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by

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## TOWARDS A MODELING FRAMEWORK WITH TEMPORAL AND UNCERTAIN DATA FOR ADAPTIVE SYSTEMS

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# Abstract

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**Vision:** As state-of-the-art techniques fail to model efficiently the evolution and the uncertainty existing in dynamically adaptive systems, the adaptation process makes suboptimal decisions. To tackle this challenge, modern modeling frameworks should efficiently encapsulate time and uncertainty as first-class concepts.

*Context* Smart grid approach introduces information and communication technologies into traditional power grid to cope with new challenges of electricity distribution. Among them, one challenge is the resiliency of the grid: how to automatically recover from any incident such as overload? These systems therefore need a deep understanding of the ongoing situation which enables reasoning tasks for healing operations. **Abstraction** is a key technique that provided an illuminating description of systems, their behaviors, and/or their environments alleviating their complexity. **Adaptation** is a cornerstone feature that enables reconfiguration at runtime for optimizing software to the current and/or future situation.

Abstraction technique is pushed to its paramountcy by the model-driven engineering (MDE) methodology. However, information concerning the grid, such as loads, is not always known with absolute confidence. Through the thesis, this lack of confidence about data is referred to as **data uncertainty**. They are approximated from the measured consumption and the grid topology. This topology is inferred from fuse states, which are set by technicians after their services on the grid. As humans are not error-free, the topology is therefore not known with absolute confidence. This data uncertainty is propagated to the load through the computation made. If it is

1 neither present in the model nor not considered by the adaptation process, then the  
2 adaptation process may make suboptimal reconfiguration decision.

3 The literature refers to systems which provide adaptation capabilities as dynam-  
4 ically adaptive systems (DAS). One challenge in the grid is the phase difference  
5 between the monitoring frequency and the time for actions to have measurable effects.  
6 Action with no immediate measurable effects are named **delayed action**. On the  
7 one hand, an incident should be detected in the next minutes. On the other hand, a  
8 reconfiguration action can take up to several hours. For example, when a tree falls  
9 on a cable and cuts it during a storm, the grid manager should be noticed in real  
10 time. The reconfiguration of the grid, to reconnect as many people as possible before  
11 replacing the cable, is done by technicians who need to use their cars to go on the  
12 reconfiguration places. In a fully autonomous adaptive system, the reasoning process  
13 should consider the ongoing actions to avoid repeating decisions.

14 *Problematic* **Data uncertainty and delayed actions are not specific to smart**  
15 **grids.**

16 First, data are, almost by definition, uncertain and developers always work with  
17 estimates. Hardware sensors have by construction a precision that can vary according  
18 to the current environment in which they are deployed. A simple example is the  
19 temperature sensor that provides a temperature with precision to the nearest degree.  
20 Software sensors approximate also values from these physical sensors, which increases  
21 the uncertainty. For example, CPU usage is computed counting the cycle used by a  
22 program. As stated by Intel, this counter is not error-prone<sup>1</sup>.

23 Second, it always exists a delay between the moment where a suboptimal state is  
24 detected by the adaptation process and the moment where the effects of decisions  
25 taken are measured. This delayed is due to the time needed by a computer to process  
26 data and, eventually, to send orders or data through networks. For example, migrating  
27 a virtual machine from a server to another one can take several minutes.

28 **Through this thesis, I argue that this data uncertainty and this delay**

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<sup>1</sup><https://software.intel.com/en-us/itc-user-and-reference-guide-cpu-cycle-counter>

cannot be ignored for all dynamic adaptive systems. To know if the data uncertainty should be considered, stakeholders should wonder **if this data uncertainty affects the result of their reasoning process, like adaptation**. Regarding delayed actions, they should verify **if the frequency of the monitoring stage is lower than the time of action effects to be measurable**. These characteristics are common to smart grids, cloud infrastructure or cyber-physical systems in general.

*Challenge* These problematics come with different challenges concerning the representation of the knowledge for DAS. The global challenge address by this thesis is: **how to represent the uncertain knowledge allowing to efficiently query it and to represent ongoing actions in order to improve adaptation processes?**

*Vision* This thesis defends the need for a unified modeling framework which includes, despite all traditional elements, temporal and uncertainty as first-class concepts. Therefore, a developer will be able to abstract information related to the adaptation process, the environment as well as the system itself.

Concerning the adaptation process, the framework should enable abstraction of the actions, their context, their impact, and the specification of this process (requirements and constraints). It should also enable the abstraction of the system environment and its behavior. Finally, the framework should represent the structure, behavior and specification of the system itself as well as the actuators and sensors. All these representations should integrate the data uncertainty existing.

*Contributions* Towards this vision, this document presents two approaches: a temporal context model and a language for uncertain data.

The temporal context model allows abstracting past, ongoing and future actions with their impacts and context. First, a developer can use this model to know what the ongoing actions, with their expect future impacts on the system, are. Second, she/he can navigate through past decisions to understand why they have been made when they have led to a sub-optimal state.

The language, named Ain'tea, integrates data uncertainty as a first-class citizen. It allows developers to attach data with a probability distribution which represents

1 their uncertainty. Plus, it mapped all arithmetic and boolean operators to uncertainty  
2 propagation operations. And so, developers will automatically propagate the uncer-  
3 tainty of data without additional effort, compared to an algorithm which manipulates  
4 certain data.

5 *Validation* Each contribution has been evaluated separately. The context model has  
6 been evaluated through the performance axis. The dissertation shows that it can  
7 be used to represent the Luxembourg smart grid. The model also provides an API  
8 which enables the execution of query for diagnosis purpose. In order to show the  
9 feasibility of the solution, it has also been applied to the use case provided by the  
10 industrial partner.

11 The language has been evaluated through two axes: its ability to detect errors at  
12 development time and its expressiveness. Ain'tea can detect errors in the combination  
13 of uncertain data earlier than state-of-the-art approaches. The language is also as  
14 expressive as current approaches found in the literature. Moreover, we use this  
15 language to implement the load approximation of a smart grid furnished by an  
16 industrial partner, Creos S.A.<sup>2</sup>.

17 **Keywords:** dynamically adaptive systems, knowledge representation, model-  
18 driven engineering, uncertainty modeling, time modeling

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<sup>2</sup>Creos S.A. is the power grid manager of Luxembourg. <https://www.creos-net.lu>

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# Table of Contents

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<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Context . . . . .	2
1.2	Problem statement . . . . .	4
1.3	Challenge . . . . .	4
1.4	Scope of the thesis . . . . .	4
1.5	Contribution & Validation . . . . .	5
1.6	Structure of the document . . . . .	5
<b>2</b>	<b>Background</b>	<b>7</b>
2.1	Model-driven engineering . . . . .	8
2.2	Adaptive systems . . . . .	8
<b>3</b>	<b>State of the art</b>	<b>9</b>
3.1	Introduction . . . . .	10
<b>4</b>	<b>A unified modeling framework</b>	<b>13</b>
<b>5</b>	<b>AinãŽtea: Managing Data Uncertainty at the Language Level</b>	<b>15</b>
<b>6</b>	<b>TKM: a temporal knowledge model</b>	<b>17</b>
6.1	Introduction . . . . .	18
6.1.1	Motivation . . . . .	19
6.1.2	Background . . . . .	25
6.1.3	Use case scenario . . . . .	28

1	6.2	Knowledge formalization . . . . .	29
2	6.2.1	Formalization of the temporal axis . . . . .	30
3	6.2.2	Formalism . . . . .	31
4	6.2.3	Application on the use case . . . . .	36
5	6.3	Modeling the knowledge . . . . .	40
6	6.3.1	Parent element: <i>TimedElement</i> class . . . . .	41
7	6.3.2	Knowledge metamodel . . . . .	41
8	6.3.3	Context metamodel . . . . .	42
9	6.3.4	Requirement metamodel . . . . .	44
10	6.3.5	Action metamodel . . . . .	45
11	6.4	Validation . . . . .	46
12	6.4.1	Diagnostic: implementation of the use case . . . . .	46
13	6.4.2	Reasoning over unfinished actions and their expected effects .	49
14	6.4.3	Performance evaluation . . . . .	51
15	6.4.4	Discussion . . . . .	54
16	6.5	Conclusion . . . . .	56
17	<b>7</b>	<b>Conclusion</b>	<b>59</b>
18	<b>8</b>	<b>This chapter concludes the thesis and presents some perspectives.</b>	<b>61</b>
19		<b>List of publications and tools</b>	<b>i</b>
20		<b>Abbreviations</b>	<b>iii</b>
21		<b>Glossary</b>	<b>v</b>



## Introduction

### Contents

<b>1.1</b>	<b>Context</b>	<b>2</b>
<b>1.2</b>	<b>Problem statement</b>	<b>4</b>
<b>1.3</b>	<b>Challenge</b>	<b>4</b>
<b>1.4</b>	<b>Scope of the thesis</b>	<b>4</b>
<b>1.5</b>	<b>Contribution &amp; Validation</b>	<b>5</b>
<b>1.6</b>	<b>Structure of the document</b>	<b>5</b>

*Model-driven engineering methodology and dynamically adaptive systems approach are combined to tackle new challenges brought by systems nowadays. After introducing these two software engineering techniques, I give one example of such systems: the Luxembourg smart grid. I will also use this example to highlight two of the problematics: uncertainty of data and delays in actions. Among the different challenges which are implied by them, I present the global one addressed by the vision defended in this thesis: modeling of temporal and uncertain data. This global challenge can be addressed by splitting up in several ones. I present two of them, which are directly tackled by two contributions presented in this thesis.*

# Context

Utilities are introducing more and more Information and Communication Technology (ICT)\* in the grid in order to face the new challenges of electricity supply [farhangi2010path; ipakchi2009grid; DBLP:journals/comsur/FangMXY12]. These nowadays power grids are referred to as smart grid\*.

In this document, we focus on the **self-healing**\* capacity of such grids. A self-healing system\* can automatically repair any incident, software or hardware, at run-time [DBLP:journals/computer/KephartC03]. For example, a smart grid can optimize the power flow to deal with failures of transformers<sup>1</sup> [DBLP:journals/comsur/FangMXY]. In this way, the incident will impact as few users as possible, ideally none.

This healing mechanism can be performed only if the smart grid has a deep understanding of itself and its environment. To tame their complexity, a common approach in software engineers is to use an **abstraction** mechanism. Abstractions provide an illuminating description of systems, their behaviours, or their environment. For example, Hartmann *et al.*, [DBLP:conf/smartgridcomm/0001FKTPTR14] provide a class diagram that describes the smart grid topology, when it uses power-line communications<sup>2</sup>.

More generally, a self-healing\* is a **self-adaptive system**\*. Cheng *et al.*, define self-adaptive systems\* as “systems that are able to adjust their behaviour in response to their perception of the environment and the system itself” [DBLP:conf/dagstuhl/ChengLGIMA]. Jeffrey O. Kephart and David M. Chess [DBLP:journals/computer/KephartC03] laid the groundwork of this approach, based on an IBM white paper [computing2006architectural]. Since then, it has been used in different domain [DBLP:journals/corr/abs-1904-01518] such as cloud infrastructure [DBLP:conf/icac/JavadiG17; OpenStack:Watcher:Wiki] DBLP:conf/icse/BarnaKFL17 or Cyber-Physical System (CPS)\* [DBLP:conf/icac/Lalanda DBLP:conf/cbse/FouquetMFBPJ12; DBLP:conf/smartgridsec/0001FKNT14]

**Model-Driven Engineering (MDE)**\* uses the abstraction mechanism to facilitate the development of nowadays software [DBLP:journals/computer/Schmidt06]

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<sup>1</sup>Transformers change the voltage in cables.

<sup>2</sup>Data are sent through cables that also distribute electricity.

1 DBLP:conf/ifm/Kent02; DBLP:series/synthesis/2017Brambilla]. This method  
2 ology can be applied to different stages of software development. In this thesis, we focus  
3 on one of its paradigm: **models@run.time**\* [DBLP:journals/computer/BlairBF09;  
4 DBLP:journals/computer/MorinBJFS09]. The state of the system or its envi-  
5 ronment, as well as its behaviour, are reflected in a model, used for analysis. Developers  
6 can use this paradigm to implement adaptive systems\* [DBLP:journals/computer/MorinBJFS09;  
7 DBLP:conf/smartgridsec/0001FKNT14].

8 Whereas smart grids introduce more and more automation capacity, human  
9 interventions are still required. First, information gathered by smart grids is therefore  
10 not always known with absolute confidence. Second, smart grids reconfigurations are  
11 not immediate, and their effects are not instantaneously measured. Third, smart grids  
12 behaviour is emergent [zio2011uncertainties], *i.e.*, it cannot be entirely known at  
13 design time.

14 Most fuses are manually open and close by technicians rather than automatically  
15 modified. Then, technicians manually report the modifications done on the grid. Due  
16 to human mistakes, this results in errors. The grid topology is thus uncertain. This  
17 uncertainty is propagated to the load approximation, used to detect overloads in the  
18 grid. Wrong reconfigurations might be triggered, which could be even worse than if  
19 no change would have been applied.

20 Reconfiguring a smart grid implied to change the power flow. It is done by  
21 connecting or disconnecting specific cables. That is, opening or closing fuses. As said  
22 before, a technician needs to drive physically to the fuse location to modify its state.  
23 Besides, in the case of the Luxembourg smart grid, meters send energy measurement  
24 every 15 mins, non-synchronously. Between the time a reconfiguration of the smart  
25 grid is decided, and the time the effects are measured, a delay of at least 15 mins  
26 occurs. On the other hand, an incident should be detected in the next minutes. If the  
27 adaptation process does not consider this difference of paces, it can cause repeated  
28 decisions.

29 Smart grid behaviour is affected by several factors that cannot be controlled by  
30 the grid manager. One example is the weather condition. Smart grids rely on an

1 energy production that is distributed over several actors. For instance, users, who  
2 were mainly consumers before, now produce energy by adding solar panels on the  
3 roof of their houses. The production of such energy depends on the weather, and  
4 even on the season<sup>3</sup>. Another example is the increasing adoption of electric vehicles,  
5 which de facto drastically increase the consumption of electricity during the night.  
6 Ignoring this characteristic of adaptive system\* may result in suboptimal situations  
7 that can be understood with difficulties.

## 8 Problem statement

9 **Data are uncertain, actions have delayed effects, and the behavior of**  
10 **adaptive systems\* is emergent.**

11 Data are, almost by definition, uncertain and developers always work with es-  
12 timates. This is due to how data are collected. We can identify three different  
13 sources. They can ..... **Uncertainty impacts the understanding of the global**  
14 **situation**

15 **Actions.... if the frequency of the monitoring stage is lower than the**  
16 **time of action effects to be measurable**

17 **Behavior ... The behavior cannot be perfectly known at design time or**  
18 **inferred from the set of executed actions.**

## 19 Challenge

20 **Global challenge:** How to represent the uncertain knowledge allowing to effi-  
21 ciently query it and to represent ongoing actions in order to improve adaptation  
processes?

## 22 Scope of the thesis

23  
24 **Sub-Challenge #1:** How to diagnose the self-adaption process?

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<sup>3</sup>The angle of the sun has an impact on the amount of energy produced by solar panels. This angle varies according to the season.

**Sub-Challenge #2:** How to enable reasoning over unfinished actions and their expected effects?

**Sub-Challenge #3:** How to ease the manipulation of data uncertainty?

## Contribution & Validation

### Structure of the document

We split the remaining part of this thesis into eight chapters. First, Chapter 2 describes the necessary background of the thesis. We present concepts related to MDE\* and adaptive system\*. Based on this background, we show the gap of the current state of the art in Chapter 3. Then, in Chapter 4, we detail the vision defended in this thesis. We present the arguments in support of it and those that are in opposition. Chapter 5 and Chapter 6 detailed our two contributions, which go towards the defended vision. The former details our language, Ain'tea, that integrates uncertainty as a first-class citizen. The latter explains our temporal metamodel that can represent past and ongoing decisions with their circumstances and effects. Finally, we conclude in Chapter 7 and we present a set of perspectives of our work.



## Background

### Contents

<b>2.1</b>	<b>Model-driven engineering . . . . .</b>	<b>8</b>
<b>2.2</b>	<b>Adaptive systems . . . . .</b>	<b>8</b>

*This chapter describes the necessary background to understand this thesis. We first describe the model-driven engineering methodology. Then we detailed the approach referred to as adaptive systems.*

<sup>1</sup> **Model-driven engineering**

<sup>2</sup> **Adaptive systems**



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## 2 State of the art

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5  
6  
8

### Contents

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<b>3.1</b>	<b>Introduction . . . . .</b>	<b>10</b>
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9

*This chapter reviews work related to the one presented in this dissertation.*

# 1 Introduction

2 **Delayed actions** General research question:

3 **RQ1:** Do current state of the art solutions allow modeling and reasoning over  
4 delayed actions?

5 Sub research questions:

- 6 • **RQ1.1:** How current approaches model the evolution of the context and/or the  
7 evolution of the behavior of systems over time?
- 8 • **RQ1.2:** Do these solutions model actions, their circumstances and their effects?
- 9 • **RQ1.3:** What are the solutions that enable the reasoning over the evolving  
10 context and/or behavior of systems?

11 **Uncertainty** Snowballing approach [DBLP:conf/ease/Wohlin14]

## 12 Inclusion criteria

- 13 • **IC1:** The paper has been published before the May 31 2019
- 14 • **IC2:** The paper is available online and written in English
- 15 • **IC3:** The paper describes a modeling approach that abstract the context or  
16 behavior of a system or an approach that enables to reason or navigate through  
17 a temporal model.

## 18 Exclusion criteria

- 19 • **EC1:** The paper has at most 4 pages (short paper).
- 20 • **EC2:** The paper presents a work in progress (workshop papers), a poster, a  
21 vision, a position, doctoral studies or the paper is a Bachelor, Master or PhD  
22 dissertation.
- 23 • **EC3:** The paper describes a secondary study (*e.g.*, literature reviews, lessons  
24 learned).
- 25 • **EC4:** The document has not been published in a venue with a peer-review  
26 process. For example, technical and research report or white papers.
- 27 • **EC5:** The document is an introduction to the proceedings of a venue or a  
28 special issue or it is a guest paper.

<sup>1</sup> However, the references of papers rejected are considered for the snowballing  
<sup>2</sup> iteration.



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## 2 A unified modeling framework

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3     *As argued in the introduction section, adaptation combined with abstraction comes*  
4     *with a novel challenge: the representation of uncertain data and delayed action. In*  
5     *this chapter, we present a vision concerning a modeling framework that should consider*  
6     *uncertainty and time as first-class concepts. We first argue towards this vision. Before*  
7     *detailing the synthesis of this vision, we show arguments against this vision. To do*  
8     *so, we answered with pros and cons to three questions: why do we need a modeling*  
9     *framework? why time and uncertainty should be put as first-class concepts? why*  
10    *should time and uncertainty combined in the same structure?*



1

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## 2 Ain'Źtea: Managing Data Uncertainty at the 3 Language Level

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chapt:aintea)?

4     *After identifying and discussing the key concepts associated with data uncertainty,*  
5 *this chapter presents Ain'tea, a language that integrates them directly into the grammar,*  
6 *type system and semantics part. To validate and exemplify our approach, we apply it*  
7 *to a smart-grid scenario and compare it to framework-based approaches. We show*  
8 *that developers benefit from the language semantics and type system which guide them*  
9 *to manipulate uncertain data without deep probability theory knowledge.*





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## A temporal knowledge meta-model to represent, reason and diagnose decisions, their circumstances and their impacts

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### Contents

6	<b>6.1</b>	<b>Introduction</b>	<b>18</b>
7	<b>6.2</b>	<b>Knowledge formalization</b>	<b>29</b>
8	<b>6.3</b>	<b>Modeling the knowledge</b>	<b>40</b>
9	<b>6.4</b>	<b>Validation</b>	<b>46</b>
10	<b>6.5</b>	<b>Conclusion</b>	<b>56</b>
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14			

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*In this chapter, we first propose a knowledge formalism to define the concept of a decision. Second, we describe a novel temporal knowledge model to represent, store and query decisions as well as their relationship with the knowledge (context, requirements, and actions). We validate our approach through a use case based on the smart grid at Luxembourg. We also demonstrate its scalability both in terms of execution time and consumed memory.*

# 1 Introduction

We consider that  
decision, delayed  
action, context  
and knowledge  
have been de-  
fined in the  
global introduc-  
tion

Adaptive systems have proven their suitability to handle the increasing complexity of systems and their ever-changing environment. To do so, they make adaptation decisions, in the form of actions, based on high-level policies. For instance, the OpenStack Watcher project [**OpenStack:Watcher:Wiki**] implements the MAPE-k loop to assist cloud administrators in their activities to tune and rebalance their cloud resources according to some optimization goals (e.g., CPU and network bandwidth). For readability purpose, we refer to adaptation decision as decision in the remaining part of this document.

Despite the reactivity of adaptation processes, impacts of their decisions can be measurable long after they have been taken. We identified two problematics caused by this difference of paces:

- How to diagnose the self-adaptation process?
- How to enable reasoning over unfinished actions and their expected effects?

To address them, we propose a temporal knowledge model which can trace decisions over time, along with their circumstances and effects. By storing them, the adaptation process could consider ongoing actions with their expected effects, also called impacts. Plus, in case of faulty decisions, developers may trace back their effects to their circumstances. Our current approach is limited to the representation of measurable effects of any decision, and therefore action.

The meta-model allow structuring and storing the state and behavior of a running adaptive system, together with a high-level API to efficiently perform diagnosis routines. Our framework relies on a temporal model-based solution that efficiently abstracts decisions and their corresponding circumstances. Specifically, based on existing approaches for modeling and monitoring adaptation processes, we identify a set of properties that characterize context, requirements, and actions in self-adaptive systems. Then, we formalize the common core concepts implied in adaptation processes, also referred to as knowledge, by means of temporal graphs and a set of relations that trace decisions impact to circumstances. Finally, thanks to exposing

1 common interfaces in adaptive processes, existing approaches in requirements and  
2 goal modeling engineering can be easily integrated into our framework.

3 The rest of this chapter is structured as follows. In the remaining part of this  
4 section, we motivate our approach, we summarize core concepts manipulated in  
5 adaptation processes, and we present a use case scenario based on the Luxembourg  
6 Smart Grid (*cf.* Chapter ). Then, we provide a formal definition of these concepts in  
7 Section 6.2. Later, we describe the proposed data model in Section 6.3. In Section 6.4,  
8 we demonstrate the applicability of our approach by applying it to the smart grid  
9 example. We conclude this chapter in Section 6.5.

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version

## 10 Motivation

### 11 Delayed action

12 In this section, we motivate the need to reason over delayed actions. To do so, we  
13 first give four examples of these actions. Then we detail why the effects of actions  
14 should be considered. Finally, we summarize and motivate the need for incorporating  
15 actions and their effects on the knowledge.

16 **Delayed action examples** Until here, we have claimed that adaptation processes  
17 should handle delayed actions. In order to show their existence, we give four different  
18 examples: two based on our use case, one on cloud infrastructure and a last one on  
19 smart homes. From our understanding, three phenomena can explain this delay: the  
20 time to execute an action(s) (Example 1), the time for the system to handle the new  
21 configuration (Example 3) and the inertia of the measured element (Example 2 and  
22 4).

23 **Example 1: Modification of fuse states in smart grids** Even if the Lux-  
24 embourg power grid is moving to an autonomous one, not all the elements can be  
25 remotely controlled. One example is fuses that still need to be open or closed by a  
26 human. Open and close actions in the Luxembourg smart grid both imply technicians  
27 who are contacted, drive to fuse places and manually change their states. If several  
28 fuses need to be changed due to one decision, only one technician will drive to them,  
29 sequentially, and executes the modifications. For example, in our case, our industrial

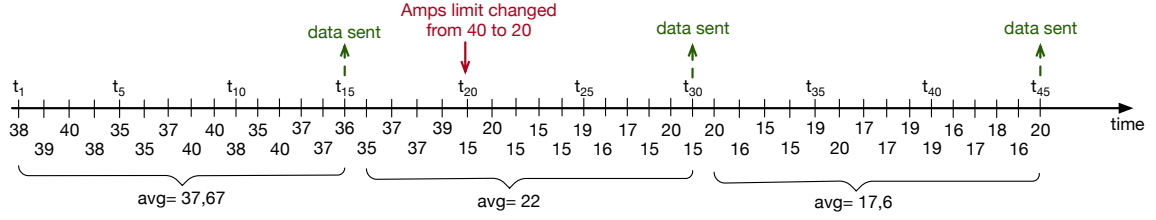


Figure 6.1: Example of consumption measurement before and after a limitation of amps has been executed at  $t_{20}$ .

1 partner asks us to consider that each fuse modification takes 15 min whereas any  
2 incident should be detected in the minute. Let's imagine that an incident is detected  
3 at 4 p.m. and can be solved by modifying three fuses. The incidents will be seen as  
4 resolved by the adaptation process at 4 p.m. + 15 min \* 3 = 4:45 p.m. In this case,  
5 the delay of the action is due to the execution time that is not immediate.

6 **Example 2: Reduction of amps limit in smart grids<sup>1</sup>** In its smart grid  
7 project, Creos S.A. envisages controlling remotely amps limits of customers. Customers  
8 will have two limits: a fixed one, set at the beginning, and a flexible one, remotely  
9 managed. The action to remotely change amps limits will be performed through  
10 specific plugs, such as one for electric vehicles. Even if the action is near instant, due  
11 to how power consumption is collected, its impacts would not be visible immediately.  
12 Indeed, data received by Creos S.A. corresponds to the total energy consumed since  
13 the installation. From this information, only the average of consumed data for the  
14 last period can be computed.

15 In Figure 6.1, we depict a scenario that shows the delay between the action is  
16 executed and the impacts are measured. Each time point represents one minute, with  
17 the consumption at this moment.

18 Let's imagine a customer who has his or her limit set to 40 amps<sup>2</sup> and consumes  
19 near this limit. We consider that data are sent every 15 min. After receiving data

<sup>1</sup>This example is based on randomly generated data. As this action is not yet available on the Luxembourg smart grid, we miss real data. However, it reflects an hypothesis shared with our partner.

<sup>2</sup>The user cannot consume more than 40 amps at a precise time  $t_i$ .

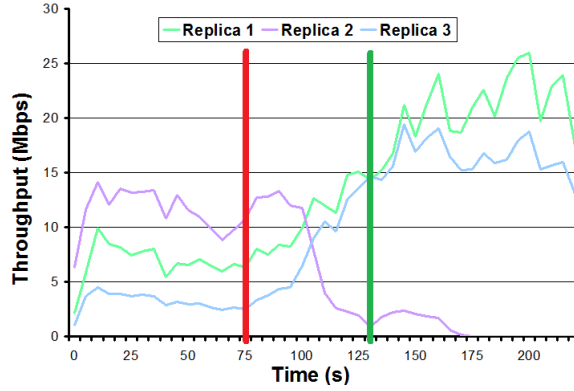


Figure 6.2: Figure extracted from [DBLP:conf/nsdi/WangBR11]. The red bar depicted the moment when Replica 2 stop receiving new connections. The green one represents the moment where all the rules in the load balancer stop considering R2. Despite these two actions, the throughput of the machine does not drop to 0 due to existing and active connections.

load-balancer)

1 sent  $t_{15}$  and processing them, the adaptation process detects an overload and decides  
2 to reduce the limits to 20 amps for the customer. However, considering the delay for  
3 data to be collected and the one to send data<sup>3</sup>, the action is received and executed  
4 at  $t_{20}$ . At  $t_{30}$ , new consumption data is sent, here equals 22 amps. Here, there are  
5 two situations. First, this reduction was enough to fix the overload. Even in this  
6 idealistic scenario, the adaptation process must wait at worst 15 min ( $t_{30} - t_{15}$ ) to see  
7 the resolution (without considering the communication time). Second, this reduction  
8 was not enough - as the adaptation process considered that the consumption data  
9 will be at worst 20 amps and here it is 22. Before seeing the incident as solved and  
10 knowing that the decision fixed the incident, the adaptation process should wait for  
11 new data, sent at  $t_{45}$ , *i.e.*, around 30 min ( $t_{45} - t_{15}$ ) after the detection.

12 In this case, the delay of this action can be explained by the inertia in the average  
13 of the consumption.

14 **Example 3: Switching off a machine from a load balancer** An example  
15 based on cloud infrastructure of delayed actions is to remove a machine from a

<sup>3</sup>Reminder: the smart grid is not built upon a fast network such a fiber network.

1 load balancer, for example during a scale down operation. Scale down operations  
 2 allows cloud managers to reduce allocated resources for a specific task. It is used  
 3 either to reduce the cost of the infrastructure or to reallocate them to other tasks.  
 4 In [DBLP:conf/nsdi/WangBR11], Wang *et al.*, present a load-balancing algo-  
 5 rithm. In their evaluation, they present the figure depicted in Figure 6.2 that shows  
 6 the evolution of the throughput after the server Replica 2 (R2) is removing from  
 7 the load balancer. The red bar shows the moment where R2 stop receiving new  
 8 connection and the green the moment where it is removed from the load balancer  
 9 algorithm. However, despite these actions have been taken, R2 should finish the  
 10 ongoing tasks that it is executing. This explains why the throughput is progressively  
 11 decreasing to 0 and there is a delay of around 100s between the red bars and the  
 12 moment where R2 stop being active.

13 This example shows a delayed action due to the time required by the system to  
 14 handle the new configuration.

15 **Example 4: Modifying home temperature through a smart home sys-**  
 16 **tem** Smart home systems have been implemented in order to manage remotely a  
 17 house or to perform automatically routines. For example, it allows users to close  
 18 or open blinds from their smartphones. Based on instruction temperatures, smart  
 19 home systems manage the heating or cooling system to reach them at the desired  
 20 time. However, heating or cooling a house is not immediate, it can take several hours  
 21 before the targeted temperature is reached. Plus, if the temperature sensor and the  
 22 heating or cooling system are not placed nearby, the new temperature can take time  
 23 before being measured. This can be explained due to the temperature inertia plus  
 24 the delay for the temperature to be propagated.

25 Through these four examples, we show that delayed actions can be found in  
 26 different kinds of systems, from CPS to cloud infrastructure. However, not only  
 27 knowing that an action is running is important but also knowing its expecting effect.  
 28 We detail this point in the following section.

29 **The need to consider effects** In the previous section, we show the existence of  
 30 delayed actions. One may argue that action statuses are already integrated into

the knowledge. For example, the OpenStack Watcher framework stores them in a database<sup>4</sup>, accessible through an API. However, for the best of our knowledge Watcher does not store the expecting effects of each action. While the adaptation process knows what action is running, it does not know what it should expect from them.

Considering our example based on the modification of fuses, if the system knows that the technician is modifying fuse states, it does not know what would be the effects. In this case, when the adaptation process analyzes the system context it may wonder: what will be the next grid configuration? How the load will be balanced? Will the future configuration fix all the current incidents? If the effects are not considered by the adaptation process, then it may take suboptimal decisions.

Let's exemplify this claim through a scenario based on the fuse example (*cf.* Example 1). As explained before, the overload detected at 4 p.m. takes around 45 min to be fixed. The system marks this incident as "being resolved". In addition to this information, the knowledge contains another one saying that it is being solved by modifying three fuses. However, during the resolution stage, a cable is also being overloaded. The adaptation process has two solutions. It can either wait for the end of the resolution of the first incident to see if both overloaded elements will be fixed or it takes other actions without considering the ongoing actions and their impacts. Applying the first strategy may make the resolution of the second incident late, whereas the second one may generate a suboptimal sequence of actions. For example, the second modifications may undo what has been done before or both actions may be conflicting.

**Conclusion** Actions, like fuse modification in a smart grid or removing a server from a load balancer, generated during by adaptation processes could take time upon completion. Moreover, the expected effects resulting from such action is reflected in the context representation only after a certain delay. One used workaround is the selection, often empirically, of an optimistic time interval between two iterations of the MAPE-K loop such that this interval is bigger than the longest action execution time. However, the time to execute an action is highly influenced by system overload

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<sup>4</sup><https://docs.openstack.org/watcher/latest/glossary.html#watcher-database-definition>

1 or failures, making such empirical tuning barely reliable. We argue that by enriching  
2 context representation with support for past and future planned actions and their  
3 expected effects over time, we can highly enhance reasoning processes and avoid  
4 empirical tuning.

5 The research question that motivates our work is thus: how to enable reasoning  
6 over unfinished actions and their expected effects?

7 Fined and rich context information directly influences the accuracy of the actions  
8 taken. Various techniques to represent context information have been proposed; among  
9 which we find the models@run.time [DBLP:journals/computer/MorinBJFS09;  
10 DBLP:journals/computer/BlairBF09]. The models@run.time  
11 paradigm inherits model-driven engineering concepts to extend the use of mod-  
12 els not only at design time but also at runtime. This model-based representation has  
13 proven its ability to structure complex systems and synthesize its internal state as  
14 well as its surrounding environment.

## 15 Diagnosis support

16 Faced with growingly complex and large-scale software systems (e.g. smart grid  
17 systems), we can all agree that the presence of residual defects becomes unavoid-  
18 able [DBLP:conf/icse/BarbosaLMJ17; DBLP:conf/icse/MongielloPS15; DBLP:conf/ics  
19 Even with a meticulous verification or validation process, it is very likely to run into  
20 an unexpected behavior that was not foreseen at design time. Alone, existing formal  
21 modeling and verification approaches may not be sufficient to anticipate these fail-  
22 ures [DBLP:conf/icse/TaharaOH17]. As such, complementary techniques need  
23 to be proposed to locate the anomalous behavior and its origin in order to handle it  
24 in a safe way.

25 As there might be many probable causes behind an abnormal behavior, de-  
26 velopers usually perform a set of diagnosis routines to narrow down the scope or  
27 origin of the failure. One way to do so is by investigating the satisfaction of its  
28 requirements and the decisions that led to this system state, as well as their tim-  
29 ing [DBLP:conf/iceccs/BencomoWSW12]. In this perspective, developers may  
30 set up a set of systematic questions that would help them understand why and how



the system is behaving in such a way. These questions may comprise:

- what goal(s) the system was trying to reach by executing a tactic  $a$ ?
- what were the circumstances used by a decision  $d$  and its expected impact on the context?
- what decision(s) influenced the system's context at a time  $t$ ?

Bencomo *et al.*, [DBLP:conf/iceccs/BencomoWSW12] argue that comprehensive explanation about the system behavior contributes drastically to the quality of the diagnosis, and eases the task of troubleshooting the system behavior. To enable this, we believe that adaptive software systems should be equipped with traceability management facilities to link the decisions made to their **(i) circumstances, that is to say, the history of the system states and the targeted requirements, and (ii) the performed actions with their impact(s) on the system.** In particular, an adaptive system should keep a trace of the relevant historical events. Additionally, it should be able to **trace the goals intended to be achieved by the system to the adaptations and the decisions that have been made, and vice versa.** Finally, in order to enable developers to interact with the system in a clear and understandable way, appropriate abstraction to **enable the navigation of the traces and their history should also be provided.** Unfortunately, suitable solutions to support these features are under-investigated.

Existing approaches [hassel13; DBLP:conf/models/HeinrichSJRMRHP14; DBLP:conf/icac/EhlersHWH11; DBLP:conf/icse/MendoncaAR14; DBLP:conf/icse/Casanov DBLP:conf/icse/IftikharW14a] are accompanied by built-in monitoring rules and do not allow to interact with the underlying system in a simple way. Moreover, they do not keep track of historical changes as well as causal relationships linking requirements to their corresponding adaptations. Only flat execution logs are stored.

## Background

Before formalizing and modeling decisions and their circumstances, we abstract common concepts implied in an adaptation process. We refer to these concepts as the knowledge.

## 1 General concepts of adaptation process

2 Similar to the definition provided by Kephart [DBLP:journals/computer/KephartC03]  
3 IBM defines adaptive systems as “a computing environment with the ability to manage  
4 itself and **dynamically adapt** to change in accordance with **business policies and**  
5 **objectives**. [These systems] can perform such activities based on **situations they**  
6 **observe or sense in the IT environment [...]**” [computing2006architectural].

7 Based on this definition, we can identify three principal concepts involved in  
8 adaptation processes. The first concept is *actions*. They are executed in order to  
9 perform a dynamic adaptation through actuators. The second concept is **business**  
10 **policies and objectives**, which is also referred to as the **system requirements** in  
11 the domain of (self-)adaptive systems. The last concept is the observed or sensed  
12 **situation**, also known as the **context**. The following subsections provide more  
13 details about these concepts.

## 14 Context

15 In this thesis, we use the widely accepted definition of context provided by  
16 Dey [DBLP:journals/puc/Dey01]: “Context is **any information that can be**  
17 **used to characterize** the situation of an entity. An entity is a person, place,  
18 or object that is considered relevant to the interaction between a user and [the  
19 system], including the user and [the system] themselves”. In this section, we list  
20 the characteristics of this information based on several works found in the litera-  
21 ture [DBLP:conf/pervasive/HenricksenIR02; DBLP:conf/seke/0001FNMKT14  
22 DBLP:journals/percom/BettiniBHINRR10; DBLP:journals/comsur/PereraZCG14]  
23 We use them to drive our design choices of our Knowledge meta-model (cf. Sec-  
24 tion 6.3.2).

25 **Volatility** Data can be either **static** or **dynamic**. Static data, also called frozen,  
26 are data that will not be modified, over time, after their creation [DBLP:conf/pervasive/Henricks  
27 DBLP:journals/comsur/MakrisSS13; DBLP:journals/percom/BettiniBHINRR10]  
28 For example, the location of a machine, the first name or birth date of a user can be  
29 identified as static data. Dynamic data, also referred to as volatile data, are data  
30 that will be modified over time.

**Temporality** In dynamic data, sometimes we may be interested not only in storing the latest value, but also the previous ones [DBLP:conf/seke/0001FNMKT14; DBLP:conf/pervasive/HenricksenIR02]. We refer to these data as **historical** data. Temporal data is not only about past values, but also future ones. Two kinds of future values can be identified, **predicted** and **planned**. Thanks to machine learning or statistical methods, dynamic data values can be **predicted**. **Planned** data are set by a system or a human to specify planned modification on the data.

**Uncertainty** One of the recurrent problems facing context-aware applications is the data uncertainty [DBLP:conf/dagstuhl/LemosGMSALSTVVWBBBBBCDDEGGGGIKKLMMM; DBLP:conf/pervasive/HenricksenIR02; DBLP:journals/comsur/MakrisSS13; DBLP:journals/percom/BettiniBHINRR10]. Uncertain data are not likely to represent the reality. They contain a noise that makes it deviate from its original value. This noise is mainly due to the inaccuracy and imprecision of sensors. Another source of uncertainty is the behavior of the environment, which can be unpredictable. All the computations that use uncertain data are also uncertain by propagation.

**Source** According to the literature, data sources are grouped into two main categories, either sensed (measured) data or computed (derived) data [DBLP:journals/comsur/PereraZCG14].

**Connection** Context data entities are usually linked using three kinds of connections: conceptual, computational, and consistency [DBLP:conf/pervasive/HenricksenIR02; DBLP:journals/percom/BettiniBHINRR10]. The conceptual connection relates to (direct) relationships between entities in the real world (e.g. smart meter and concentrator). The computational connection is set up when the state of an entity can be linked to another one by a computation process (derived, predicted). Finally, the consistency connection relates entities that should have consistent values. For instance, temperature sensors belonging to the same geographical area.

## Requirement

Adaptation processes aim at modifying the system state to reach an optimal one. All along this process, the system should respect the **system requirements**

1 established ahead. Through this paper, we use the definition provided by IEEE [iso2017systems]  
2 “(1) Statement that translates or expresses a need and its associated **constraints**  
3 and **conditions**, (2) **Condition or capability that must be met or possessed**  
4 by a system [...] to satisfy an agreement, standard, specification, or other formally  
5 imposed documents”.

6 Although in the literature, requirements are categorized as functional or non-func-  
7 tional, in this paper we use a more elaborate taxonomy introduced by Glinz [DBLP:conf/re/Glinz0  
8 It classifies requirements in four categories: functional, performance, specific quality,  
9 and constraint. All these categories share a common feature: they are all temporal.  
10 During the life-cycle of an adaptive system, the developer can update, add or remove  
11 some requirements [DBLP:conf/icse/ChengA07; pandey2010effective].

## 12 Action

13 In the IEEE Standards [iso2017systems], an action is defined as: “**process of**  
14 **transformation** that **operates upon data** or other types of inputs to create data,  
15 produce outputs, or **change the state** or condition of the subject software”.

16 Back to adaptive systems, we can define an action as a process that, given the  
17 context and requirements as input, adjusts the system behavior. This modification will  
18 then create new data that correspond to an output context. In the remainder of this  
19 paper, we refer to output context as impacted context, or simply impact(s). Whereas  
20 requirements are used to add preconditions to the actions, context information is  
21 used to drive the modifications. Actions execution have a start time and a finish time.  
22 They can either succeed, fail, or be canceled by an internal or external actor.

## 23 Use case scenario

<sec:tkm:intro:uc>  
24 In order to provide a readable and understandable example of the formalism, we  
25 give a simplified version of the use case presented in Section ??.

26 **Excerpt of a smart grid** Figure 6.3 shows a simplified version of a smart grid  
27 with one substation, one cable, three smart meters and one dead-end cabinet. Both  
28 the substation and the cabinet have one fuse each. The meters regularly send con-  
29 sumption data at the same timestamp. For this example, we consider one requirement:

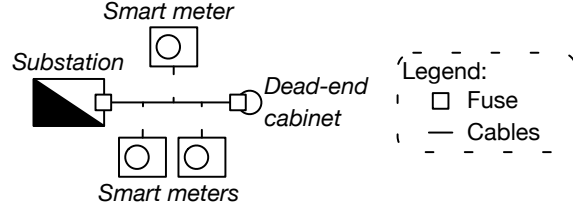


Figure 6.3: Simplified version of a smart grid

1 minimizing the number of overloads. To achieve so, among the different actions, two  
2 actions are taken into account in this example: decreasing or increasing the amps  
3 limits of smart meters.

4 **Adaptation scenario** The system starts at  $t_0$  with the actions, the requirements  
5 and all element of the context that remain fixed: the grid installation. Meters send  
6 their values at  $t_1$ ,  $t_2$  and  $t_3$ . Based on these data, the load on cables and substation is  
7 computed. On  $t_1$ , an overload is detected on the cable, which breaks the requirement.  
8 At the same time point, the system decides to reduce the load of all smart meters.  
9 The impact of these actions will be measured at  $t_2$  and  $t_3$ , *i.e.*, the consumption will  
10 slowly reduce until the cable is no longer overloaded from  $t_3$ .

11 **Diagnosis scenario** As all adaptive systems, smart grids are prone to  
12 failures [DBLP:conf/smartgridsec/0001FKNT14]. Using our approach, an engi-  
13 neer could diagnose the system, and determine the adaptation process responsible for  
14 this failure. For instance, considering some reports about regular power cuts during  
15 the last couple of days, in a particular area, a stakeholder may want to interrogate  
16 the system and determine what past decision(s) have led to this suboptimal state.  
17 More concretely, he will ask: did the system make any decisions that could have  
18 impacted the customer consumption? If so, what goal(s) the system was trying to  
19 reach and what were the values used at the time the decision(s) was(were) made?

## 20 Knowledge formalization

m:k-formalism) As discussed previously, we consider knowledge\* to be the association of context\*  
22 information, requirements\*, and action\* information, all in one global and unified

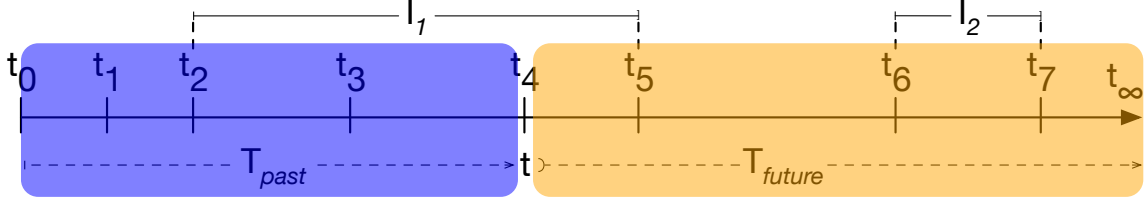


Figure 6.4: Time definition used for the knowledge formalism

1 model. While context\* information captures the state of the system environment and  
 2 its surroundings, the system requirements\* define the constraints that the system  
 3 should satisfy along the way. Actions\*, on the other hand, are meant to reach the  
 4 goals of the system.

5 In this section, we provide a formalization of the knowledge\* used by adaptation  
 6 processes based on a temporal graph. Indeed, due to the complexity and interconnec-  
 7 tivity of system entities, graph data representation is an appropriate way to represent  
 8 the knowledge\*. Augmented with a temporal dimension, temporal graphs are then  
 9 able to symbolize the evolution of system entities and states over time. We benefit  
 10 from the well-defined graph manipulation operations, namely temporal graph pattern  
 11 matching and temporal graph relations to represent the traceability links between  
 12 the decisions\* made and their circumstances\*.

13 Before describing this formalism, we describe the semantics used for the temporal  
 14 axis. Then, we exemplify the knowledge formalism using the Luxembourg smart grid  
 15 use case, detailed in Section 6.1.3.

## 16 Formalization of the temporal axis

17 The formalism described below has been made with two goals in mind. First, the  
 18 definition of the time space should allow the distinction between past and future.  
 19 Doing this distinction enable the differentiation between measured data and predicted  
 20 (or planned data). Second, it should permit the definition of the life cycle of an  
 21 element of the knowledge\*, which can be seen as a succession of states with a validity  
 22 period that should not overlap each other.

23 Time space  $T$  is considered as an ordered discrete set of time points non-uniformly

distributed. As depicted in Figure 6.4, this set can be divided into 3 different subsets

$T = T_{past} \cup \{t\} \cup T_{future}$ , where:

- $T_{past}$  is the subdomain  $\{t_0; t_1; \dots; t_{current-1}\}$  representing graph data history starting from  $t_0$ , the oldest point, until the current time,  $t$ , excluded.
- $\{t\}$  is a singleton representing the current time point
- $T_{future}$  is subdomain  $\{t_{current+1}; \dots; t_\infty\}$  representing future time points

The three domains depend completely on the current time  $\{t\}$  as these subsets slide as time passes. At any point in time, these domains never overlap:  $T_{past} \cap \{t\} = \emptyset$ ,  $T_{future} \cap \{t\} = \emptyset$ , and  $T_{past} \cap T_{future} = \emptyset$ . The definition of these three subsets reaches the first goal.

In addition, there is a right-opened time interval  $I \in T \times T$  as  $[t_s, t_e)$  where  $t_e - t_s > 0$ . In English words, it means that the interval should represent at least one time point and should follow the time order. For any  $i \in I$ ,  $start(i)$  denotes its lower bound and  $end(i)$  its upper bound. As detailed in Section 6.2.2, these intervals are used to define the validity period for each node of the graph (our second goal).

Figure 6.4 displays an example of a time space  $T_1 = \{t_0, t_1, t_2, t_3, t_4, t_5, t_6, t_7\}$ . Here, the current time is  $t = t_4$ . According to the definition of the past subset ( $T_{past}$ ) and the future one ( $T_{future}$ ), there is:  $T_{past1} = \{t_0, t_1, t_2, t_3\}$  and  $T_{future1} = \{t_5, t_6, t_7\}$ . Two intervals have been defined on  $T_1$ , namely  $I_1$  and  $I_2$ . The first one starts at  $t_2$  and ends at  $t_5$  and the last one is defined from  $t_6$  to  $t_7$ . As shown with  $I_1$ , an interval could be defined on different subsets, here it is on all of them ( $T_{past}$ ,  $t$ , and  $T_{future}$ ).

## Formalism

**Graph definition** First, let  $K$  be an adaptive process over a system knowledge\* represented by a graph such as  $K = (N, E)$ , comprising a set of nodes  $N$  and a set of edges  $E$ . Nodes represent any element of the knowledge (context, actions, etc.) and edges represent their relationships. Nodes have a set of attribute values:  $\forall n \in N, n = (id, P)$ , where  $P$  is the set of key-value attributes. An attribute value has a type (numerical, boolean, ...). Every relationship  $e \in E$  can be considered as a couple of nodes with a label  $(n_s, n_t, label) \in N \times N$ , where  $n_s$  is the source node and  $n_t$  is the target node.

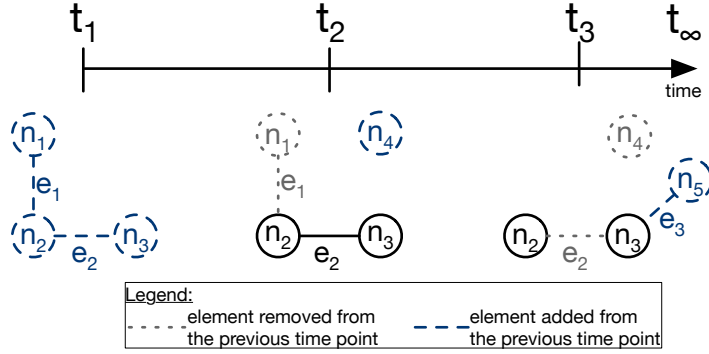


Figure 6.5: Evolution of a temporal graph over time

1 **Adding the temporal dimension** In order to augment the graph with a temporal  
2 dimension, the relation  $V^T$  is added. So now the knowledge  $K$  is defined as a temporal  
3 graph such as  $K = (N, E, V^T)$ .

4 A node is considered valid either until it is removed or until one of its attributes  
5 value changes. In the latter case, a new node with the updated value is created.  
6 Whilst, an edge is considered valid until either its source node and target node are  
7 valid, or until the edge itself is removed. Otherwise, nodes and edges are considered  
8 invalid. The temporal validity relation is defined as  $V^T : N \cup E \rightarrow I$ . It takes as  
9 a parameter a node or an edge ( $k \in N \cup E$ ) and returns a time interval ( $i \in I$ , cf.  
10 Section ??) during which the graph element is valid.

11 Figure 6.5 shows an example of a temporal graph  $K_1$  with five nodes ( $n_1, n_2, n_3,$   
12  $n_4,$  and  $n_5$ ) and three edges ( $e_1, e_2,$  and  $e_3$ ) over a lifecycle from  $t_1$  to  $t_3$ . In this  
13 way,  $K_1$  equals  $(\{n_1, n_2, n_3, n_4, n_5\}, \{e_1, e_2, e_3\}, V_1^T)$ . Let's assume that the graph is  
14 created at  $t_1$ . As  $n_1$  is modified at  $t_2$ , its validity period starts at  $t_1$  and ends at  $t_2$ :  
15  $V_1^T(n_1) = [t_1, t_2]$ .  $n_2$  and  $n_3$  are not modified; their validity period thus starts at  $t_1$   
16 and ends at  $t_\infty$ :  $V_1^T(n_2) = V_1^T(n_3) = [t_1, t_\infty]$ . Regarding the edges, the first one,  $e_1$ ,  
17 is between  $n_1$  and  $n_2$  and the second one,  $e_2$  from  $n_2$  to  $n_3$ . Both are created at  $t_1$ .  
18 As  $n_1$  is being modified at  $t_2$ , its validity period goes from  $t_1$  to  $t_2$ :  $V_1^T(e_1) = [t_1, t_2]$ .  
19  $e_2$  is deleted at  $t_3$ . Its validity period is thus equal to:  $V_1^T(e_2) = [t_1, t_3]$ .



**Lifecycle of a knowledge element** One node represents the state of exactly one knowledge element during a period named the validity period. The lifecycle of a knowledge element is thus modeled by a unique set of nodes. By definition, the validity periods of different nodes cannot overlap. A same time period cannot be represented by two different nodes, which could create inconsistency in the temporal graph.

To keep track of this knowledge element history, the  $Z^T$  relation is added to the graph formalism:  $K = (N, E, V^T, Z^T)$ . It serves to trace the updates of a given knowledge element at any point in time. This relation can also be seen as a temporal identity function which takes as parameters a given node  $n \in N$  and a specific time point  $t \in T$ , and returns the corresponding node at that point. Formally,  $Z^T : N \times T \rightarrow N$ .

In order to consider this new relation in the example presented in Figure 6.5, the definition of  $K_1$  is modified to  $K_1 = (\{n_1, n_2, n_3, n_4, n_5\}, \{e_1, e_2, e_3\}, V_1^T, Z_1^T)$ . In Figure 6.5, let's imagine that  $n_1$ ,  $n_4$ , and  $n_5$  represent the same knowledge element  $k_e$ . The lifecycle of  $k_e$  is thus:

- $n_1$  for period  $[t_1, t_2)$ ,
- $n_4$  for period  $[t_2, t_3)$ ,
- $n_5$  for period  $[t_3, t_\infty)$ .

Let  $t'_1$  be a timepoint between  $t_1$  and  $t_2$ . When one wants to resolve the node representing the knowledge element at  $t'_1$ , she or he gets  $n_1$  node, no matter of the node input ( $n_1$ ,  $n_4$ , or  $n_5$ ):  $Z_1^T(n_4, t_1) = n_1$ . On the other hand, applying the same relation with another node ( $n_2$  or  $n_3$ ) returns another node. For example, if  $n_2$  and  $n_3$  do not belong to the same knowledge element, then it will return the node given as input, for example  $Z_1^T(n_2, t_1) = n_2$ .

**Knowledge elements stored in nodes** Nodes are used to store the different knowledge elements: context, requirements and actions. The set of nodes  $N$  is thus split in three subsets:  $N = C \cup R \cup A$  where  $C$  is the set of nodes which store context information,  $R$  a set of nodes for requirement information and  $A$  a set of nodes for action information.

1      Actions define processes that indirectly impact the context: they will change  
2 the behavior of the system, which will be reflected in the context information.  
3 Requirements are also processes that are continuously run over the system in order  
4 to check the specifications. Here, the purpose of the  $A$  and  $R$  subset is not to store  
5 these processes but to list them. It can be thought as a catalogue of actions and  
6 requirements, with their history.

7      Using a high-level overview, these processes can be depicted as: taking the  
8 knowledge as input, perform tasks, and modify this knowledge as output. As detailed  
9 in the next two paragraphs, action executions and requirement analysis can be  
10 formalized by relations.

11 **Temporal queries for requirements** At the current state, the formalism of the  
12 knowledge  $K$  does not contain any information regarding the requirement analysis.  
13 To overcome this, system requirements analysis  $R_A$  are added such as  $K = (N, E,$   
14  $V^T, Z^T, R_A)$ .  $R_A$  is a set of couples composed of patterns  $P_{[t_j, t_k]}(K)$  and requirements  
15  $R$  over these patterns:  $R_P = P \cup R$ .

16       $P_{[t_j, t_k]}$  denotes a temporal graph pattern, where  $t_j$  and  $t_k$  are the lower and upper  
17 bound of the time interval respectively.  $P_{[t_j, t_k]}$  is the result of a function which takes  
18 the knowledge and an interval as input:  $P_{[t_j, t_k]} : K \times I$ . The time interval can be  
19 either fixed (absolute), *i.e.*, both bounds are precisely defined, or sliding (relative),  
20 *i.e.*, the upper bound is computed from the lower bound. For example,  $P_{[t_0, t_4]}$  is  
21 considered as fixed and  $P_{[t_0, t_0+4]}$  is considered as relative. Each element of the pattern  
22 should be valid for at least one timepoint:  $\forall p \in P_{[t_j, t_k]}, V^T(e) \cap [t_j, t_k] \neq \emptyset$ . Patterns  
23 can be seen as temporal subgraphs of  $K$ , with a time limiting constraint coming in  
24 the form of a time interval.

25 **Temporal relations for actions** Like for  $R_A$ , the knowledge  $K$  needs to be aug-  
26 mented with action executions  $A_E$ :  $K = (N, E, V^T, Z^T, R_A, A_E)$ . Actions executions  
27  $A_E$  can be regarded as a couple  $(A, A_F)$ , where  $A$  is the action that is executed and  
28  $A_F$  a set of relations or isomorphisms mapping a source temporal graph pattern  
29  $P_{[t_j, t_k]}$  to a target one  $P_{[t_l, t_m]}$ ,  $A_F : K \times I \rightarrow K \times I$ .

30      The left-hand side of the  $A_F$  relation depicts the temporal graph elements over

which an action is applied. Every relation may have a set of application conditions. They describe the circumstances under which an action should take place. These application conditions are either positive, should hold, or negative, should not hold. Application conditions come in the form of temporal graph invariants. The side effects of these actions are represented by the right-hand side.

Finally, we associate to  $A_E$  a temporal function  $E_{A_E}$  to determine the time interval at which an action has been executed. Formally,  $E_{A_E} : A_E \rightarrow I$ .

**Temporal relations for decisions** Finally, the knowledge formalism needs to include the last, but not the least, element: decisions made by the adaptation,  $K = (N, E, V^T, Z^T, R_A, A_E, D)$  While the source of relations in  $D$  represents the state before the execution of an action, the target shows its impact on the context\*. Its intent is **to trace back impacts of action executions to the decisions they originated from**.

A decision present in  $D$  is defined as a set of actions executed, *i.e.*, a subset of  $A_E$ , combined with a set of requirement analysis, *i.e.*, a subset of  $R_A$ . Formally,  $D = \{ A_D \cup R_D \mid A_D \subseteq A_E, R_D \subseteq R_A \}$ . We assume that each action should result from only one decision:  $\forall a \in A, \forall d1, d2 \in D \mid a \in d1 \wedge a \in d2 \rightarrow d1 = d2$ .

The temporal function  $E_{A_E}$  is extended to decisions in order to represent the execution time:  $E_{A_E} : (A \cup D) \rightarrow I$ . For decision, the lower bound of the interval corresponds to the lowest bound of the action execution intervals. Following the same principle, the upper bound of the interval corresponds to the uppermost bound of the action execution intervals. Formally,  $\forall d \in D \rightarrow E_{A_E}(d) = [l, u]$ , where  $l = \min_{a \in A_d} \{E_{A_E}(a)[start]\}$  and  $u = \max_{a \in A_d} \{E_{A_E}(a)[end]\}$ .

**Sum up** Knowledge of an adaptive system can be formalism with a temporal graph such as  $K = (N, E, V^T, Z^T, R_A, A_E, D)$ , wherein:

- $N$  is a set of nodes to represent the different information (context, actions and requirements)
- $E$  is a set of edges which connects the different nodes,
- $V^T$  is a temporal relation which defines the temporal validity of each element,
- $Z^T$  is a relation to track the history of each knowledge elements,

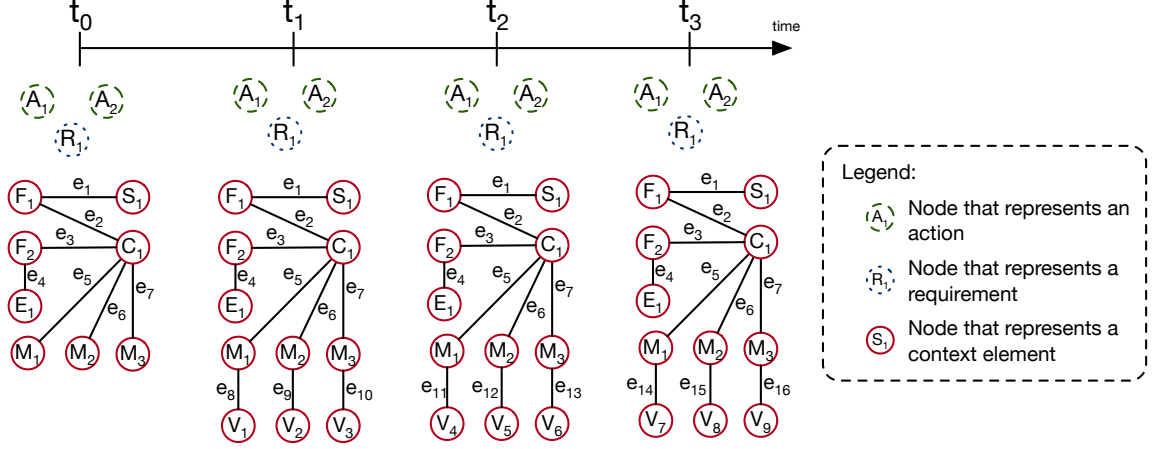


Figure 6.6: Application of the formalism with a temporal graph that represents the knowledge of the smart grid described in Section 6.1.3

ormalism:application)

- 1 •  $R_A$  is a relation that defines the different requirements processes,
- 2 •  $A_E$  is a relation that defines the different action processes,
- 3 •  $D$  is a set of action executions, which result from the same decision, and
- 4 requirement analysis.

5 Decisions  $D$  can allow adaptation processes to reason over ongoing and future  
6 executions of decisions. Moreover, it allows tracing the state of the knowledge before  
7 and after the decision has been or is executed, thanks to its  $A_D$  component. Plus, it  
8 represents which action has been used for this. Thanks to the  $R_A$  relation, one can  
9 access the requirements at the root of the decision and the state of the knowledge  
10 used by this requirement.

11 In the next section, we exemplify this formalism over our case study.

## 12 Application on the use case

13 In this section we apply the formalism described on the use case presented in  
14 Section 6.1.3.

15 Let  $K_{SG}$  be the temporal graph that represents the knowledge of this adaptive  
16 system:  $K_{SG} = (N_{SG}, E_{SG}, V_{SG}^T, Z_{SG}^T, R_{PSG}, A_{PSG}, D_{SG})$ . Figure 6.6 shows the nodes  
17 and edges of this knowledge.

### 1 **Description of $N_{SG}$**

2  $N_{SG}$  is divided into three subsets:  $C_{SG}$ ,  $R_{SG}$  and  $A_{SG}$ .  $R_{SG}$   
 3 contains one node,  $R_1$  in Figure 6.6, which represents the requirement of this example  
 4 (minimizing the number of overloads):  $R_{SG} = \{R_1\}$ . Two nodes,  $A_1$  and  $A_2$ , belong to  
 5  $A_{SG}$ :  $A_{SG} = \{A_1, A_2\}$ . They represent the two actions of this example, respectively  
 6 decreasing and increasing amps limits. Regarding the context  $C_{SG}$ , there are three  
 7 nodes to represent the three smart meters ( $M_1$ ,  $M_2$ , and  $M_3$ ), one for the substation  
 8 ( $S_1$ ), two for the fuses ( $F_1$  and  $F_2$ ), one for the dead-end cabinet ( $E_1$ ), one for the  
 9 cable ( $C_1$ ) and one node per consumption value received ( $V_i$ ):  $C_{SG} = \{M_1, M_2, M_3,$   
 $S_1, F_1, F_2, E_1, C_1\} \cup \{V_i | i \in [1..9]\}$ .

10 According to the scenario, except for nodes to store consumption values, the other  
 11 nodes are created at  $t_0$  and are never modified. Therefore, their validity period starts  
 12 at  $t_0$  and never ends:  $\forall n \in A_{SG} \cup R_{SG} \cup \{M_1, M_2, M_3, S_1, F_1, F_2, E_1, C_1\}, V_{SG}^T(n) = [t_0,$   
 13  $t_\infty)$ . Considering the consumption values, all the nodes represent the history of the  
 14 values for the three smart meters. In other words, there are three knowledge elements:  
 15 the consumption measured for each meter. Let  $C_i$  notes the consumption measured  
 16 by the smart meter  $M_i$ . As shown in Figure ??, there is:

- 17 •  $C_1$  of  $M_1$  is represented by  $\{V_1, V_4, V_7\}$ ,
- 18 •  $C_2$  of  $M_2$  is represented by  $\{V_2, V_5, V_8\}$ ,
- 19 •  $C_3$  of  $M_3$  is represented by  $\{V_3, V_6, V_9\}$ .

20 Taking  $C_2$  as an example,  $V_2$  is the initial consumption value, replaced by  $V_5$  at  $t_2$ ,  
 21 itself replaced by  $V_8$  at  $t_3$ . Applying the  $V_{SG}^T$  on these different values, results are  
 22 thus:

- 23 •  $V_{SG}^T(V_2) = [t_1, t_2)$ ,
- 24 •  $V_{SG}^T(V_5) = [t_2, t_3)$ ,
- 25 •  $V_{SG}^T(V_8) = [t_3, t_\infty)$ .

26 These validity periods are shown in Figure 6.7a. As meters send the new consumption  
 27 values at the same time, this example can also be applied to  $C_1$  and  $C_3$ .

28 From these validity periods, the  $Z_{SG}^T$  can be used to navigate to the different  
 29 values over time. Let's continue with the same example,  $C_2$ . In order to get the  
 30 evolution of the consumption value  $C_2$ , given the initial one, one will use the  $Z_{SG}^T$   
 31 relation:

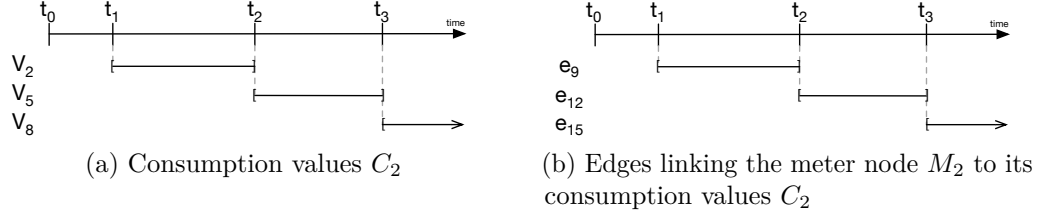


Figure 6.7: Validity periods of consumption values and their edges to the smart meter  $M_2$

- 1 •  $Z_{SG}^T(V_2, t_{s1}) = \emptyset$ , where  $t_0 \leq t_{s1} < t_1$
- 2 •  $Z_{SG}^T(V_2, t_{s2}) = V_2$ , where  $t_1 \leq t_{s2} < t_2$
- 3 •  $Z_{SG}^T(V_2, t_{s3}) = V_5$ , where  $t_2 \leq t_{s3} < t_\infty$ .
- 4 •  $Z_{SG}^T(V_2, t_{s4}) = V_8$ , where  $t_2 \leq t_{s4} < t_\infty$ .

5 **Description of  $E_{SG}$**  In this example, edges are used to store the relationships  
6 between the different context elements. For example, the edge between the substation  
7  $S_1$  and the fuse  $F_1$  allow representing the fact that the fuse is physically inside the  
8 substation. Another example, edges between the cable  $C_1$  and the meters  $M_1$ ,  $M_2$   
9 and  $M_3$  represent the fact that these meters are connected to the smart grid through  
10 this cable.

11 One may consider that relations (validity,  $Z^T$ , decisions, action executions and  
12 requirements analysis) will be stored as edges. But this decision is let to the imple-  
13 mentation part of this formalism.

14 In our model, only consumption values ( $V_i$  nodes) are modified over time. Plus,  
15 since the scenario does not imply any edge modifications, only those between meters  
16 and values are modified. The edge set contains thus sixteen edges:  $E_{SG} = \{e_i \mid i \in$   
17  $[1..16]\}$ .

18 By definition, the unmodified edges have a validity period starting from  $t_0$  and  
19 never ends:  $\forall i \in [1..7], V_{SG}^T(e_i) = [t_0, t_\infty)$ . The history of the three knowledge  
20 elements that represent consumption values do not only impact the nodes which  
21 represent the values but also the edges between those nodes and the meters ones:

- 22 •  $C_1$  impacts edges between  $M_1$  and  $V_1$ ,  $V_4$ , and  $V_7$ , i.e.,  $\{e_8, e_{11}, e_{14}\}$ ,

- $C_2$  impacts edges between  $M_2$  and  $V_2$ ,  $V_5$ , and  $V_8$ , *i.e.*,  $\{e_9, e_{12}, e_{15}\}$ ,
- $C_3$  impacts edges between  $M_3$  and  $V_3$ ,  $V_6$ , and  $V_9$ , *i.e.*,  $\{e_{10}, e_{13}, e_{16}\}$ .

Continuing with  $C_2$  as an example, the initial edge value is  $e_9$  from  $t_1$ , which is replaced by  $e_{12}$  from  $t_2$ , itself replaced by  $e_{15}$  from  $t_2$ . The validity relation, applied to these edges, thus returns:

- $V_{SG}^T(e_9) = [t_1, t_2) = V_{SG}^T(V_2)$ ,
- $V_{SG}^T(e_{12}) = [t_2, t_3) = V_{SG}^T(V_5)$ ,
- $V_{SG}^T(e_{15}) = [t_3, t_\infty) = V_{SG}^T(V_8)$ ,

These validity periods are depicted in Figure 6.7b. As they are driven by those of consumption values ( $V_2$ ,  $V_5$ , and  $V_8$ ), they are equal.

As for nodes, the  $Z_{SG}^T$  relation can navigate over time through these values. For example, to get the history of the edges between the consumption value  $C_2$  and the meter represented by  $M_2$ , one can apply the  $Z_{SG}^T$  relation as follows:

- $Z_{SG}^T(e_9, t_{s1}) = \emptyset$ , where  $t_0 \leq t_{s1} < t_1$
- $Z_{SG}^T(e_9, t_{s2}) = e_9$ , where  $t_1 \leq t_{s2} < t_2$ ,
- $Z_{SG}^T(e_9, t_{s3}) = e_{12}$ , where  $t_2 \leq t_{s3} < t_3$ ,
- $Z_{SG}^T(e_9, t_{s4}) = e_{15}$ , where  $t_3 \leq t_{s4} < t_\infty$ .

**Description of  $D_{SG}$ ,  $A_{ESG}$ , and  $R_{ASG}$**  As described in the scenario (cf. Section 6.1.3), the requirement analysis detects that  $t_1$  the requirement is broken. The adaptation process will thus apply the “decreasing amps limits” action on the three meters. Following Example 2 detailed in Section 6.1.1, we consider that the action will impact the consumption values on the next two measurements:  $t_2$  and  $t_3$ .

In the knowledge, we thus have one decision:  $D_{SG} = D_1$ . This decision has been taken after one requirement analysis,  $R_{ASG1}$ , that detects no respect of the requirement  $R_1$ . To determine if there is an overload, this analysis needs to know the topology and the consumption values. The pattern is thus defined by all nodes related to the grid network and consumption values at  $t1$ :  $P_{1[t_1, t_1+1]} = \{S_1, F_1, F_2, C_1, E_1, M_1, M_2, M_3, V_1, V_2, V_3\}$ . So we have:  $R_{ASG1} = \{R_1, P_{1[t_1, t_1+1]}\}$ .

The knowledge also includes the three action executions:  $A_{ESG1}$ ,  $A_{ESG2}$ , and  $A_{ESG3}$ . These actions have been executed on, respectively,  $M_1$ ,  $M_2$ , and  $M_3$ . Following the

definition, they all contain the action  $A_1$  and similar relation which linked the circumstances to the impacts. The circumstances are the state of the knowledge at  $t_0$ , which contain all information of the grid network and the consumption values. We denote them  $P_{2[t_1, t_1+1]}$ ,  $P_{3[t_1, t_1+1]}$ , and  $P_{4[t_1, t_1+1]}$ , all equal  $P_{1[t_1, t_1+1]}$ . The impact contains all consumption values received at  $t_2$  and  $t_3$ . Each action impacts the consumption value of the meter that it modifies. For example,  $A_{ESG2}$  only impacts values of meter  $M_2$ . For this action, the output pattern is thus :  $P_{5[t_2, t_3]} = \{V_5, V_8\}$ .

In summary,  $A_{ESG1}$ ,  $A_{ESG2}$ , and  $A_{ESG3}$  are defined as follows:

- for the action executed on  $M_1$ :  $A_{ESG1} = (A_1, A_{F1})$ , with  $A_{F1} : P_{2[t_1, t_1+1]} \rightarrow \{V_4, V_7\}$ ,
- for the action executed on  $M_2$ :  $A_{ESG2} = (A_1, A_{F2})$ , with  $A_{F2} : P_{3[t_1, t_1+1]} \rightarrow \{V_5, V_8\}$ ,
- for the action executed on  $M_3$ :  $A_{ESG3} = (A_1, A_{F3})$ , with  $A_{F3} : P_{4[t_1, t_1+1]} \rightarrow \{V_6, V_9\}$ ,

The decision described in the scenario is thus equal to:  $D_1 = \{R_{ASG1}, A_{ESG1}, A_{ESG2}, A_{ESG3}\}$ . At  $t_2$ , this decision will still be valid. The adaptation process can thus include it in the adaptation process to reason over the ongoing actions. If at  $t_3$  the cable remains overloaded, then one may use this element to check if the system tried to fix it, how and based on which information.

## Modeling the knowledge

(sec:tkm:mm) In order to simplify the diagnosis of adaptive systems, this thesis proposes a novel metamodel\* that combines, what we call, design elements and runtime elements. Design elements abstract the different elements involved in knowledge\* information to assist the specification of the adaptation process. Runtime elements instead, represent the data collected by the adaptation process during its execution. In order to maintain the consistency between previous design elements and newly created ones, instances of design elements (*e.g.*, actions) can be either added or removed. Modifying these elements would consist in removing existing elements and creating new ones. Combining design elements and runtime elements in the same model helps not only to acquire the evolution of system but also the evolution of its structure and



specification (e.g. evolution of the requirements of the system). Design time elements are depicted in gray in the Figures 6.8– 6.11. Note that, this thesis does not address how runtime information is collected.

For the sake of modularity, the metamodel\* has been split into four packages: Knowledge, Context, Requirement and Action. All the classes of these packages have a common parent class that adds the temporality dimension: *TimedElement* class. Before describing the Knowledge (core) package, we detail this element. Then, we introduce in more details the other three packages used by the Knowledge package: Context, Requirement, and Action. In below sections, we use "*Package::Class*" notation to refer to the provenance of a class. If the package is omitted, then the provenance package is this one described by the figure or text.

## Parent element: *TimedElement* class

we assume that all the classes in the different packages extend a *TimedElement* class. This class contains three methods: *startTime*, *endTime*, and *modificationsTime*. The first two methods allow accessing the validity interval bounds defined by the previously discussed  $V^T$  relation. The last method resolves all the timestamps at which an element has been modified: its history. This method is the implementation of the relation  $Z^T$  described in our formalism (cf. Section 6.2.2).

## Knowledge metamodel

In order to enable interactive diagnosis of adaptive systems, traceability links between the decisions made and their circumstances should be organized in a well-structured representation. In what follows, we introduce how the knowledge\* metamodel\* helps to describe decisions\*, which are linked to their goals and their context (input and impact). Figure 6.8 depicts this metamodel\*.

Knowledge package is composed of a *context\**, a set of *requirements\**, a set of *strategies*, and a set of *decisions\**. A decision\* can be seen as the output of the Analyze and Plan steps in the Monitor, Analyze, Plan, and Execute over knowledge (MAPE-k)\* loop.

Decisions comprise target *goals* and trigger the execution of one *tactic* or more.

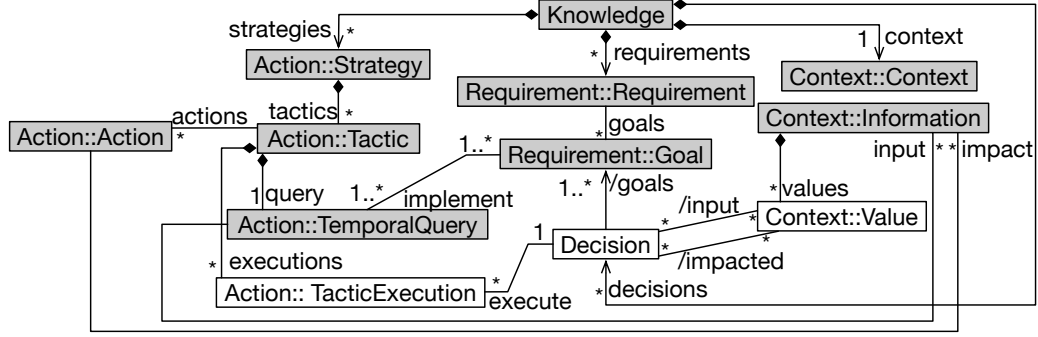


Figure 6.8: Excerpt of the knowledge metamodel

(fig:knowledge-mm)

1 A decision has an *input* context and an *impacted* context. The context impacted  
 2 by a decision (*Decision.impact*) is a derived relationship computed by aggregating  
 3 the impacts of all actions belonging to a decision (see Fig. 6.11). Likewise, the *input*  
 4 relationship is derived and can be computed similarly. In the smart grid example, a  
 5 decision can be formulated (in plain English) as follows: since the district D is almost  
 6 overloaded (*input context*), we reduce the amps limit of greedy consumers using the  
 7 “*reduce amps limit*” action in order to reduce the load on the cable of the district  
 8 (*impact*) and satisfy the “*no overload*” policy (*requirement*).

9 As all the elements inherit from the *TimedElement*, we can capture the time at  
 10 which a given decision and its subsequent actions were executed, and when their impact  
 11 materialized, *i.e.*, measured. Thanks to this metamodel representation, a developer  
 12 can apprehend the possible causes behind malicious behavior by navigating from the  
 13 context values to the decisions that have impacted its value (*Property.expected.impact*)  
 14 and the goals it was trying to reach (*Decision.goals*). In Section 6.1.3, we present an  
 15 example of interactive diagnosis queries applied to the smart grid use case.

## 16 Context metamodel

17 Context models structure context information acquired at runtime. For example,  
 18 in a smart-grid system, the context model would contain information about smart-grid  
 19 users (address, names, etc.) resource consumption, etc.

20 An excerpt of the context model is depicted in Figure 6.9. we propose to rep-

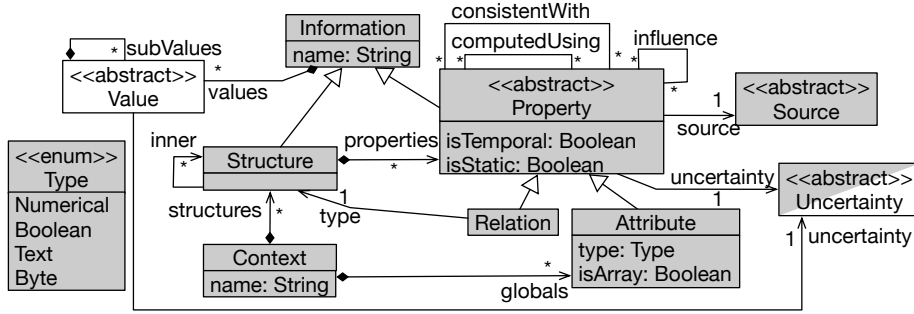


Figure 6.9: Excerpt of the context metamodel

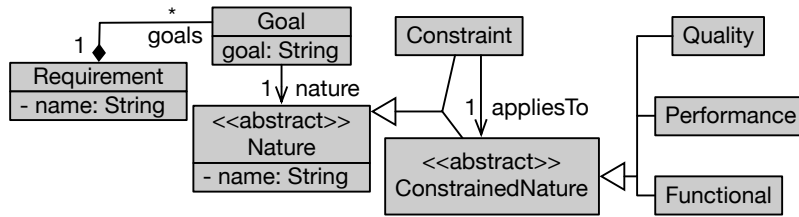


Figure 6.10: Requirement metamodel

1 represent the context as a set of structures (*Context.structures*) and global attributes  
 2 (*Context.globals*). A structure can be viewed as a C-structure with a set of properties  
 3 (*Property*): attributes (*Attribute*) or relationships (*Relation*). A structure may contain  
 4 other nested structures (*Structure.inner*). Structures and properties have values.  
 5 They correspond to the nodes described in the formalization section (*cf.* Section 6.2.2).  
 6 The connection feature described in Section 6.1.2 is represented thanks to three recur-  
 7 sive relationships on the Property class: *consistentWith*, *computedUsing* and *influence*.  
 8 Additionally, each property has a source (*Source*) and an uncertainty (*Uncertainty*).  
 9 It is up to the stakeholder to extend data with the appropriate source: measured,  
 10 computed, provided by a user, or by another system (*e.g.*, weather information coming  
 11 from a public API). Similarly, the uncertainty class can be extended to represent the  
 12 different kinds of uncertainties. Finally, a property can be either historic or static.



## 1 Action metamodel

ec:action-mm)?

2 Similar to the requirements metamodel, the actions metamodel also abstracts main  
3 concepts shared among existing solutions to describe adaptation processes and how  
4 they are linked to the context. Figure 6.11 depicts an excerpt of the action metamodel.  
5 we define a strategy as a set of tactics (*Strategy*). A tactic contains a set of actions  
6 (*Action*). A tactic is executed under a precondition represented as a temporal query  
7 (*TemporalQuery*) and uses different data from the context as input. In future work, we  
8 will investigate the use of preconditions to schedule the executions order of the actions,  
9 similarly to existing formalisms such as Stitch [DBLP:journals/jss/ChengG12].  
10 The query can be as complex as needed and can navigate through the whole knowledge  
11 model. Actions have impacts on certain properties, represented by the *impacted*  
12 reference.

13 The different executions are represented thanks to the *Execution* class. Each  
14 execution has a status to track its progress and links to the impacted context  
15 values(*Execution.impactedValues*). Similarly, input values are represented thanks to  
16 the *Execution.inputValues* relationship. An execution has *start* and *end* time. Not  
17 to confuse with the *startTime* and *endTime* of the validity relation  $V^T$ . Whilst the  
18 former corresponds to the time range in which a value is valid, the *start* and *stop* time  
19 in the class execution correspond to the time range in which an action or a tactic  
20 was being executed. The start and stop attributes correspond to the relation  $E_{A_E}$   
21 (see Section 6.2.2). These values can be derived based on the validity relation. They  
22 correspond to the time range in which the status of the execution is “*RUNNING*”.  
23 Formally, for every execution node  $e$ ,  $E_{A_E}(e) = (V(e) \mid e.status = \text{“RUNNING”})$ .

24 Similarly to requirement models, it is possible to automatically infer design  
25 elements of action models by statically analyzing actions specification. Since acquiring  
26 information about tactics and actions executions happens at runtime, one way to  
27 achieve this is by intercepting calls to actions executions and updating the appropriate  
28 action model elements accordingly. This is out of the scope of this paper and planned  
29 for future work.

## Validation

To validate and evaluate our approach, we implemented a prototype publicly available online<sup>5</sup>. This implementation leverages the GreyCat framework<sup>6</sup>, more precisely the modeling plugin, which allows designing a metamodel using a textual syntax. Based on this specification, GreyCat generates a Java and a JavaScript API to create and manipulate models that conform to the predefined metamodel. The GreyCat framework handles time as a built-in concept. Additionally, it has native support of a lazy loading mechanism and an advanced garbage collection. This is achieved by dynamically loading and unloading model elements from the main memory when necessary.

The validation of our approach has been driven by the two research questions formulated in the introduction section:

- How to diagnose the self-adaptation process?
- How to enable reasoning over unfinished actions and their expected effects?

To address the first one, we describe how one can use our approach to represent the knowledge of an adaptation process for a smart grid system. Then, we present a code to extract the circumstances and the goals of a decision. For the second one, we present a scenario where a developer can use our approach to reason over unfinished actions and their expected effects. The presented code shows how information can be extracted from our model to enable any reasoning algorithm. Finally, we present a performance evaluation to show the scalability of our approach.

### Diagnostic: implementation of the use case

In what follows, we explain how a stakeholder, Morgan, can apply our approach to a smart grid system in order to, first, abstract adaptive system concepts, then, structure runtime data, and finally, query the model for diagnosis purpose. The corresponding object model is depicted in Figure 6.12. Due to space limitation, we only present an excerpt of the knowledge model. An elaborate version is accessible in the tool repository.

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<sup>5</sup><https://github.com/lmouline/LDAS>

<sup>6</sup><https://github.com/datathings/greycat>

**Abstracting the adaptive system** At design time ( $t_d$ ), either manually or using an automatic process, Morgan abstracts the different tactics and actions available in the adaptation process. Among the different tactics that Morgan would like to model is “*reduce amps limit*”. It is composed of three actions: sending a request to the smart meter (*askReduce*), checking if the new limit corresponds to the desired one (*checkNewLimit*), and notifying the user by e-mail (*notifyUser*). Morgan assumes that the *askReduce* action impacts consumption data (*csmpt*). This tactic is triggered upon a query (*tempQ*) that uses meter (*mt*), consumption (*csmpt*) and customer (*cust*) data. The query implements the “*no overload*” goal: the system shall never have a cable overload. Figure 6.12 depicts a flattened version of the temporal model representing these elements. The tag at upper-left corner of every object illustrates the creation timestamp. All the elements created at this stage are tagged with  $t_d$ .

**Adding runtime information** The adaptation process checks if the current system state fulfills the requirements by analyzing the context. To perform this, it executes the different temporal queries, including *tempQ*. For some reasons, the *tempQ* reveals that the current context does not respect the “*no overload*” goal. To adapt the smart grid system, the adaptation process decides to start the execution of the previously described tactic (*exec1*) at  $t_s$ . As a result, a decision element is added to the model along with a relationship to the unsatisfied goal. In addition, this decision entails the planning of a tactic execution, manifested in the creation of the element *exec1* and its subsequent actions (*notifyU*, *checkLmt*, and *askRed*). At  $t_s$ , all the actions execution have an IDLE status and an expected start time. All the elements created at this stage are tagged with the  $t_s$  timestamp in Figure 6.12.

At  $t_{s+1}$ , the planned tactic starts being executed by running the action *askReduce*. The status of this action turns from *IDLE* to *RUNNING*. Later, at  $t_{s+2}$ , the execution of *askReduce* finishes with a *SUCCEED* status and triggers the execution of the actions *notifyUser* and *checkNewLimit* in parallel. The status of *askReduce* changes to *SUCCEED* while the status of *notifyUser* and *checkNewLimit* turns to *RUNNING*. The first action successfully ends at  $t_{s+3}$  while the second ends at  $t_{s+4}$ . As all actions terminates with a *SUCCEED* status at  $t_{s+4}$ , accordingly, the final status of the tactic

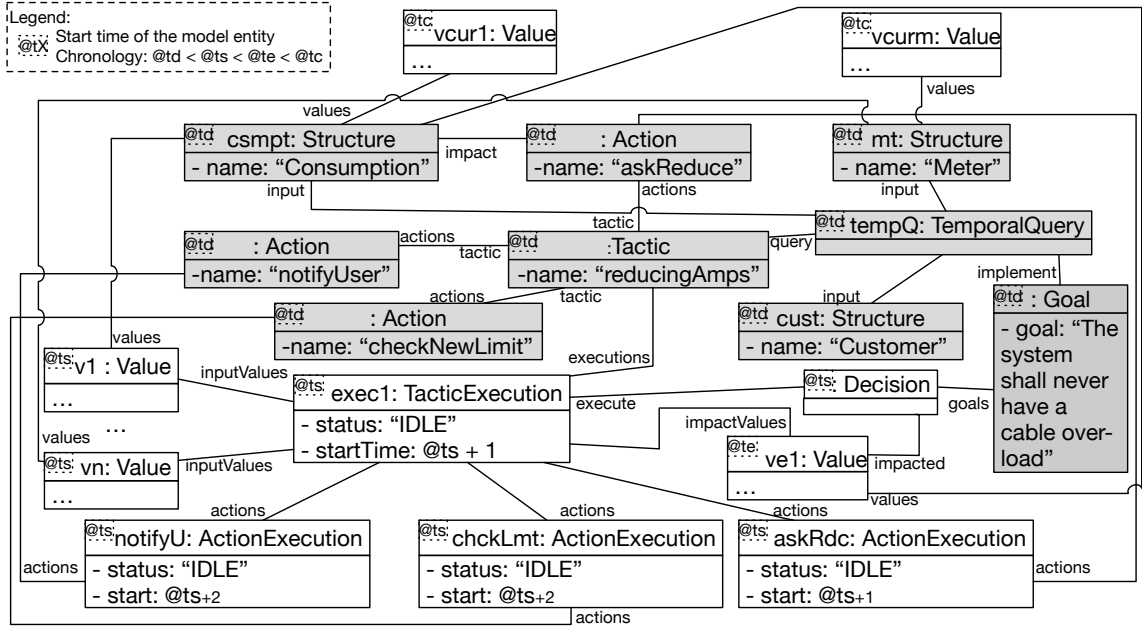


Figure 6.12: Excerpt of the knowledge object model related to our smart grid example

- 1 is set *SUCCEED* and the *stop* attribute value is set to  $t_e$ .
- 2 **Interactive diagnosis query** After receiving incident reports concerning regular
- 3 power cuts, and based on the aforementioned knowledge model, Morgan would be
- 4 able to query the system's states and investigate why such incidents have occurred.
- 5 As described in Section 6.1.3, she/he will interactively diagnose the system by
- 6 interrogating the context, the decisions made, and their circumstances.
- 7 The first function, depicted in Listing 6.1, allows to navigate from the currently
- 8 measured values ( $vcur1$ ) to the decision(s) made. The for-loop and the if-condition are
- 9 responsible for resolving the measured data for the past two days. Past elements are
- 10 accessed using the *resolve* function that implements the  $Z^T$  relation (*cf.* Section 6.2.2).
- 11 After extracting the decisions leading to power cuts, Morgan carries on with the
- 12 diagnosis by accessing the circumstances of this decision. The code to perform this
- 13 task is depicted in Listing 6.1, the second function (*getCircumstances*). Note that
- 14 the relationship *Decision.input* is the aggregation of *Decision.execute.inputValues*.

```

ode:actions-to-goals
15 // extracting the decisions
16

```



```

1 Decision [] impactedBy(Value v) {
2   Decision [] respD
3   for( Time t: v.modificationTimes() ):
4     if (t >= v.startTime() - 2 day)
5       Value resV = resolve(v, t)
6       respD.addAll(from(resV).navigate(Value.impactd))
7   return respD
8 }
9 // extracting the circumstances of the made decisions
10 Tuple<Value[], Goal[]> getCircumstance(Decision d) {
11   Value[] resValues = from(d).navigate(Decision.input)
12   Goal[] resGoals = from(d).navigate(Decision.goals)
13   return Tuple<>(resValues, resGoals)
14 }
15 }

```

Listing 6.1: Get the goals used by the adaptation process from executed actions

## Reasoning over unfinished actions and their expected effects

By associating the action model to the knowledge model, we aim at enhancing adaptation processes with new abilities to reason. In this section, we present an example of a reasoning algorithm which considers the impacts of running actions. This example is based on our use case (*cf.* Section ??).

Let's imagine that the adaptation process detects overloaded cables in the smart grid. To fix this situation, it takes several countermeasures, among which there are fuse state modifications. As detailed in Section 6.1.1, this action is considered as delayed action. Later, another incident is detected, for example, a substation is being overloaded. Before taking any actions, the adaptation process can, thanks to our solution, verify if the running actions will be sufficient to solve this new incident. If not, it can either take additional actions or replan the running one. The algorithm to reschedule current actions or to compute additional actions is out of the scope of this thesis. Here, we present the code to extract the required information from our model.

Checking if the running actions will be sufficient to solve all current issues can also be thought as: will the issue remain with the new context, *i.e.*, after each action have been executed. In our case, it is like verifying if the second overload will still remain with the new topology, which is coming. The adaptation process, therefore, needs to extract the context in the future. To do so, the adaptation process should know the

1 latest timepoint at which the impact will be measured. Listing 6.2 shows the code  
2 to get this timepoint. Running, idle and finished actions are accessed thanks to the  
3 first two nested loops with the if-condition. We consider that failed and canceled  
4 actions have no effects. As finished actions may still have effects, we also consider  
5 them. Then we navigate through all impacted values to get their start time, *i.e.*, the  
6 beginning of their validity period ( $V^T$  relation, *cf.* Section 6.2.2). Doing so, we are  
7 sure to get the latest timepoint at which an impact will be measurable.

```

8 1 Time latestImpact(Knowledge k) {
9     Time latestTime = CURRENT_TIME
10
11
12     for (Decision d: from(k).navigate(decisions))
13         for (TacticExecution te: from(d).navigate(execute))
14             if (te.status == "RUNNING" || te.status == "IDLE" || te.status == "SUCCEEDED")
15                 for (Value v: from(te).navigate(impactedValues))
16                     if (v.startTime() > latestTime)
17                         latestTime = v.startTime()
18
19     return latestTime
20 }
21

```

Listing 6.2: Get latest timepoint at which the impact will be measured

22 Using this timepoint, then the adaptation process can then compute how the  
23 grid should be after the actions have been executed. If the system has no prediction  
24 mechanism, then the adaptation process can verify how the power will be balanced  
25 over the new topology. Otherwise, it can use this prediction feature to compute the  
26 expected loads with the coming topology. Using this information, it can verify if all  
27 current incidents will be solved by the ongoing actions or not. If not, it may take  
28 additional actions or reschedule them.

29 Listing 6.3 depicts the code to extract all running actions. The nested loops  
30 allow accessing all executions made by decision. Then, we filter only those with the  
31 “RUNNING” status. The resulting collection should then be given to the scheduling  
32 algorithm, which will decide if rescheduling is possible and how.

```

33 1 TacticsExecution [] runningActions(Knowledge k) {
34     TacticsExecution [] resA
35     for (Decision d: k.decisions) {
36         for (TacticExecution te: d.execute) {
37

```

```

1      if(te.status == Status.RUNNING) {
2          resA.add(te)
3      }
4  }
5  }
6  return resA
7  }

```

Listing 6.3: Extract ongoing actions and their effects

Using our model, developers have two solutions to model a rescheduling operation. Either they modify the actions, which may delete the history of the previous decision, or they mark all running and idle actions as “CANCELED” and create a new decision, with new actions, which update the circumstances and re-use the same requirements.

### Performance evaluation

GreyCat stores temporal graph elements in several key/value maps. Thus, the complexity of accessing a graph element is linear and depends on the size of the graph. Note that in our experimentation we evaluate only the execution performance of diagnosis algorithms. For more information on I/O performance in GreyCat, please refer to the original work by Hartmann *et al.*, [DBLP:conf/seke/0001FJRT17; DBLP:phd/basesearch/Hartmann16].

```

20 MATCH (input)-[*4]->(output)
21
22 WHERE input.id IN [randomly generated set]
23
24 RETURN output
25
LIMIT 0

```

Listing 6.4: Traversal used during the experimentations

We consider a diagnosis algorithm to be a graph navigation from a set of nodes (input) to another set of nodes (output). Unlike typical graph algorithms, diagnosis algorithms are simple graph traversals and do not involve complex computations at the node level. Hence, we believe that three parameters can impact their performance (memory and/or CPU): the global size of the graph, the size of the input, and the number of traversed elements. In our evaluation, we altered these parameters and report on the behavior of the main memory and the execution time. The code of

1 our evaluation is publicly available online<sup>7</sup>. All experiments reporting on memory  
2 consumption were executed 20 times after one warm-up round. Whilst, execution  
3 time experiments were run 100 times after 20 warm-up rounds. The presented results  
4 correspond to the mean of all the iterations. We randomly generate graph with sizes  
5 ( $N$ ) ranging from 1 000 to 2 000 000. At every execution iteration, we follow these  
6 steps: (1) in a graph with size  $N$ , we randomly select a set of  $I$  input nodes, (2) then  
7 traverse  $M$  nodes in the graph, (3) and we collect the first  $O$  nodes that are at four  
8 hops from the input element. Listing 6.4 describes the behavior of the traversal using  
9 Cypher, a well-known graph traversal language.

10 We executed our experimentation on a MacBook Pro with an Intel Core i7  
11 processor (2.6 GHz, 4 cores, 16GB main memory (RAM), macOS High Sierra version  
12 10.13.2). We used the Oracle JDK version 1.8.0\_65.

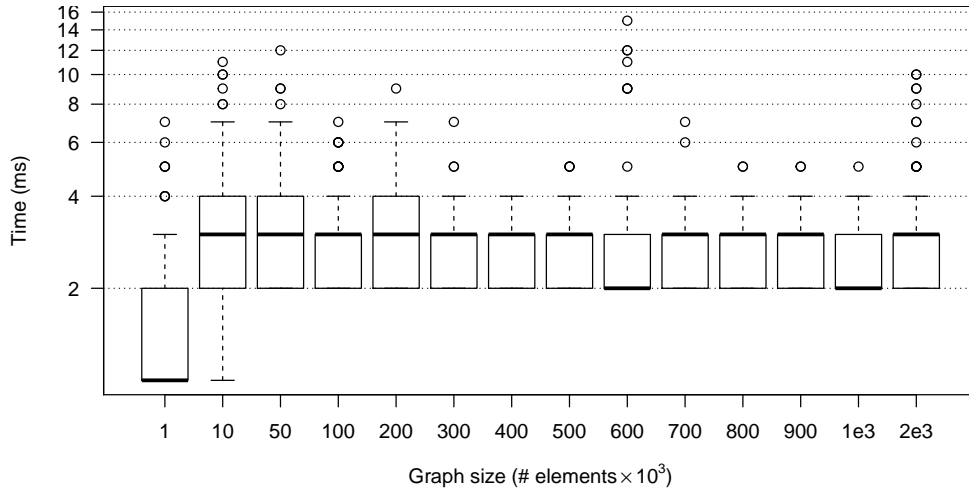
13 **How performance is influenced by the graph size  $N$ ?** This experimentation  
14 aims at showing the impact of the graph size ( $N$ ) on memory and execution time  
15 while performing common diagnosis routines. We fix the size of  $I$  to 10. To assure  
16 that the behavior of our traversals is the same, we use a seed value to select the  
17 starting input elements. We stop the algorithm when we reach 10 elements. Results  
18 are depicted in Figure 6.13.

19 As we can notice, the graph size does not have a significant impact on the execution  
20 time of diagnosis algorithms. For graphs with up to 2,000,000 elements, execution  
21 time remains between 2 ms and four 4 ms. We can also notice that the memory  
22 consumption insignificantly increases. Thanks to the implementation of a lazy loading  
23 and a garbage collection strategy by GreyCat, the graph size does not influence  
24 memory or execution time performance. The increase in memory consumption can  
25 be due to the internal indexes or stores that grow with the graph size.

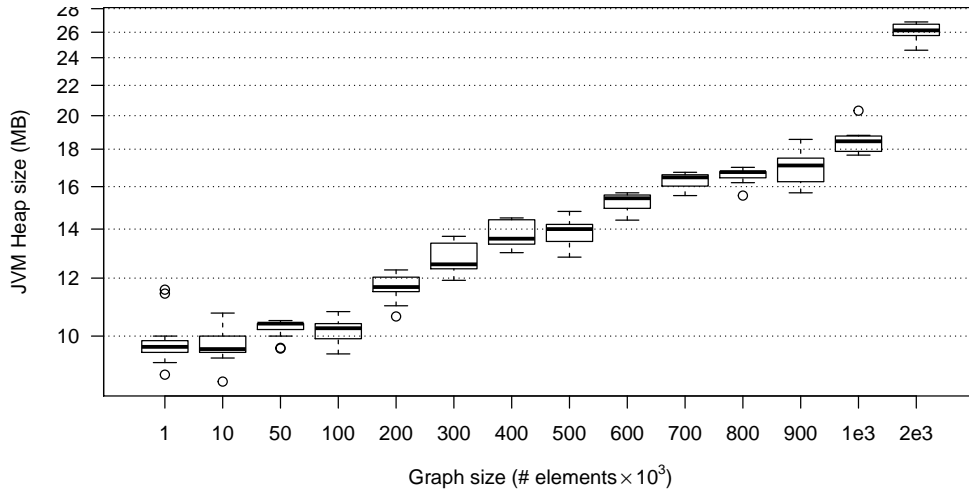
26 **How performance is influenced by the input size ( $I$ )?** The second experiment  
27 aims to show the impact of the input size ( $I$ ) on the execution of diagnosis algorithms.  
28 We fix the size of  $N$  to 500 000 and we variate  $I$  from 1 000 nodes to 100 000, *i.e.*,  
29 from 0.2% to 20% of the graph size. The results are depicted in Figure 6.14 (straight

---

<sup>7</sup><https://bitbucket.org/ludovicpapers/icac18-eval>



(a) Execution time evolution



(b) Memory evolution

Figure 6.13: Experimentation results when the knowledge based size increases

`<fig:exp1>`

1 lines).

2 Unlike to the previous experiment, we notice that the input size ( $I$ ) impacts the  
3 performance, both in terms of memory consumption and execution time. This is  
4 because our framework keeps in memory all the traversed elements, namely the input  
5 elements. The increase in memory consumption follows a linear trend with regards to  
6  $N$ . As it can be noticed, it reaches 2GB for  $I=100\,000$ . The execution time also shows  
7 a similar curve, while the query response time takes around 60ms to run  
8 for  $I=1\,000$ , it takes a bit more than 4 seconds to finish for  $I=100\,000$ . Nonetheless,  
9 these results remain very acceptable for diagnosis purposes.

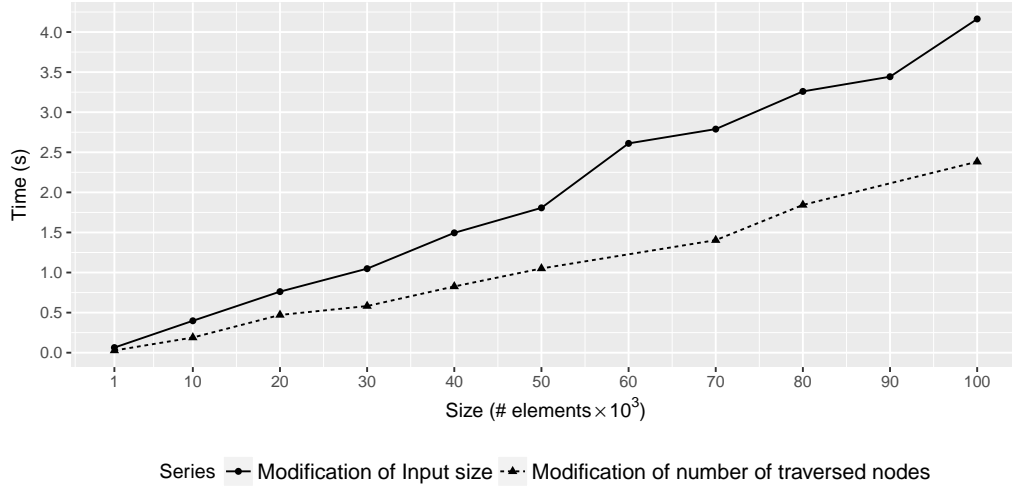
## 10 **How performance is influenced by the number of traversed elements ( $M$ )?**

11 For the last experiment, we aim to highlight the impact of the number of traversed  
12 elements ( $M$ ). For this, we fix  $I$  and  $O$  to 1, and randomly generate a graph with sizes  
13 ranging from 1 000 to 100 000. Our algorithm navigates the whole model ( $M=N$ ).  
14 We depict the results in Figure 6.14 (dashed curve). As we can notice, the memory  
15 consumption increases in a quasi-linear way. The memory footprint to traverse  $M =$   
16 100 000 elements is around 0.9GB. The progress of the execution time curve behaves  
17 similarly, in a quasi-linear way. Finally, the execution time of a full traversal over the  
18 biggest graph takes less than 2.5 seconds.

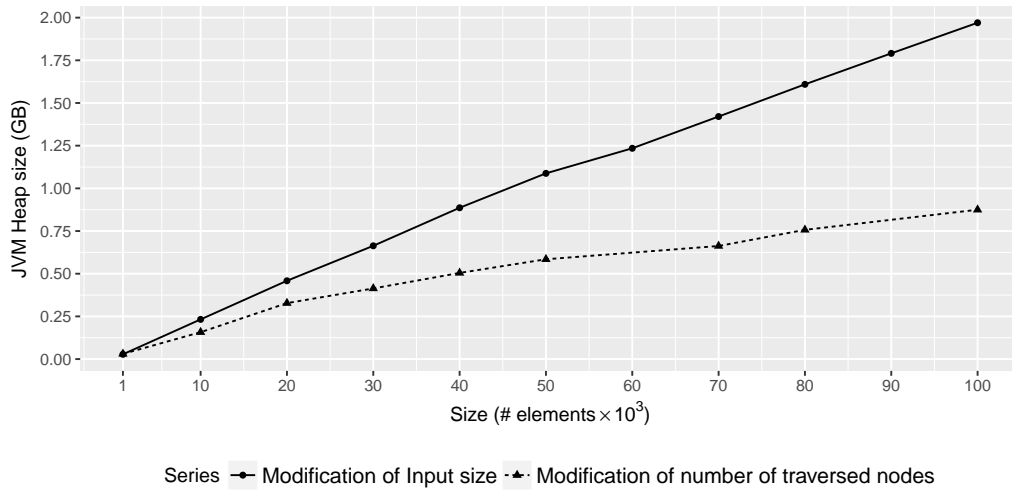
## 19 **Discussion**

20 By linking context, actions, and requirements using decisions, data extraction for  
21 explanation or fault localization can be achieved by performing common temporal  
22 graph traversal operations. In the detailed example, we show how a stakeholder  
23 could use our approach to define the different elements required by such systems, to  
24 structure runtime data, finally, to diagnose the behavior of adaptation processes.

25 Our implementation allows to dynamically load and release nodes during the  
26 execution of a graph traversal. Using this feature, only the needed elements are  
27 kept in the main memory. Hence, we can perform interactive diagnosis routines on  
28 large graphs with an acceptable memory footprint. However, the performance of  
29 our solution, in terms of memory and execution time, is restricted by the number  
30 of traversed elements and the number of input elements. Indeed, as shown in our



(a) Evolution of the execution time



(b) Evolution of the memory consumption

Figure 6.14: Results of experiments when the number of traversed or input elements increases

(fig:exp-res)

1 experimentation, both the execution time and the memory consumption grow linearly.

2 In the Luxembourg smart grid, a district contains approximatively 3 data con-  
3 centrators and 227 meters<sup>8</sup>. Counting the global datacenter, the network is thus  
4 composed of 231 elements. Each meter sends the consumption value every 15 min,  
5 being 908 every hours. Plus, there is from 0 to 273 topology modifications in the  
6 network. In total, the system generates from 908 to 1,181 new values every hour. If we  
7 consider that we have one model element per smart grid entity and one model element  
8 per new value, 100,000 model elements correspond thus from  $((100,000 - 231) * 1H) / 1,$   
9  $181 = 84,5H$  ( $\sim 3,5$  days) to  $((100,000 - 231) * 1H) / 908 = 109,9H$  ( $\sim 4,6$  days) of  
10 data. In other word, our approach can efficiently interrogate up to  $\sim 5$  days history  
11 data in 2.4s of one district.

## 12 Conclusion

`<sec:tkm:conclusion>` 13 Adaptive systems are prone to faults given their evolving complexity. To enable  
14 interactive diagnosis over these systems, we proposed a temporal data model to  
15 abstract and store knowledge elements. We also provided a high-level API to specify  
16 and perform diagnosis algorithms. Thanks to this structure, a stakeholder can  
17 abstract and store decisions made by the adaptation process and link them to their  
18 circumstances –targeted requirements and used context– as well as their impacts.  
19 In our evaluation, we showed that our solution can efficiently handle up to 100 000  
20 elements, in a single machine. This size is comparable to 5 days history of one district  
21 in the Luxembourg smart grid.

22 Throughout this work, we assumed that designers are able to link actions with  
23 their expected impacts at design time. However, this is not always true. Some  
24 impacts cannot be known in advance. In this perspective, in addition to the future  
25 plans already mentioned throughout the paper, we will investigate techniques to  
26 identify unknown impacts on the context model, for instance, by studying the use  
27 of machine learning techniques. In order to improve the accuracy and correctness

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<sup>8</sup>Previously, our studies uses the data described in [DBLP:conf/smartgridcomm/0001FKTPTR14] which corresponded to the all Luxembourg at this date. Since 2014, the smart grid has been more and more deployed. Numbers present in this paper now correspond more to one district.



1 of diagnosis routines, another aspect to be considered for future work is handling  
2 uncertainty in self-adaptive systems. Understanding the effect of uncertainty on the  
3 development of self-adaptive systems and their diagnosis is still an open question.  
4 We plan to explore this research direction by answering the following questions: How  
5 to represent and express uncertainty in self-adaptive systems at design time? How to  
6 efficiently interrogate data with uncertainty in self-adaptive systems, for instance, for  
7 troubleshooting purpose?



1

---

2 **Conclusion**

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t:conclusion)?



1

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2 This chapter concludes the thesis and presents  
3 some perspectives.

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## List of publications and tools

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### Papers included in the dissertation

- 2018
  - DBLP:conf/icac/MoulineBFBB18
  - DBLP:conf/sac/MoulineB0FBMB18
- in the process of submission
  - insubmission:2019:comlan:datauncertainty

### Papers not included in the dissertation

- 2017
  - DBLP:conf/models/Benelallam0MFBB17
  - DBLP:conf/programming/Mouline0FTBB17
- 2018
  - DBLP:conf/mobiquitous/GuineaBMT18

### Tools included in the dissertation

- Ain'tea: a language which integrated data uncertainty as a first-class citizen
  - <https://github.com/lmouline/aintea>
- LDAS: a meta-model of knowledge for adaptive systems
  - <https://github.com/lmouline/LDAS>





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# 1 Abbreviations

---

2 **CPS** Cyber-Physical System. 2

3 **ICT** Information and communication technology. 2

4 **MAPE-k** Monitor, Analyze, Plan, and Execute over knowledge. 41, *Glossary:*

5 MAPE-k

6 **MDE** Model-Driven Engineering. 2, 5



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## Glossary

---

- action** In this document, I use the definition provided by IEEE Standards [iso2017systems]: “Process that, given the context\* and requirements\* as input, adjusts the system behavior”. 29, 30
- adaptive system** In this document, I modified the definition of self-adaptive systems provided by Cheng *et al.*, in [DBLP:conf/dagstuhl/ChengLGIMABBBCSDFGGGKKKLMMMP]: Adaptive systems are able to have their behavior adjusted in response to the perception of the environment and the system themselves. If a system perform this adjustment on itself, the literature refers to it as self-adaptive system.. 3–5
- circumstance** State of the knowledge\* when a decision\* has been taken. 30
- context** In this document, I use the definition provided by Anind K. Dey [DBLP:journals/puc/Dey01]: “Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and [the system], including the user and [the system] themselves”. 29, 30, 35, 41
- decision** A set of actions\* taken after comparing the state of the knowledge\* with the requirement\*. 30, 41
- knowledge** The knowledge of an adaptive system gathers information about the context\*, actions\* and requirements\*. 29–31, 40, 41
- MAPE-k** A theoretical model of the adaptation process proposed by Kephart and Chess [DBLP:journals/computer/KephartC03]. It divides the process in four

1 stages: monitoring, analysing, planning and executing. These four stages share a  
2 knowledge\*. 41, *Abbreviation*: MAPE-k

3 **metamodel** In this document, I use the definition provided by Ed Seidewitz [DBLP:journals/softw  
4 “A metamodel is a specification model for a class of [system under study] where  
5 each [system under study] in the class is it-self a valid model expressed in a certain  
6 modeling language”. 40, 41

7 **models@run.time** In this document, I use the definition provided by Blair *et*  
8 *al.*, [DBLP:journals/computer/BlairBF09]: “A model@run.time is a causally  
9 connected self-representation of the as-sociated system that emphasizes the structure,  
10 behavior, or goals of the system from a problem space perspective”. 3

11 **requirement** In this document, I use the definition provided by IEEE Standards [iso2017systems]  
12 “(1) Statement that translates or expresses a need and its associated constraints  
13 and conditions, (2) Condition or capability that must be met or possessed by a  
14 system [...] to satisfy an agreement, standard, specification, or other formally imposed  
15 documents”. 29, 30, 41

16 **self-adaptive system** See adaptive system\*. 2

17 **self-healing** Refers to the capacity of detecting, diagnosing, and repairing any error  
18 in the system. See self-healing system\*. 2

19 **self-healing system** In this document, I use the definition provided by Kephart and  
20 Chess [DBLP:journals/computer/KephartC03]: “[A self-healing] system auto-  
21 matically detects, diagnoses, and repairs localized software and hardware problems.”.  
22 2

23 **smart grid** In this document, I use the definition provided by the National Institute of  
24 Standards and Technology (NIST)\* [NIST:SmartGrid:Def:What]: “a modernized  
25 grid that enables bidirectional flows of energy and uses two-way communication and  
26 control capabilities that will lead to an array of new functionalities and applications.”.  
27 2