A Unified Modeling Framework to Abstract Knowledge of Dynamically Adaptive Systems

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Abstract

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 neither present in the model nor not considered by the adaptation process, then the adaptation

process may make suboptimal reconfiguration decision.

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

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

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

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

Through this thesis, I argue that this data uncertainty and this delay cannot be ignored for all dynamic adaptive systems. To know if the data uncertainty should be considered, stakeholders should wonder **if this data uncertainty**

[1] https://software.intel.com/en-us/itc-user-and-reference-guide-cpu-cycle-counter

affects the result of their reasoning process, like adaptation. Regarding delayed action, 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 concept. It allows developers to attach data with a probability distribution which represents their uncertainty. Plus, it mapped all arithmetic and boolean operators to uncertainty propagation operations. And so, developers will automatically propagate the uncertainty of data without additional effort, compared to an algorithm which manipulates certain data.

Validation Each contribution has been evaluated separately. The language has been evaluated through two axes: its ability to detect errors at development time and its expressiveness. Ain'tea can detect errors in the combination of uncertain data earlier than state-of-the-art approaches. The language is also as expressive as current approaches found in the literature. Moreover, we use this language to implement the load approximation of a smart grid furnished by an industrial partner, Creos S.A.[2].

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

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

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

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Introduction

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Abstract: *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.*

1.1 Use case: Luxembourg smart grid

Should contain: -

2

TKM: a temporal knowledge model to represent actions, their contexts and their impacts

Contents

Abstract: *The evolving complexity of adaptive systems impairs our ability to deliver anomaly-free solutions. Fixing these systems require a deep understanding on the reasons behind decisions which led to faulty or suboptimal system states. Developers thus need diagnosis support that trace system states to the previous circumstances –targeted requirements, input context– that had resulted in these decisions. However, the lack of efficient temporal representation limits the tracing ability of current approaches. To tackle this problem, we first propose a knowledge formalism to define the concept of a decision. Second, we describe a novel temporal data model to represent, store and query decisions as well as their relationship with the knowledge (context, require- ments, 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.*

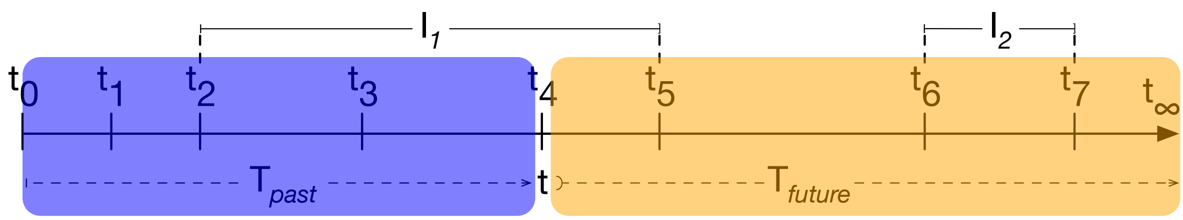


Figure 2.1: Time definition used for the knowledge formalism

2.1 Introduction

should define: decision, action, context, knowledge

2.2 Knowledge formalization

As discussed previously, I consider knowledge to be the association of context information, requirements, and action information, all in one global and unified model. While context information captures the state of the system environment and its surroundings, the system requirements define the constraints that the system should satisfy along the way. The actions, on the other hand, are means to reach the goals of the system.

In this section, I provide a formalization of the knowledge used by adaptation processes based on a temporal graph. Indeed, due to the complexity and interconnectivity of system entities, graph data representation seems to be an appropriate way to represent the knowledge. Augmented with a temporal dimension, temporal graphs are then able to symbolize the evolution of system entities and states over time. We benefit from the well-defined graph manipulation operations, namely temporal graph pattern matching and temporal graph relations to represent the traceability links between the decisions made and their circumstances.

Before describing this formalism, I describe the semantic used for the temporal axis. Then, I exemplify the knowledge formalism using the Luxembourg smart grid use case.

2.2.1 Formalization of the temporal axis

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

Time space T is considered as an ordered discrete set of time points non-uniformly distributed. As depicted in Figure 2.1, this set can be divided into 3 different subsets $T = T_{past} \cup \{t\} \cup T_{future}$, where:

- T_{past} is the sub-domain $\{t_0;t_1;\ldots;t_{current-1}\}$ representing graph data history starting from t_0, the oldest point, until current time, t, excluded.
- {t} is a singleton representing the current time point
- T_{future} is sub-domain $\{t_{current+1};\ldots;t_\infty\}$ 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 reachs 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 cannot represent a single 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 2.2.2, these intervals are used to define the validity period for each node of the graph.

Figure 2.1 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}).

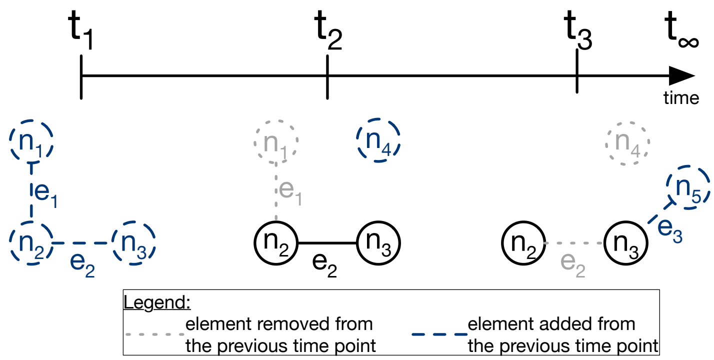


Figure 2.2: Evolution of a temporal graph over time

2.2.2 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. An attribute value has a type (numerical, boolean, ...). Every relationship $e \in E$ can be considered as a couple of nodes $(n_s, n_t) \in N \times N$, where n_s is the source node and n_t is the target node.

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

A node is considered valid either until it is removed or until one of its attributes value changes. In the latter case, a new node with the updated value is created. Whilst, an edge is considered valid until either its source node and target node is valid, or until the edge itself is removed. Otherwise, nodes and edges are considered invalid. The temporal validity relation is defined as $V^T : N \cup E \to I$. It takes as a parameter a node or an edge ($k \in N \cup E$) and returns a time interval ($i \in I$, *cf.* Section 2.2.1) during which the graph element is valid.

Figure 2.2 shows an example of a temporal graph K_1 with five nodes (n_1, n_2,n_3, 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 way, K_1 equals to $(\{n_1, n_2, n_3, n_4, n_5\}, \{e_1, e_2, e_3\}, V_1^T)$. Let's assume that the graph is created at t_1. As n_1 is modified at t_2, its validity period starts at t_1 and ends at t_2: $V_1^T(n_1) = [t_1, t_2)$. n_2 and n_3 are not modified; their validity period thus starts at t_1 and ends at t_∞: $V_1^T(n_2) = V_1^T(n_3) = [t_1, t_\infty)$. Regarding the edges, the first one, e_1, 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. As n_1 is being modified at t_2, its validity period goes from t_1 to t_2: $V_1^T(e_1) = [t_1, t_2)$. 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 the 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, $Z^T : N \times T \to N$.

In order to consider this new relation in the example presented in Figure 2.2, 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 2.2, 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 belongs 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 subset: $N = C \cup R \cup A$ where C is the set of nodes which store context information, R a set of nodes for requirement information and A the set of nodes for actions information.

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

Using a high level overview, these processes can the depicted as: taking the knowledge as input, perform task, and modify this knowledge as output. As detailed in the next two paragraphs, they can be formalized by relations.

Temporal queries for requirements At the current state, the formalism of the knowledge K do not contain any information regarding the requirement processes. To overcome this, system requirements processes R_P are added such as $K = (N, E, V^T, Z^T, R_P)$. R_P is a set of patterns $P_{[t_j,t_k]}(K)$ and queries Q over these patterns: $R_P = P \cup Q$.

$P_{[t_j,t_k]}$ denotes a temporal graph pattern, where t_j and t_k are the lower and upper bound of the time interval respectively. The time interval can be either fixed (absolute) or sliding (relative). Each element of the pattern should be valid for at least one time point: $\forall\ p \in P_{[t_j,t_k)}, V^T(e) \cap [t_j, t_k) \neq \emptyset$. Patterns can be seen as temporal subgraph of K, with a time limiting constraint coming in the form of a time interval. Temporal graph queries Q consist commonly of two parts: (i) path description to traverse the graph nodes, at both structural and temporal dimensions; (ii) arithmetic expressions on nodes, edges, and attribute values.

Temporal relations for actions Like for R_P, the knowledge K needs to be augmented with the action processes A_P: $K = (N, E, V^T, Z^T, R_P, A_P)$. Actions processes A_P can be regarded as a set of relations or isomorphisms mapping a source temporal graph pattern $P_{[t_j,t_k]}$ to a target one $P_{[t_l,t_m]}$, $A_P : K \times I \to K \times I$.

The left-hand side of the 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_P a temporal function E_{A_P} to determine the time interval at which an action has been executed. Formally, $X : A \to I$.

Temporal relations for decisions Finally, the knowledge formalism needs to include the last, but not the least, element: decisions made by the adaptation, $K = (N, E, V^T, Z^T, R_P, A_P, D)$ 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 actions execution to the decisions they originated from**.

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

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

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

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

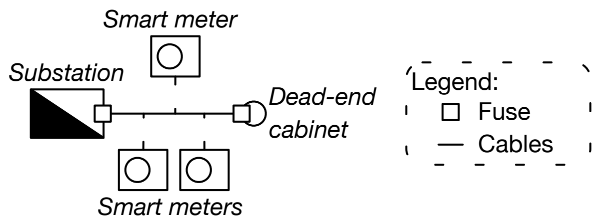


Figure 2.3: Simplified version of a smart grid

Figure 2.4: Representation of the smart grid context depicted in Figure 2.3

- R_P is a relation that define the different requirements processes,
- A_P is a relation that define the different action processes,
- D is a set of action processes that result from a same decision.

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

2.2.3 Application on the use case

The example presented in Section 1.1 contain too much detail to provide a readable and understandable example of the formalism. Below, an excerpt of it is thus presented in order to overcome this problem.

Excerpt of a smart grid Figure 2.3 shows a simplified version of a smart grid with one substation, one cable, three smart meters and one dead-end cabinet. Both the substation and the cabinet have a fuse. The meters regularly send consumption data at the same time. One requirement is considered for this example: minimizing the number of overloads. To achieve so, among the different actions, two actions are taken into account in this example: decreasing or increasing the amps limits of smart meters.

Let K_{SG} be the temporal graph that represents the knowledge of this adaptive system: $K_{SG} = (N_{SG}, E_{SG}, V^T_{SG}, Z^T_{SG}, R_{P_{SG}}, A_{P_{SG}}, D_{SG})$. Figure 2.4 shows the nodes and edges of this knowledge.

Scenario The system starts at t_0 with the actions, the requirements and the context, which also include initial value for the consumption values. Meters send their values at t_2 and t_3. Based on these data, the load on cables and substation is computed. On t_2, an overload is detected on the cable, which break the requirement. At the same time point, the system decides to reduce the load of all smart meters. The impact of these actions will be measured at t_4, *i.e.,* the cable will not be overloaded from t_4.

Description of N_{SG} N_{SG} is divided into three subset: C_{SG}, R_{SG} and A_{SG}. R_{SG} contains one node, R_1 in Figure 2.4, which represents the requirement of this example: $R_{SG} = \{R_1\}$ Two nodes, A_1 and A_2, belong to A_{SG}: $A_{SG} = \{A_1, A_2\}$. They represent represent the two actions of this example, respectively decreasing and increasing amps limits. Regarding the context C_{SG}, there is three nodes to represent the three smart meters (M_1, M_2, and M_3), one for the substation (S_1), two for the fuses (F_1 and F_2), one for the dead-end cabinet (D_{C_1}) and one node per consumption value received (V_i): $C_{SG} = \{M_1, M_2, M_3, S_1, F_1, F_2, D_{C_1}\} \cup \{V_i | i \in [1..9]\}$.

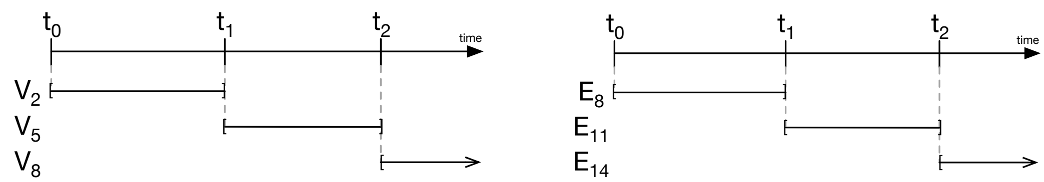
According to the scenario, all nodes are created at t_0 and are never modified, except for nodes to store consumption values. Therefore, their validity period starts at t_0 and never ends: $\forall n \in A_{SG} \cup R_{SG} \cup \{M_1, M_2, M_3, S_1, F_1, F_2, D_{C_1}\}, V^T_{SG}(n) = [t_0, t_\infty)$. Considering the consumption values, all the nodes represent the history of the values for the three smart meters. In other words, there is three knowledge element: the consumption measured for each meter. Let C_i notes the consumption measured by the smart meter M_i. As shown in Figure 2.4, there is:

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

Taking C_2 as example, V_2 is the initial consumption value, replaced by V_5 at t_1, itself replaced by V_8 at t_2. Applying the V^T_{SG} on these different values, results are thus:

- $V^T_{SG}(V_2) = [t_0, t_1)$,
- $V^T_{SG}(V_5) = [t_1, t_2)$,
- $V^T_{SG}(V_8) = [t_2, t_\infty)$.

These validity periods are shown in Figure 2.5a. As meters send the new consumption values at the same time, this example can be also applied to C_1 and C_3.



(a) Consumption values (b) Edges

Figure 2.5: Validity periods of the consumptions values and their edges to the smart meter M_2

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

- $Z_{SG}^T(V_2, t_{s1}) = V_2$, where $t_0 \leqslant t_{s1} < t_1$
- $Z_{SG}^T(V_2, t_{s2}) = V_5$, where $t_1 \leqslant t_{s2} < t_2$
- $Z_{SG}^T(V_2, t_{s3}) = V_8$, where $t_2 \leqslant t_{s3} < t_\infty$.

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

One may consider that relations (validity, Z^T, decisions, action processes and requirements processes) will be stored as edges. But, this decision is let to the implementation part of this formalism.

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

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

- 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 example, the initial edge value is E_8 from t_0, which is replaced by E_{11} from t_1, itself replaced by E_{14} from t_2. The validity relation, applied on these edges, thus returns:

- $V^T_{SG}(E_8) = [t_0, t_1) = V^T_{SG}(V_2)$,
- $V^T_{SG}(E_{11}) = [t_1, t_2) = V^T_{SG}(V_5)$,
- $V^T_{SG}(E_{14}) = [t_2, t_\infty) = V^T_{SG}(V_8)$,

These validity periods are depicted in Figure 2.5b. As they are driven by those of consumption values (V_2, V_5, and V_8), they are equals.

As for nodes, the Z^T_{SG} 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^T_{SG} relation as following:

- $Z^T_{SG}(E_8, t_{s1}) = E_8$, where $t_0 \leqslant t_{s1} < t_1$,
- $Z^T_{SG}(E_8, t_{s2}) = E_8$, where $t_1 \leqslant t_{s1} < t_2$,
- $Z^T_{SG}(E_8, t_{s3}) = E_8$, where $t_2 \leqslant t_{s1} < t_\infty$.

Description of $R_{P_{SG}}$ The requirement calls for minimizing overloads. It means that when the system detects at least one overload, for example in cables, it will take counter actions. As the system has prediction capabilities, it will not only check is there is one at the current time t but also if one will come in the next hour. The pattern will be defined as follow: $P_{[t,t+15min]}$. To determine if there is an overload, the system needs to know: the current and future consumption, the current and future topology. The last one is used to compute the loads from the consumption (cf. Section 1.1).

Let's consider that time points are regular and there is one every 15 minutes and that current time is t_0. The pattern, $P_{[t_0,t_1]}$, will thus contain all nodes that are valid between t_0 and t_1 (included):

- all topology nodes between: $\{S_1, C_1, F_1, F_2, D_{C_1}, M_1, M_2, M_3\}$
- all consumption values between: $\{V_i \mid i \in [1..6]\}$,

- all edges that connected these nodes: $\{E_i \mid i \in [1..13]\}$

From these values, the loads is computed and the system checks that none will exceed the capacity of the infrastructure (cables, substations, cabinets).

Description of $\boldsymbol{A_{P_{SG}}}$ Now, let us assume that the execution of $R_{P_{SG}}$ detects an overload on the cable (C_1) at t_0. The system decides to reduce the amps limits, and thus the load, on the three meters. The action A_1 (decreasing amps limits) is thus executed three times: one time per meter. For each of these action, the input context will correspond to the pattern used by the requirement relation: $P_{[t_0,t_1]}$. The output context will contain the predicted values after the actions have been executed. Here, the actions are executed in parallel and their execution time is in seconds. So the impact will be visible from t_1. So the output pattern contain the three values at t_1: $P_{[t_1,t_1]}$. In summary:

- Action 1: $A_{P_1} : P_{[t_0,t_1]} \rightarrow P_{[t_1,t_1]}$,
- Action 1: $A_{P_2} : P_{[t_0,t_1]} \rightarrow P_{[t_1,t_1]}$,
- Action 1: $A_{P_3} : P_{[t_0,t_1]} \rightarrow P_{[t_1,t_1]}$.

Description of $\boldsymbol{D_{SG}}$ Following the scenario, there is one decision, D_{SG_1}, which try to achieve the requirement R_1 by executing the actions A_1: A_{P_1}, A_{P_2}, and A_{P_3}. Then, here the decision is equals to: $D_{SG_1} = \{R_1, A_{P_1}, A_{P_2}, A_{P_3}\}$.

Summrarize Through this section, I explifyed how the formalism can be used to define an adaptation decision on a smart grid system. As the decision contains information about the circumstances and the impact, one may use it to debug the process and/or try to explain the behavior of such systems.

2.3 Modeling the knowledge