Runtime Norm Revision using Bayesian Networks

Davide Dell'Anna, Mehdi Dastani, Fabiano Dalpiaz

Department of Information and Computing Sciences, Utrecht University, The Netherlands

D.DellAnna@uu.nl, M.M.Dastani@uu.nl, F.Dalpiaz@uu.nl

Universiteit Utrecht

Motivation

Context: normative multi-agent systems, where norms are used to control and influence the behavior of autonomous agents to guarantee the overall system objectives.
Problem: misalignment between norms and system objectives at runtime.
Proposal: revision of norms at runtime to ensure system objectives.

Illustrative Scenario: Smart Roads

System **Objectives**:

- *minimize average travel time.*
- *minimize unmber of accidents.*

Enforced **Norms**:

- N_1: cars should follow static/adaptive navigation system.
- N_2: junctions should use static/adaptive traffic lights or line panels.

Execution **Context**: extreme/normal weather and day/night time.
⇒ Norm N_2 may not be appropriate for extreme weather.

Research Question

How to design and develop a **runtime supervision framework** that learns at runtime the **effectiveness of the enforced norms** and **automatically revises** them, when necessary, to ensure the overall objectives of a multiagent system?

Supervising a Normative MAS

The supervision framework continuously monitors the execution of a multiagent system, evaluates its behavior against the currently enforced norms by means of a Bayesian Network, and intervenes by deciding which norms should be revised.

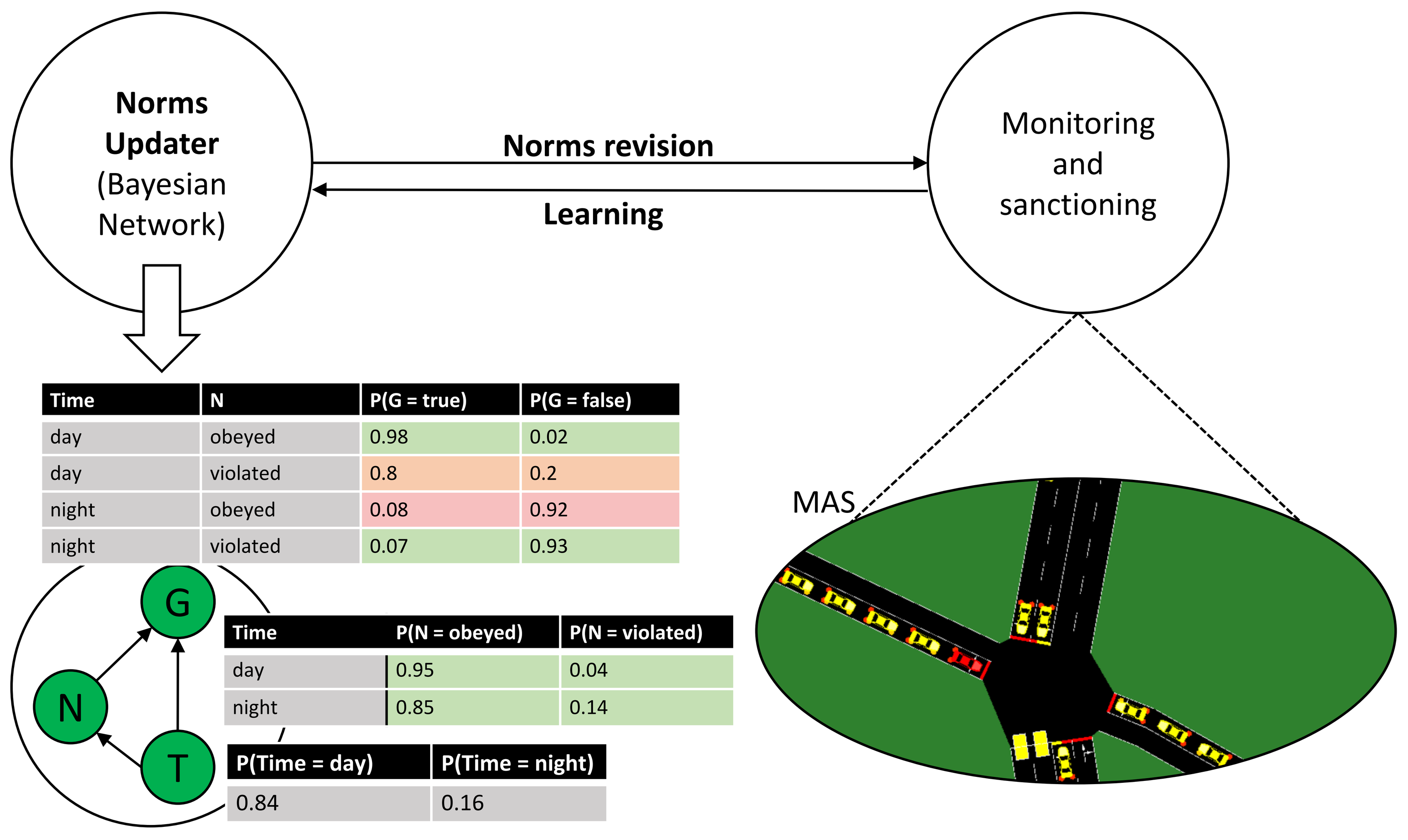


Figure 1: The main components of the proposed runtime supervision framework.

Bayesian Network with Norms

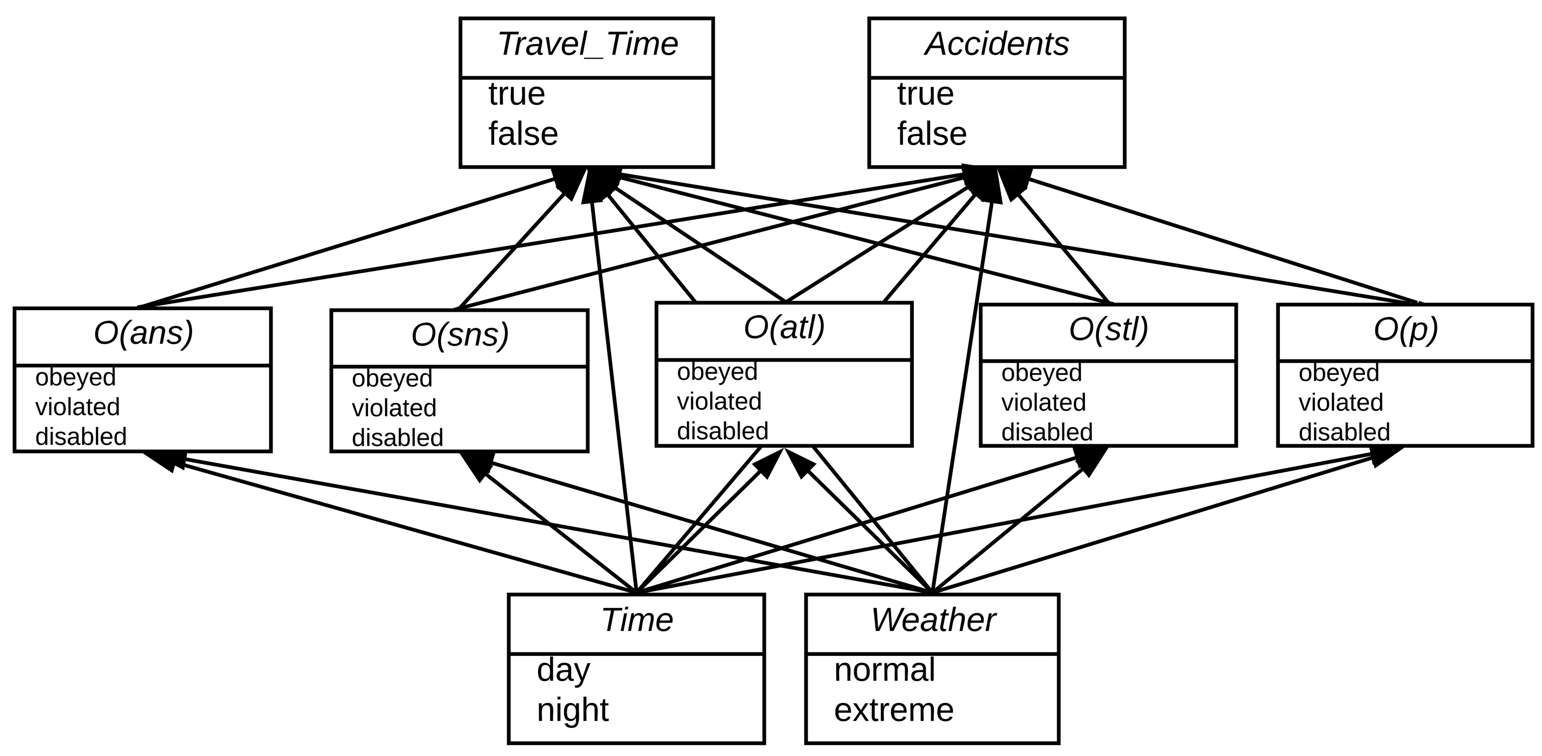


Figure 2: A Bayesian Network with objectives, norms and context variables.

Norm Revision

A norm revision is triggered when (i) changes in the probability distributions in the Bayesian Network are not significant anymore, and (ii) the objectives of the system are still not achieved, e.g.,

$$P(Travel\_Time_{true} \wedge Accidents_{true}) \geq 0.95$$

Norms in the most problematic context **mpc** are subject to revision

$$\mathbf{mpc} = argmax_{\mathbf{c} \in \mathbf{all(c)}}\ P(\mathbf{O}_{false} |\ \mathbf{c})$$

Harmful norms: the set **D** of norms with value *dis* in assignment **h**. The remaining set $\mathbf{A} = \mathbf{N} \setminus \mathbf{D}$ is the set of *useful norms*.

$$\mathbf{h} = argmax_{\mathbf{n} \in \mathbf{N}_{\{dis,\neg dis\}}}\ P(\mathbf{O}_{true} |\ \mathbf{n} \wedge \mathbf{mpc})$$

Norms more useful when obeyed (violated): The subset of **A** with value *ob* (*viol*) in **u**.

$$\mathbf{u} = argmax_{\mathbf{n} \in \mathbf{A}_{\{ob,viol\}}}\ P(\mathbf{O}_{true} |\ \mathbf{n}\ \wedge \mathbf{mpc} \wedge \mathbf{D}_{dis})$$

Useful norms often obeyed (violated) when $\mathbf{O}_{false}$: The subset of **A** with value *ob* (*viol*) in **mle** (*most likely explanation* **mle** for $\mathbf{O}_{false}$ in **mpc**).

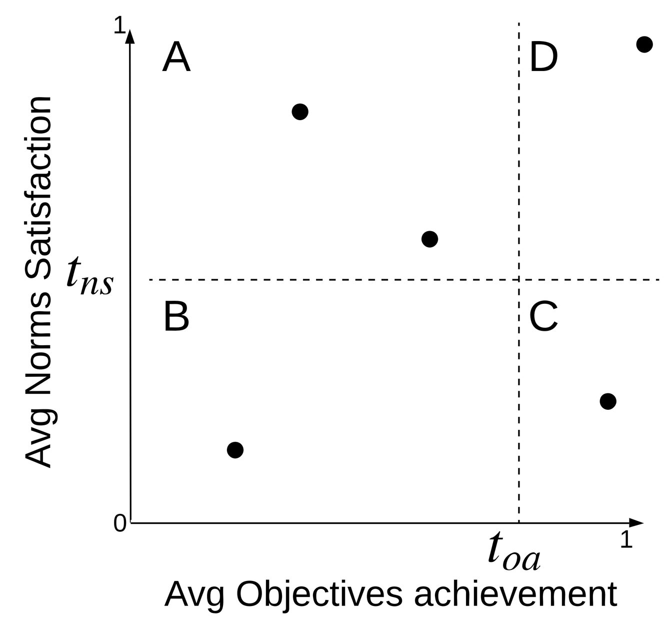
$$\mathbf{mle} = argmax_{\mathbf{n} \in \mathbf{A}_{\{ob,viol\}}}\ P(\mathbf{n}\ |\mathbf{O}_{false} \wedge \mathbf{mpc} \wedge \mathbf{D}_{dis})$$

Algorithm PB

(1) *Disable/Relax* harmful norms. (2) *Relax* norms more useful when violated. (3) *Strengthen/Alter* norms more useful when obeyed but often violated when $\mathbf{O}_{false}$. (4) All other norms: unrevised, or *strengthen* them.

Algorithm SB

(1) Calculate avg. norms satisfaction probability and avg. objectives achievement probability.
(2) *Disable* harmful norms, if any. Else, proceed with step 3.
(3a) State A: *Relax* norms more useful when violated but often obeyed when $\mathbf{O}_{false}$, if any. Otherwise, *Strengthen/Alter* all useful norms.



(3b) State B: *Strengthen/Alter* norms more useful when obeyed but often violated when $\mathbf{O}_{false}$ and *Relax* norms more useful when violated.
(3c) State C: *Relax* norms more useful when violated and often violated when $\mathbf{O}_{false}$, if any. Otherwise, *Strengthen/Alter* norms more useful when obeyed but often violated when $\mathbf{O}_{false}$.

PB and SB as Hill Climbing Heuristics

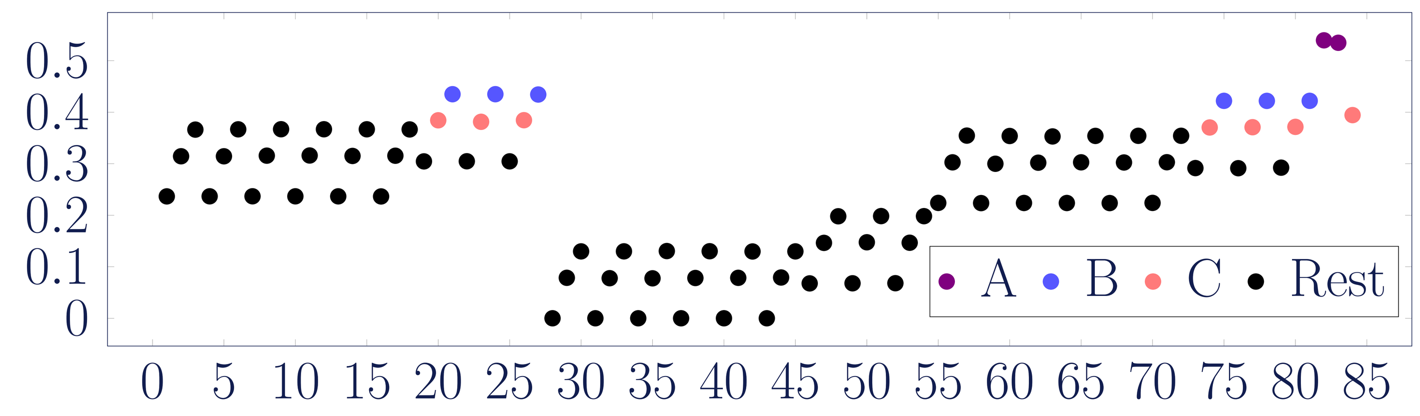


Figure 3: Avg. probability of objectives achievement for 84 tried configurations.

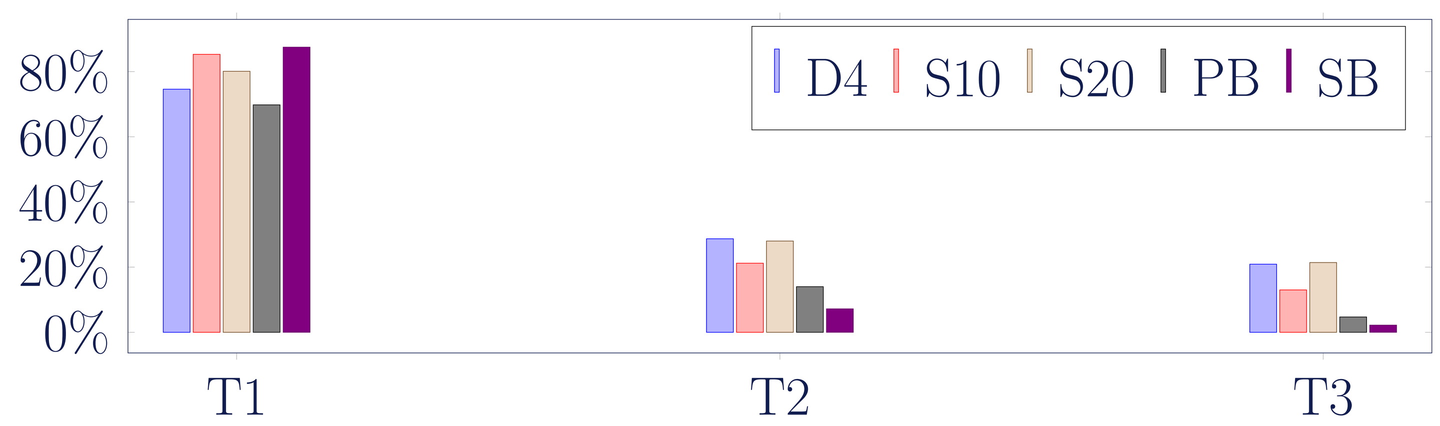


Figure 4: Average percentage of explored configurations before finding an optimal one.

Current and Future Work

Runtime norm-based mechanism design; integration of sanctions revision; Evaluation on case studies involving rational agents; Bayesian Networks vs other probabilistic approached; "On-demand" norm synthesis.