{c} NRC : instance(\langle \mathcal{O}, abort(gateHouse), fireman, risky(gateHouse), \\ fireExtingished(gateHouse), -, -\rangle, f_{Relevance}(0.64, 0.5, 1)) \end{array}}$$

where $\sigma = \{R/gateHouse\}$. Thus, a new instance is generated. The relevance of this new instance is 0.32[15]. This instance triggers the execution of the operational Rule (b), and, as a consequence, the NRC contains the following expression (see row NRC of Table 1):

$$\begin{array}{c} instance(\langle \mathcal{O}, abort(gateHouse), fireman, risky(gateHouse), \\ fireExtingished(gateHouse), -, -\rangle, 0.32) \end{array}$$

[12]For the purpose of this paper it is only necessary to know that n-BDI agents have graded beliefs that represent their knowledge about the environment and the roles played by agents in the environment. The process by which agents use their perceptions for inferring these beliefs is beyond the scope of this paper

[13]For a review and classification of data fusion operators see [7].

[14]$n_{fireAdoption}$ was defined in Section 2.3

[15]$f_{Relevance}(0.64, 0.5, 1) = 0.64 \times 0.5 \times 1 = 0.32$

5.2.2. Instance Expiration Bridge Rule

Once the expiration condition of an instance holds, then the certainty of the instance must be reduced. To model this reasoning process we define the *instance expiration* bridge rule as follows:

$$\frac{\begin{array}{c} NRC : instance(\langle D, C, AgentID, A, E, S, R\rangle, \rho_{NRC}), \\ BC : (\mathcal{B}\, E, \rho_E) \end{array}}{\begin{array}{c} NRC : instance(\langle D, C, AgentID, A, E, S, R\rangle, \\ f_{Expiration}(\rho_{NRC}, \rho_E)) \end{array}}$$

If the NRC of an agent contains an instance — represented by the expression $instance(\langle D, C, AgentID, A, E, S, R\rangle, \rho_{NRC})$ — and it has a belief that sustains its expiration — represented by the expression $(\mathcal{B}\, E, \rho_E)$ —, then the degree of the instance must be reduced[16]. Specifically, the belief $(\mathcal{B}\, E, \rho_E)$ disconfirms with the instance. Thus, any fusion operator that combines evidences that confirm and disconfirm an hypothesis can be used. In this paper we use a simple fusion operator that reduces the relevance of the instance by the certainty of the disconfirming belief. Thus, we define the $f_{Expiration}$ function as follows:

$$f_{Expiration}(\rho_{NRC}, \rho_E) = max(0, \rho_{NRC} - \rho_E)$$

Therefore, the $f_{Expiration} : [0,1] \times [0,1] \rightarrow [0,1]$ is a function such that [45] the unit element is 0, which is an information that says nothing and does not influence the combination. If there is a high certainty about the expiration of the instance, the relevance degree of the instance would become 0. In this case, the instance would no longer be considered by the n-BDI agent.

In the n-BDI proposal the notion of role has been used to define the sphere of influence of norms. The use of norms for defining the responsibilities, duties and rights of roles has been proposed also in other works such as [33, 37, 22]. Similarly, in the n-BDI proposal, activation and expiration conditions have been used to define the period in which norms come into effect. Activation and expiration conditions have been considered in other well-known proposals on normative agents [33, 37, 31]. However, all of these previous proposals do not consider that agents have an uncertain knowledge of the world. Therefore, only the n-BDI proposal confronts with the activation and expiration of norms under uncertainty.

6. Norm Compliance Bridge Rules

Once norms have been instantiated and their relevance has been determined, a n-BDI agent must decide whether it observes or violates each specific instance (i.e. it makes a decision about norm compliance) and how its behaviour will be

[16]Note that the expiration condition of any instance is grounded and, as a consequence, no substitution is applied in the *instance expiration bridge rule*.

modified according to its decision (e.g., to comply with an obligation instance). To model this reasoning process we propose the *norm compliance* bridge rules. These rules are executed once a new instance has been created or an existing instance has been updated. Then, the agent makes a decision about norm compliance (i.e., it calculates its willingness to comply with the instance) and updates its mental state accordingly. The process by which agents extend their mental state according to their decisions about norm compliance (i.e., according to the instances that they want to follow or transgress) has been described by the self-determination theory [19] as a dynamic relation between norms and goals. Accordingly, we have considered the translation of norms into desires. Depending on the desirability degree of these new desires, they may generate new intentions to be executed or they may be used to select the most suitable plan that achieves another goal that is more desired.

Norm compliance bridge rules (see Figure 1(b)) relate instances (NRC) with the agent beliefs (BC) and desires (DC) to infer new desires according to norms. These bridge rules depend on the deontic modality of the instance that is considered.

Obligation Compliance Bridge Rule. If the agent is affected by an obligation and the agent is willing to comply with this obligation, then desire for reaching the state imposed by the obligation must be created. Specifically, we propose the following bridge rule:

$$\frac{NRC : instance(\langle \mathcal{O}, C, self, A, E, S, R\rangle, \rho_{NRC}) \quad f_{Willingness}(\langle \mathcal{O}, C, self, A, E, S, R\rangle, \Gamma_{BC}, \Gamma_{DC}) > \delta_{Compliance}}{DC : (\mathcal{D}\ C, f_{SubjectiveValue}(\rho_{NRC}, f_{Willingness}(\langle \mathcal{O}, C, self, A, E, S, R\rangle, \Gamma_{BC}, \Gamma_{DC})))}$$

where $\delta_{Compliance} \in [0,1]$ is the norm compliance threshold. The $f_{Willingness}$ function[17] calculates the agent willingness to comply with a given instance as a real value within the $[-1,1]$ interval. When it takes a value higher than $\delta_{Compliance}$, it means that the agent is willing to comply with the obligation. The degree assigned to the new desire inferred from the obligation instance is calculated by the $f_{SubjectiveValue}$ function[18].

Prohibition Compliance Bridge Rule. If the agent is affected by a prohibition and the agent wants to obey it, then a negative desire must be created to avoid the forbidden state. Specifically, we propose the following bridge rule:

$$\frac{NRC : instance(\langle \mathcal{F}, C, self, A, E, S, R\rangle, \rho_{NRC}) \quad f_{Willingness}(\langle \mathcal{F}, C, self, A, E, S, R\rangle, \Gamma_{BC}, \Gamma_{DC}) > \delta_{Compliance}}{DC : (\mathcal{D}\neg C, f_{SubjectiveValue}(\rho_{NRC}, f_{Willingness}(\langle \mathcal{F}, C, self, A, E, S, R\rangle, \Gamma_{BC}, \Gamma_{DC}))}$$

As in case of obligations, the degree assigned to the new desire is calculated by the $f_{SubjectiveValue}$ function.

[17] To be explained in Section 6.1.
[18] To be explained in Section 6.2.

The *norm compliance* bridge rules, explain how the instances are considered for extending the agent mental state in order to fulfil these instances. There are two key functions for the norm compliance bridge rules: the function that calculates the willingness to comply with an instance ($f_{Willingness}$), and the function that assigns a degree to the new desire ($f_{SubjectiveValue}$). Next, we define these two functions.

6.1. Willingness Function.

The results calculated by the $f_{Willingness}$ function represent the agent willingness to comply with norms; i.e., it models the decisions about norm compliance. To calculate this willingness agents consider the situations that are predicted to occur when norms are fulfilled and violated (i.e., the norm consequences). We define the consequences of obeying an instance as follows:

Definition 4 (Fulfilment Consequences). Given an instance $(\langle D, C, self, A, E, S, R\rangle)$ and a theory of beliefs (Γ_{BC}), the predicted consequences of fulfilling this instance are defined as follows:

$$f_F(\langle D, C, self, A, E, S, R\rangle, \Gamma_{BC}) =$$
$$\begin{cases} \{(C,1),(R,1)\} \cup \{(\gamma_j,\rho_j) | \forall \gamma_j, \rho_j : \Gamma_{BC} \vdash (\mathcal{B}\ C \rightarrow \gamma_j, \rho_j)\} & \text{if } D = \mathcal{O} \\ \{(\neg C,1),(R,1)\} \cup \{(\gamma_j,\rho_j) | \forall \gamma_j, \rho_j : \Gamma_{BC} \vdash (\mathcal{B}\ \neg C \rightarrow \gamma_j, \rho_j)\} & \text{if } D = \mathcal{F} \end{cases}$$

Thus, the fulfilment consequences are a set of pairs (γ, ρ), where $\gamma \in \mathcal{L_P}$ represents a situation that is predicted to occur if the norm is fulfilled; and $\rho \in [0, 1]$ is the probability of this predicted situation. Specifically, we consider three kind of consequences:

- *Direct Consequence.* In case of an obligation, the direct consequence of the fulfilment of the obligation is the norm condition (C) that will be achieved with a probability of 1. The direct consequence of an obligation instance is denoted by the pair $(C, 1)$ in the previous definition; where C is the obliged condition and 1 is the probability in which the C will be true if the obligation instance is fulfilled. In case of a prohibition, obeying this prohibition implies that the norm condition will be avoided ($\neg C$). The direct consequence of complying with a prohibition instance is denoted by the pair $(\neg C, 1)$ in the previous definition; where C is the forbidden condition and 1 is the probability in which the $\neg C$ will be true if the prohibition instance is fulfilled.

- *Enforcement Mechanisms.* The reward (R) is another consequence of the norm fulfilment. For simplicity, we assume that there is a perfect enforcement that always punishes offenders and rewards obedience. As a consequence, the probability[19] of being rewarded is 1. Therefore, the enforcement consequences of fulfilling instances is denoted by the pair $(R, 1)$ in the previous definition; where R is the reward and 1 is the probability in which the R will be true if the instance is fulfilled.

- *Indirect Consequences.* The logical connective $\rightarrow$ is used to represent explanatory relationships between propositions. Thus, a belief such as $(\alpha \rightarrow \gamma_j, \rho_j)$ means that the situation or state represented by α explains or causes γ_j with a probability of ρ_j. An obligation is obeyed when the norm condition (C) is achieved. Therefore, the indirect consequences of obeying the obligation are defined by considering those beliefs such as $(\mathcal{B}\ C \rightarrow \gamma_j, \rho_j)$. Similarly, the indirect consequences of fulfilling of a prohibition is calculated by considering those beliefs such as $(\mathcal{B}\ \neg C \rightarrow \gamma_j, \rho_j)$.

We define the consequences of violating an instance as follows:

Definition 5 (Violation Consequences). Given an instance $(\langle D, C, self, A, E, S, R\rangle)$ and a theory of beliefs (Γ_{BC}), the predicted consequences of violating this instance are defined as follows:

$$f_V(\langle D, C, self, A, E, S, R\rangle, \Gamma_{BC}) =$$
$$\begin{cases} \{(\neg C, 1), (S, 1)\} \cup \{(\gamma_j, \rho_j) | \forall \gamma_j, \rho_j : \Gamma_{BC} \vdash (\mathcal{B}\ \neg C \rightarrow \gamma_j, \rho_j)\} & \text{if } D = \mathcal{O} \\ \{(C, 1), (S, 1)\} \cup \{(\gamma_j, \rho_j) | \forall \gamma_j, \rho_j : \Gamma_{BC} \vdash (\mathcal{B}\ C \rightarrow \gamma_j, \rho_j)\} & \text{if } D = \mathcal{F} \end{cases}$$

Again, the consequences of violating a norm are calculated considering the direct consequence, the enforcement mechanisms (i.e., the sanction) and the indirect consequences of violating the instance. Specifically, the three kind of consequences are:

- *Direct Consequence.* In case of an obligation, the direct consequence of the violation of the obligation is the negation of the norm condition $(\neg C)$. In contrast, violating a prohibition implies that the norm condition will be achieved (C).

- *Enforcement Mechanisms.* The sanction (S) is another consequence of the norm violation. This consequence is denoted by the pair $(S, 1)$ in the previous definition.

- *Indirect Consequences.* An obligation is violated when the norm condition (C) is achieved. Therefore, the indirect consequences of violating the obligation are defined by considering those beliefs such as $(\mathcal{B}\ \neg C \rightarrow \gamma_j, \rho_j)$. Similarly, the indirect consequences of violating of a prohibition is calculated by considering those beliefs such as $(\mathcal{B}\ C \rightarrow \gamma_j, \rho_j)$.

[19] If agents are able to perceive the probability of being punished or rewarded, then these probabilities may be used.

As previously mentioned, n-BDI agents calculate its willingness to comply with norms considering the consequences of violating and fulfilling an instance. Specifically, the main factors on the willingness functions are the probability of the predicted consequences and the desirability (vs. undesirability) of these consequences. We formally define the willingness function as follows:

Definition 6 (Willingness Function). Given an instance i, a set of beliefs Γ_{BC}, a set of desires Γ_{DC} and an instance i; the agent's willingness to follow this instance is calculated by the $f_{Willingness}$ function as follows:

$$f_{Willingness}(i, \Gamma_{BC}, \Gamma_{DC}) = \frac{\sum\limits_{\forall(\gamma_j,\rho_j)\in f_F(i,\Gamma_{BC})} \rho_j * des(\gamma_j, \Gamma_{DC})}{\sum\limits_{\forall(\gamma_j,\rho_j)\in f_F(i,\Gamma_{BC})} \rho_j} - \frac{\sum\limits_{\forall(\gamma_j,\rho_j)\in f_V(i,\Gamma_{BC})} \rho_j * des(\gamma_j, \Gamma_{DC})}{\sum\limits_{\forall(\gamma_j,\rho_j)\in f_V(i,\Gamma_{BC})} \rho_j}$$

where the function des calculates the desirability of a proposition[20].

Thus, $f_{Willingness}$ is a function that calculates the willingness of a n-BDI agent to comply with an instance as a real value within the $[-1, 1]$ interval. Specifically, it considers the desirability of the fulfilment consequences minus the desirability of the violation consequences. Specifically, the first element of the subtraction in the $f_{Willingness}$ function is an average among the desirability (denoted by $des(\gamma_j, \Gamma_{DC})$) of the consequences that are predicted to occur if the instance is fulfilled[21]. Given that all consequences are not predicted to occur with the same probability, the desirability of consequences has been weighted by the probability of their occurrence (denoted by ρ_j). Thus, those consequences more likely to occur are the most important when calculating the desirability of fulfilment consequences. In contrast, the second element of the subtraction in the $f_{Willingness}$ function is an average among the desirability of the consequences that are predicted to occur if the instance is violated[22]. Again, these desirabilities have been weighted by the probability of their occurrence.

A positive value of $f_{Willingness}$ means that the agent hopes that the fulfilment of the instance entails desirable consequences and, as a consequence,

[20]The desirability of a proposition is formally defined as:

$$des(\gamma, \Gamma_{DC}) = \begin{cases} \rho_\gamma - \rho_{\neg\gamma} & \text{if } \Gamma_{DC} \vdash (\gamma, \rho_\gamma) \text{ and } \Gamma_{DC} \vdash (\neg\gamma, \rho_{\neg\gamma}) \\ \rho_\gamma & \text{if } \Gamma_{DC} \vdash (\gamma, \rho_\gamma) \text{ and } \Gamma_{DC} \not\vdash (\neg\gamma, \rho_{\neg\gamma}) \\ -\rho_{\neg\gamma} & \text{if } \Gamma_{DC} \vdash (\neg\gamma, \rho_{\neg\gamma}) \text{ and } \Gamma_{DC} \not\vdash (\gamma, \rho_\gamma) \\ 0 & \text{otherwise} \end{cases}$$

Therefore, the desirability of a proposition γ (i.e., $des(\gamma, \Gamma_{DC})$) is a real value within the $[-1, 1]$ interval such that: the -1 value means that the proposition γ is absolutely rejected, a desirability value of 0 means that the agent is indifferent to γ (i.e., it does not benefit from γ), and 1 means that the agent has maximum preference on γ.

[21]Note that the two summations on the first element on the subtraction are calculated over the result of function f_F.

[22]Note that the two summations on the second element on the subtraction are calculated over the result of function f_V.

sustains the fulfilment of the instance. In contrast, a negative value of the $f_{Willingness}$ function sustains the violation of the instance.

In the proposed case study, the fireman is affected by the $i_{fireAbortion}$ instance. This instance causes the execution of the *obligation compliance* as follows:

$$\frac{\begin{array}{c} NRC : instance(i_{fireAbortion}, 0.32) \\ f_{Willingness}(i_{fireAbortion}, \Gamma_{BC}, \Gamma_{DC}) > \delta_{Compliance} \end{array}}{\begin{array}{c} DC : (\mathcal{D}\ abort(gateHouse), \\ f_{SubjectiveValue}(0.32, f_{Willingness}(i_{fireAbortion}, \Gamma_{BC}, \Gamma_{DC}))) \end{array}}$$

According to the information that is contained in the fireman theory (see Table 1), the predicted consequences of fulfilling the $i_{fireAbortion}$ instance are defined as follows:

$$f_F(i_{fireAbortion}, \Gamma_{BC}) = \{(abort(gateHouse), 1)\} \cup \{(survive(self), 0.5)\}$$

Similarly, the predicted consequences of violating i are defined as follows:

$$f_V(i_{fireAbortion}, \Gamma_{BC}) = \{(\neg abort(gateHouse), 1)\} \cup \{(survive(victims), 0.25)\}$$

Since the $i_{fireAbortion}$ instance is not enforced, then the fireman has no expectation of being neither sanctioned nor rewarded (i.e. the probability of these consequences is 0). So, the $f_{Willingness}$ function is calculated as follows:

$$f_{Willingness}(i_{fireAbortion}, \Gamma_{BC}, \Gamma_{DC}) = \frac{1\times 0+0.5\times 1}{1+0.5} - \frac{1\times 0+0.25\times 1}{1+0.25} = \\ 0.33 - 0.2 = 0.13$$

6.2. Subjective Value Function.

The degree assigned to the desires generated by the norm compliance bridge rules is defined by the $f_{SubjectiveValue}$ function, which combines the relevance of the instance and the motivation to comply with this instance as a real value within the $[0, 1]$ interval. Both conditions, the relevance of the instance and the motivation to comply with it, are required for creating a new desire. Again, we consider that these two conditions are independent and we combine the uncertain values that cause the translation of the norm into a desire as a product:

$$f_{SubjectiveValue}(\rho_{NRC}, \rho_{Willingness}) = \rho_{NRC} \times \rho_{Willingness}$$

where $\rho_{Willingness} = f_{Willingness}(\langle D, C, self, A, E, S, R\rangle, \Gamma_{BC}, \Gamma_{DC})$.

In our example, the $f_{SubjectiveValue}$ is calculated as follows:

$$f_{SubjectiveValue}(0.32, 0.13) = 0.32 \times 0.01 = 0.04$$

Thus the the obligation compliance bridge rule is instantiated as follows:

$$\frac{NRC : instance(i_{fireAbortion}, 0.32), 0.13 > \delta_{Compliance}}{DC : (\mathcal{D}\ abort(gateHouse), 0.04)}$$

Assuming $\delta_{Compliance} = 0.05$ (in the next section we describe how the most suitable value for this threshold has been estimated in this case-study) then a new desire to abort rescue is inferred inside the DC. Since this desire that can be achieved through a plan, then the fireman aborts its intention to continue with the rescue and creates a new intention to abort the rescue. This will cause that the agent executes the plan for abandoning the *gateHouse* building.

In this section we have proposed several bridge rules and functions that allow agents to reason about norm compliance. Specifically, in this section we have described how n-BDI agents consider both their preferences and the norm repercussions when they determine their willingness to comply with norms. In the next section we describe the experiment that we have carried out to evaluate the performance of n-BDI agents under uncertainty within dynamic environments.

7. Evaluation

We have performed an experiment to evaluate to what extent having an explicit declarative procedure for reasoning about norms under uncertainty helps agents to adapt successfully to dynamic environments. Specifically, we seek to compare the results obtained by n-BDI agents with agents that are unaware of norms and with agents that make decisions about norm compliance using a static method. To this aim, we have developed a simulator of the fire-rescue scenario.

7.1. Fire-Rescue Scenario Modelling

The fire-rescue case study has been modelled as a grid. Thus, victims are randomly located in the grid. The fireman is initially located at the door of the building. For simplicity we have assumed that the building has one door. Initially there is one fire that is randomly positioned in the grid. In each iteration a new fire is created on a free position of the grid. Figure 2 illustrates an example of a rescue grid. Specifically, this fire-rescue scenario is modelled as a grid of size 4, the door size is 3 and there are 3 victims that have not been rescued yet.

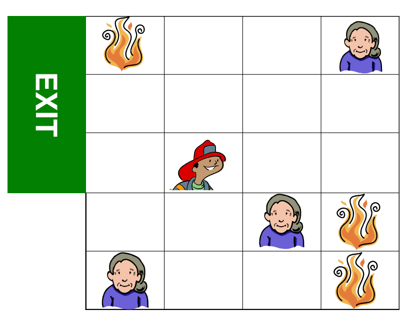


Figure 2: Example of a grid that models a fire-rescue scenario

We have performed different simulations for comparing the results that are obtained by three different implementations of the fireman: (i) *non-normative* fireman, which does not consider norms; (ii) *norm-constrained* fireman, which translates norms into constraints; and (iii) *n-BDI* fireman, which is implemented using the n-BDI architecture. Next, the different fireman implementations and the results obtained by these implementations are described in detail.

7.2. Fireman Modelling

7.2.1. Non-Normative Fireman

In this implementation the fireman is not aware of norms. It moves randomly along the grid searching for victims. When the fireman finds a victim, it builds a path to the reach the victim. If this path exists, then the fireman tries to reach the victim. If the fireman is able to reach the victim, then it carries the victim to the door. Once the victim has been rescued, the fireman moves randomly again to find another victim. The fireman follows this pattern until it completes the rescue (i.e., it rescues all victims that are reachable) or it dies.

7.2.2. Norm-Constrained Fireman

In this implementation the fireman has knowledge about the $n_{fireAbortion}$ norm. However, the fireman uses static and fixed mechanisms for reasoning about norms. Specifically, this obligation norm has been translated into a constraint using a static threshold. In each iteration, the fireman calculates the risk. If the risk is higher than a fixed risk threshold, then the fireman stops the fire-rescue and it goes to the door. Therefore, norm-constrained fireman is not able to adapt their norm compliance decisions to different situations since it always follows the same constraint determined by a static risk threshold. The risk of a given situation is calculated as the percentage of the surrounding positions that are in flames. In this simulation, we assume that the fireman is able to determine whether the positions that are next to it are in flames or not.

7.2.3. n-BDI Fireman

The n-BDI fireman has explicit knowledge about the $n_{fireAbortion}$ norm and it uses expressive and flexible methods for reasoning about norm compliance.

For simplicity, we assume that the n-BDI fireman has been informed about the salience of the obligation by three experts and that the salience it assigns to this norm is 0.64 (as described in Section 4.2).

As explained before in Section 5.2, norms become relevant when their activation condition holds and the agent believes that it is under the influence of the norm. In this implementation, we assume that the fireman believes that it is playing fireman role with the highest certainty (i.e., the fireman is working at this moment and according to Table 1 the certainty of this belief is 1). The risk of a situation is calculated as in in case of the norm-constrained fireman. According to the definition of the $f_{Relevance}$ function (see Section 5.2), the relevance of the obligation is calculated as a product between the certainty about the activation condition (or the risk), the certainty in which the agent believes that it is under the influence of the norm and the norm salience (according to Table 1 the salience of the norm is 0.64). Once the relevance of the obligation norm has been calculated, then the fireman executes the Obligation Compliance Bridge Rule (described in Section 6). According to this rule, when the value calculated by the willingness function is higher than the norm compliance threshold, then a new desire is created for achieving the obligatory condition.

According to the definition of the willingness function (explained in Section 6.1), its value is calculated considering the fulfilment and violation consequences. The predicted consequences of fulfilling the $i_{fireAbortion}$ instance are defined as follows:

$$f_F(i_{fireAbortion}, \Gamma_{BC}) = \{(abort(gateHouse), 1)\} \cup \{(survive(self), probSurvive)\}$$

where $probSurvive$ stands for the probability of surviving if the fireman aborts the rescue. Similarly, the predicted consequences of violating i are defined as follows:

$$f_V(i_{fireAbortion}, \Gamma_{BC}) = \{(\neg abort(gateHouse), 1)\} \cup \{(survive(victims), probSaveVictims)\}$$

where $probSaveVictims$ stands for the probability of saving one more victim. Thus, the indirect consequence of the obligation fulfilment is that the fireman survives to the fire-rescue, whereas the indirect consequence of the obligation violation is that more victims can be rescued.

We assume that the fireman does not have any desire related to the cancellation of the fire-rescue. Thus, this case study helps us to illustrate how n-BDI agents are able to make decisions about norm compliance even if norms do not affect directly the agent goals. In this situation, the willingness function is calculated as follows:

$$\frac{(1*0) + (probSurvive * desSurvive)}{1 + probSurvive} - \frac{(1*0) + (probSaveVictims * desSaveVictims)}{1 + desSaveVictims}$$

The concrete desirability of these prepositions ($desSurvive$ and $desSaveVictims$) determines the personality of the fireman.

The probability of saving one more victim is calculated as follows:

- When the fireman is carrying a victim then the probability of saving this victim is 1.
- If it is not the case, the fireman looks its surroundings and searches for victims. The probability of saving these victims is calculated by considering the Manhattan distance [32] between the positions of the fireman and the victim. Specifically, this probability is calculated by a function that returns value that decreases linearly as the distance increases.

Similarly, the probability of saving the fireman life is calculated considering the Manhattan distance [32] between the positions of the fireman and the door.

7.3. Experiment

The main goal of the experiments that we have performed is to determine whether the use of the n-BDI architecture to implement the fireman agent improves its performance in a wide-range of situations. With this aim we performed simulations in which the different parameters of the grids (i.e., their size, the number of victims and the size of the door) are changed. Next, we compare the results obtained by the three implementations.

7.3.1. Experiment Metrics

There are two main factors that determine the success of a fire-rescue: the percentage of victims that are rescued and the survival of the fireman.

A simulation is represented as a set (G, D, V, R, F), where: G is the size of the grid; D is the door size; V is the total number of victims; R is the number of victims that have been rescued; and F takes value 1 when the fireman survives to the fire-rescue operation, otherwise it takes value 0.

The victim survival percentage achieved in a single simulation (G, D, V, R, F) is defined as:

$$\frac{R}{f_{MaxRescuedVictims}(G, D, V)}$$

where $f_{MaxRescuedVictims}$ is a function such that for each grid size, door size and number of victims returns the maximum number of victims that can be rescued on average[23]. Given a set of simulations ($\mathcal{N} = \{(G_1, D_1, V_1, R_1, F_i), ..., (G_N, D_N, V_N, R_N, F_n)\}$) the *victim survival percentage* (S_V) is defined as:

$$S_V(\mathcal{N}) = \frac{\displaystyle\sum_{i=1}^{N} \frac{R_i}{f_{MaxRescuedVictims}(G_i, D_i, V_i)}}{N} \times 100$$

The *fireman survival percentage* achieved in a set of simulations $\mathcal{N} = \{(G_1, D_1, V_1, R_1, F_i), ..., (G_N, D_N, V_N, R_N, F_N)\}$ is defined as:

$$S_F(\mathcal{N}) = \frac{\displaystyle\sum_{i=1}^{N} F_i}{N} \times 100$$

We define the *success* (S) of a set of simulations as a product between the values calculated by S_V and S_F for this simulation set.

Threshold Estimation. To determine which are the most suitable values for the risk threshold and the compliance threshold, we have performed a set of simulations varying the value of these thresholds. In each simulation, a fireman (norm-constrained or n-BDI) is allocated in a grid. The size of these grids (G)

[23] To estimate the values returned by this function we have performed a set of simulations of the non-normative fireman.

ranges randomly within the $[3, 10]$ interval. The size of the door (D) ranges randomly within the $[1, G]$ interval. The number of victims (V) ranges within the $[1, \frac{(G-1)^2}{2}]$ interval. For each value of the thresholds we have performed 1000 simulations. Figure 3 shows the success (S) obtained by norm-constrained fireman with respect to the value of the risk threshold. As illustrated by this figure, the best result is obtained when the risk threshold is set to 0.31. Figure 4 shows the success (S) obtained by n-BDI fireman[24] with respect to the value of the compliance threshold. As illustrated by this figure, the best result is obtained by n-BDI fireman when the compliance threshold is set to 0.08. Therefore, in the rest of experiments we have fixed the thresholds to these two values.

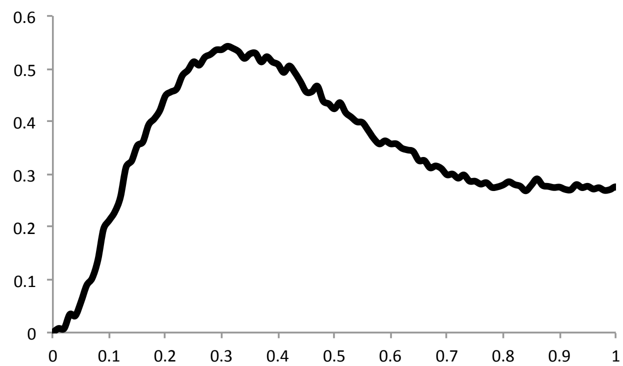


Figure 3: Success obtained by norm-constrained fireman with respect to the risk threshold. The X-axis represents the risk threshold and the Y-axis represents the success (S).

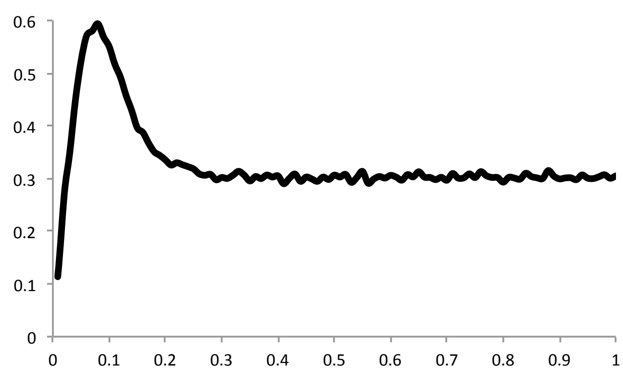


Figure 4: Success obtained by n-BDI fireman with respect to the compliance threshold. The X-axis represents the compliance threshold and the Y-axis represents the success (S).

[24]Note that in this experiment both $desSurvive$ and $desSaveVictims$ have been set to 1.

7.3.2. Experiment Description

We have performed different simulations for comparing the results obtained by the three types of fireman. In the n-BDI architecture, the specific values given to the $desSurvive$ and $desSaveVictims$ parameters determine the personality of the fireman. In this experiment, we consider three different personalities:

- *Empathetic* fireman, which wants to preserve victims' life as much as it wants to preserve its own life. Therefore, both $desSurvive$ and $desSaveVictims$ have been set to 1.0.
- *Coward* fireman, which wants to preserve victims' life less than it wants to preserve its own life. Therefore, $desSurvive = 1$ and $desSaveVictims = 0.5$.
- *Brave* fireman, which wants to preserve victims' life more than it wants to preserve its own life. Therefore, $desSurvive = 0.5$ and $desSaveVictims = 1.0$.

Therefore, we have experimented with 5 types of fireman; non-normative fireman, norm-constrained fireman, empathetic fireman, coward fireman and brave fireman.

In each simulation the size of the grid (G) ranges within the $[3, 10]$ interval, the size of the door (D) ranges within the $[1, G]$ interval and the number of victims (V) ranges within the $[1, \frac{(G-1)^2}{2}]$ interval. For each value of G, D and V we have performed 1000 different simulations to support the findings.

7.3.3. Experiment Results

Table 2 shows the results obtained by the simulations.

Fireman Implementation	$\mathbf{S_V}$	$\mathbf{S_F}$	$\mathbf{S}$
Non-Normative	$99.96 \pm 0.04\%$	$22.49 \pm 0.64\%$	$22.48 \pm 0.64\%$
Norm-Constrained	$80.95 \pm 1.26\%$	$79.16 \pm 0.89\%$	$63.14 \pm 1.14\%$
Empathetic n-BDI	$87.83 \pm 0.43\%$	$76.8 \pm 0.86\%$	$66.76 \pm 0.62\%$
Coward n-BDI	$84.22 \pm 0.56\%$	$79.8 \pm 0.87\%$	$66.17 \pm 0.57\%$
Brave n-BDI	$99.87 \pm 0.05\%$	$36.46 \pm 0.76\%$	$36.41 \pm 0.76\%$

Table 2: 95% confidence interval for the victim survival percentage ($\mathbf{S_V}$), the fireman survival percentage ($\mathbf{S_F}$) and the success ($\mathbf{S}$) that each implementation achieves.

As one could expect, the non-normative fireman is able to rescue almost all the victims that can be rescued, since the fireman does not abort the fire-rescue ever. However, the fireman survival is very low. Therefore, the lowest success is obtained by the non-normative fireman.

In case of the norm-constrained fireman, it achieves better results since the fireman survival percentage is significantly higher than the non-normative fireman, whereas the victim survival percentage decreases in a lesser degree. The confidence intervals in case of the norm-constrained fireman are the largest. Hence, the behaviour exhibited by the norm-constrained fireman is more variable: i.e., the results obtained change from rescue to rescue which implies that the norm-constrained fireman has some difficulties to adapt to different rescue operations.

The empathetic n-BDI fireman is more altruistic than norm-constrained fireman and the victim survival percentage (S_V) increases. Moreover, is survival is lightly lower. As a consequence, a higher success is obtained by empathetic fireman.

The coward n-BDI firemean wants to preserve victims' life less than it wants to preserve its own life. As a consequence, the fireman survival percentage (S_F) increases. Since the coward fireman takes less risks, then the number of rescued victims decreases lightly. As a consequence, the success that is obtained by the coward fireman is similar to the empathetic fireman. Moreover, we can observe that the coward fireman obtains a fireman survival percentage similar to the norm-constrained fireman, while it obtains better results in terms of victim survival. Thus, the n-BDI architecture can be used to model an improved version of the norm-constrained fireman.

Finally, the brave n-BDI fireman wants to preserve victims' life more than it wants to preserve its own life. As a consequence, the victim survival percentage (S_V) increases. However, the brave fireman takes more risks and its survival decreases notably. As a consequence, the success obtained by the brave fireman is lower than the other n-BDI fireman. Nonetheless, we can observe that the brave fireman is able to rescue a percentage of victims similar to the non-normative, while it obtains better results in terms of fireman survival. Thus, the n-BDI architecture can be used to model an improved version of the non-normative fireman.

In general, empathetic and coward n-BDI firemen achieve a small improvement with respect to the norm-constrained fireman (e.g., success in empathetic fireman improves a 5.73%). This small improvement is due to the fact that only one fireman participates in the fire-rescue operation. If more firemen participated, more victims would be rescued and the difference between the results achieved by n-BDI firemen and norm-constrained firemen would also increase[25].

As the experimental results illustrate, the use of the n-BDI architecture allows a more dynamic behaviour to be modelled. Specifically, we have demonstrated that due to the expressive and flexible rules used to reason about norms n-BDI agents achieve a better adaptation to dynamic environments by making more reasoned decisions about when a norm should be complied or violated. n-BDI agents are capable of self-adjusting their behaviour to the features of the fire-rescue operation in which they are involved. Moreover, different agent personalities can be modelled. Thereby, the behaviour of agents is predictable

[25]The use of several firemen leads us to the problem of coordinating teams of firemen which is out of the scope of this paper. For this reason, we have carried experiments in which only one fireman participates.

to some degree and MAS designers can decide the behaviour of the agents according to the functionality that is required.

8. Related Work

The first proposal that defined a *norm-autonomous agent* as an agent whose behaviour is influenced by norms that are explicitly represented inside its mind was made by Conte et al. in [17]. Conte et al. also stated that norm- autonomous agents have capabilities for acquiring norms, accepting a recognized norm, determining whether a norm concerns their case, and making decisions about norm compliance. From that moment on, several proposals on norm-autonomous agents have been made. For example, Castelfranchi et al. in [14] described how an agent architecture can be extended with an explicit norm notion. Similarly, Dignum et al. proposed in [21] an extension of the classic BDI architecture for considering norms. These first proposals provide intuitive ideas and recommendations to meet the main requirements to norm-autonomous agents. However, the authors did not specify a solution to meet these requirements. The work of Boella & Lesmo in [8], was one of the first proposals on the MAS field that provided a solution to the autonomous decision on norm compliance. Specifically, the authors provided some strategies for making a decision about norm compliance. However, they did not provide enough details about how agent programmers can develop norm-autonomous agents that implement these strategies.

More recent works have also confronted with the problem of how agents reason about norms. Specifically, this problem has been faced from a logical and formal perspective, e.g., the proposals contained in [27, 34] describe logic formalisms and axioms for representing norms. Besides that, there are proposals on the development of agent architectures that provide means to software agents to take norms into account in their practical reasoning; i.e., proposals on the development of algorithms and procedures for allowing agents to decide the next action to be executed according to norms. Given that our proposal falls into this last category, this section reviews the most relevant architectures for norm-autonomous agents. These architectures have been classified into norm-oriented or goal-oriented according to the priority that agents give to norms with respect to their internal goals.

8.1. Norm-oriented Agents

The main purpose of norm-oriented agents is to always observe norms, even if this implies that they are unable to achieve their internal goals. An example of norm-oriented agent architecture is the noA architecture [31], which is a practical agent architecture with an explicit notion of obligation and prohibition. noA agents are not endowed with capabilities for acquiring norms and, as a consequence, the norms that the agent take into account are a priori defined. Basically, noA agents determine which norms are relevant to the agent at a given moment. As in our proposal, norms have activation and expiration conditions define when norms become relevant. However, the noA proposal assumes that agents are able to perceive and act upon a certain environment. Another example of norm-oriented agent are Normative KGP agents, which are described in [42]. This proposal consists of extending KGP *(Knowledge-Goal-Plan)* agents [30] with explicit normative notions such as obligations, prohibitions, and roles. Thus, norms define which are the responsibilities of a specific set of agents which are playing a given role. As in our proposal, KGP agents consider as relevant all norms that affect the roles being played by them.

As previously mentioned norm-oriented agents always try to fulfil norms. Thus, they assume that the best course of action in any case is to follow norms. This assumption may be valid for static environments. In dynamic environments the circumstances may change drastically making norms to loose their validity. Therefore, agents situated in this type of scenarios require more elaborated processes for reasoning about norms (i.e., acquiring norms, accepting norms and making decisions about norm compliance).

8.2. Goal-Oriented Agents

In contrast, goal-oriented normative agents always seek to achieve their desires, fulfilling norms whenever possible.

BOID. In [10], Broersen et al. propose the extension of the BDI architecture with an explicit notion of obligation. This is one of the first proposals on norm-autonomous agents that describes how these agents (known as BOID) can be designed in practise. Thus, BOID agents are formed by four *components* that are associated with Beliefs, Obligations, Intentions and Desires. Obligations are the external motivations of agents and their validity is taken for granted. In this proposal, agents can violate norms only due to a conflict among obligations, desires or intentions. This type of conflicts is solved by means of a static ordering function that resolves conflicts between components and within components. In contrast to our proposal, BOID agents always follow a rigid protocol for making decisions about norm compliance; i.e., they cannot decide to follow or not a given norm according to their circumstances.

López y López's Proposal. One of the first proposals on goal-oriented agents that have explicitly considered the current circumstances of agents for making decisions regarding norms is made by López y López's et al. in [33]. Specifically, this work proposes methods for agents that are autonomous to come to decisions about norms. The main drawbacks of this proposal are: (i) norm compliance is only based on the existence of an external mechanism of norm enforcement and , as a consequence, in absence of information about the enforcement mechanisms agents have no motivation to comply with norms; and (ii) it assumes that agents are situated in a certain and deterministic environment, therefore agents make decisions about norms upon certain and perfect knowledge about the environment. In practice, agents interact by means of sensors and actuators under uncertainty with a non-deterministic environment. Therefore, even López y López proposal is unsuitable to be applied in real applications. In response to this problem we have developed the n-BDI architecture.

EMIL. In all of the aforementioned proposals, either norms are hard-coded on agents off-line or agents are informed by authorities about norms on-line. Therefore, agents are not capable of learning new norms on-line and adapting their behaviours according to these unforeseen norms. To address this, the EMIL proposal [3] developed a framework for autonomous norm recognition. Thus, agents would be able to acquire new norms by observing the behaviour of other agents that are located in their environments. EMIL agents make decisions about norm by means of static utility functions that calculate the expected outcomes of compiling with norms. This solution is suitable for controlled environments in which agents confront with foreseeable situations. However, the kind of scenarios addressed in this paper, which are dynamic environments characterized by uncertainty, require more flexible solutions to the norm compliance dilemma. As stated in [14] "if protocols that agents use to react to the environment are fixed, they have no ways to respond to unpredictable changes".

Although several proposals have been made to define norm-autonomous agents [13], the definition of an agent architecture for norm-autonomous agents that have a physical presence in a real word environment remains unsolved. All these proposals assume that agents are situated in a certain and deterministic environment. Thus, these proposals define static procedures for reasoning about norms such as blind obedience to norms, static utility functions, or static priority orders. For example, the BOID architecture [10] defines a static priority order among mental attitudes that is programmed on agents. These static mechanisms entail a limitation on the agent capacities for adapting to new societies or to the environmental changes. Only the proposal of López y López et al., defined mechanisms for allowing agents to reason about norms according to current circumstances of the agent. However, López y López assumed that agents are situated within a certain environment that can be perceived by agents with complete precision. The added value of our proposal with respect to the existing literature is that our agents have been designed to achieve a better adaptation to dynamic environments under uncertainty. To this aim n-BDI agents are able to represent the uncertainty of the environment explicitly, which implies that the norm reasoning process is more fine-grained. We defined n-BDI agents using declarative procedures for norm reasoning and empirically proved that they perform better than more static approaches when dealing with uncertainty within dynamic environments.

9. Conclusions

Uncertainty is one of the most important problems when agents have a physical presence in some real-world environment. However, uncertainty has received little attention in the existing literature on norm-autonomous agents. To address this problem, we propose the n-BDI architecture in this paper. n-BDI agents are able to represent the uncertainty about the environment. Moreover, we have endowed them with declarative procedures that allow them to represent the norms that are *in force* in their environment, to accept them, to detect which ones are relevant at a given moment and to make a decision about norm compliance. The main goal of the n-BDI architecture is to model agents that are able to reason about norms while being able to adapt to dynamic environments under uncertainty. To evaluate the n-BDI architecture, we have implemented a simulator of a fire-rescue case study. Specifically, we have modelled the behaviour of the fireman that participates in a fire-rescue following three different approaches: ignoring norms, implementing norms using static procedures and using the n-BDI architecture to implement firemen agents. As the experimental results illustrate, the fact that agents have more expressive procedures for reasoning about norms allows them to better adapt under uncertainty to a dynamic environment. Specifically, we have demonstrated that n-BDI agents are capable of self-adjusting their behaviour to the features of the fire-rescue operation in which they are involved.

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