A Comparison of Smart Grids Domain Ontologies

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Abstract: Smart Grids (SG) represent one of the key critical infrastructures. Over time, several ontologies were defined in the SG domain to model aspects such as devices and sensors integration, and prosumers' communication needs. In this paper, we review the state of the art regarding semantic web reasoning in the domain of SGs. We compare five main ontologies in terms of descriptive statistics (e.g., number of axioms), load time and reasoners runtime performance. Results show that not all the ontologies in the SG domain are readily available, and that some of them might be more appropriate for deployment in devices with limited computational resources.

1 INTRODUCTION

Smart Grids (SG) have become one of the most important Critical Infrastructures (CI) and Cyber–Physical Systems (CPS) in the modern society. The potential for the improvement of the energy sector has been seen as a key factor, driven by the smart integration of users' behaviour leading to a more sustainable and secure electricity supply driven by renewable energy sources (Yu et al., 2011). However, as a representative of a typical CPS, the grid has many complexities in the integration of cyber resources (e.g., computing algorithms, communication and control software) with physical parts (e.g., sensors, smart meters) (Farhangi, 2009).

To tackle the complexity of SGs, the Smart Grid Architecture Model (SGAM) (Bruinenberg et al., 2012) was proposed, aiming at dividing the complexity into several layers and their integration: a component layer (the physical devices), a communication layer (protocols), a data layer (information data models), a function layer (functionalities to be provided), and a business layer (the business requirements). At the data layer level, the adoption of domain ontologies aims at allowing reasoning over the many devices and interactions with different goals like tracking information about reliability of devices or their integration (Zhou et al., 2012; Catterson et al., 2005; Gillani et al., 2014; Schachinger et al., 2016).

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Many ontologies have been defined over time for the energy sector (e.g., SEPA's Smart Grid Ontology, Open Energy Ontology, like we will discuss in section 3). Yet, there is no comprehensive evaluation of the proposed ontologies related to the current state of the art. In this paper, we want to provide evaluation of existing SGs ontologies: what is their availability / support, how much are they usable, and what is the performance overhead considering the possibility of deployment in devices such as smart meters with relatively low computational power available.

In particular, we are interested into looking at the impact of each different ontology in terms of performance (execution time) of the reasoner — It has been shown that different ontologies have better or worse performance depending on the reasoner they are loaded in (Kang et al., 2014; Kang et al., 2012).

We have one main Research Question (RQ) for this paper: *What is the state of different Smart Grids domain ontologies that were defined over the years?* We answer this RQ by looking both at the availability of ontologies, some descriptive statistics of the ontologies representing the size, and at the performance when used in a reasoner, taking into account the potential limited resources of embedded devices such as smart meters.

The paper is structured as follows. In Section 2, we provide related works in the area of SGs ontologies and related semantic technologies, reasoners improvements, and ontologies performances. In Section 3, we discuss existing ontologies for the SG domain. In Section 4, we analyze the main SGs ontologies identified, in terms of metrics related to size, and

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performance of the reasoners. In Section 5 we present the main results of the analysis. In Section 6, we conclude the paper.

2 RELATED WORKS

There are several research articles that focus on the topic of SG, ontologies, and semantic web reasoners. These papers can be classified in three different categories. First of all, we have papers that introduce new ontologies or semantic technologies relative to the domain (Section 2.1); secondly we have papers that describe ways to improve the performance by defining new semantic web reasoners or updating already existing ones (Section 2.2). Finally, the third category refers to papers that focus on measuring the metrics of a number of ontologies, usually in more general way and without focusing in a domain or another, but providing an invaluable value for this article (Section 2.3). With this in mind we proceed to describe each paper in relation to these categories.

2.1 SG-related Ontologies and Semantic Technologies

Regarding SG-related ontologies, (Zhou et al., 2012) main aim is to introduce an ontology with the benefit of being extensible to other domains close to the SG domain. Authors provide a case study on Complex Event Processing (CEP) with the use of SPARQL, that should be, or can be, as lightweight as possible. In the same vein, (Cuenca et al., 2017) defines the OEMA ontology created to deal with energy management. The ontology has high modularity to allow for very specific domain applications without wasting resources.

Another ontology to be used in the SG domain is presented in (Gillani et al., 2014). It describes a series of cases for which it could be useful and the whole ontology is divided into classes applicable to many different infrastructures. Finally, authors introduce inductive inferences going over patterns that could be identifiable thanks to the ontology and a non-monotonic approach. In the end, they propose the ontology to be used for CEP. Similarly, (Hippolyte et al., 2016) describes the implementation of an ontology for Multi Agent Systems (MAS) in SGs for the automatic negotiation between different members of a network, adding to the flexibility of the system. They base the work on a Java-based implementation, providing a tool to convert the ontology into a code-based implementation.

Yet another ontology for energy management in SGs is introduced in (Schachinger et al., 2016). The main aim of the work is to unify the domain of SGs. Authors provide theoretical testing of the ontology to showcase all the relations between classes and instances of the ontology which ends up being shown in a comprehensive diagram. Finally, (Li et al., 2019) develops an ontology focused on key performance indicators to show the elements that require more energy given their power consumption patterns. Furthermore, the authors intend to use the ontology as a way to interchange data between different stakeholders of the network, thus enabling potential support to Big Data scenarios.

Nevertheless, describing the provided ontologies in the SG domain is not enough if there are no semantic tools to work with them. In this sense, (Atanasov, 2015) describes in great detail a semantic model for prepaid smart metering devices. They gloss over all the data that is generated from the smart meters, and define all the semantic labels required for the data to be processed. The main strength of the work resides in the fact that just from time and volume (of power consumption) we can derive some effective semantics. The work of (Santodomingo et al., 2015) is devoted to standardizing the different data types that might come into play in a SG. It offers an advantage and usage scenario if the same ontology has not been used in all the devices or if the sources are not based on Web of Things (WoT).

The state of the semantic technologies can be seen in (Dogdu et al., 2014), where authors reflect on the state of the art implementation of semantic technologies in SGs, giving a precise overview of what they are good for and how they behave better and are more conveniently than usual data models. The work done is based on a real-world implementation of semantic technologies in SGs. Similarly, (Donohoe et al., 2015) acts as a survey about which technologies are available when dealing with the data of the SGs focusing on the context-aware ones. They propose a further direction on which a middleware platform could be developed, listing the possible associated requirements and the challenges they might face.

In (Wemlinger and Holder, 2011), the authors focus on providing a semantic framework for smart environments. This could potentially lead to integrating all data generated by the smart devices into the semantic web reasoner, therefore, strengthening the conclusions obtained. Supposedly helping to trace the patterns of malfunctioning appliances. As in the previous cited paper, (Flores-Martin et al., 2019) proposes another unifying method for different smart devices, but with the advantage of being more general:

from smart environments to smart devices. They expand their results by being able to integrate wearables in the detection of malfunctioning smart meters.

To conclude, (Hippolyte et al., 2018) defines the structure and the rationale behind an ontology that might be used to establish a relationship between energy consumption, data visualization and decision support. Authors focus on the web-based scalability of the proposed structure.

2.2 Reasoners Improvements

There are several recent improvements in semantic web reasoners that can help considering the potentially limited computational power of devices such as smart meters. (Tai et al., 2011) provides a reasoner designed to be implemented in a resource-constrained platform. This makes it interesting to be considered for an implementation in a smart meter, given the small overhead. The downside is that it is based on OWL instead of OWL2, so an update might be needed to work with the current ontologies. Similarly, (Ali and Kiefer, 2009) introduces a light-weight semantic reasoner for constrained resources. Nevertheless, the approach is quite different from the previous one and the performance is not as good.

Also, (Speiser et al., 2013) outlines the use of Linked Data in SGs communication, reinforcing the idea that it should be lightweight. Authors produce an evaluation based on connection time. They use resource constrained devices by today's standards and a lightweight SPARQL engine programmed on C. The obtained metrics are all under a second distance between them, so the added value regarding the SGs domain is quite high, taking into account the goal of real-time data processing.

2.3 Ontologies Performance

The works presented in this section deal with the performance of ontologies, but all of them are built upon wide domains, with no specific SGs ontologies considered, as there is no specific study that deals with performance in the SG domain. In particular, (Kang et al., 2012) measures the performance of 350 real-world ontologies and 4 OWL2 reasoners. The goal is to identify a set of metrics that can predict the performance of a semantic web reasoner. Eight ontology-level metrics are considered to be good predictors for ontologies performance. As a conclusion they try to use machine learning to see which metrics could be the best predictors. More recently, (Kang et al., 2014) uses an even larger number of ontologies, 450, as an extension and with the same goal of the previous paper. Authors also focus more on the identification of performance hotspots, identifying the bottlenecks when designing an ontology. Similarly, (Wang and Parsia, 2007) identifies semantic web reasoners bottlenecks for performance. Four case studies based on generated and real-world ontologies are provided. Authors identify challenges for ontologies engineering and implement a tool to support statistical analysis of performance of ontologies.

Recently, (Peña et al., 2020) shows some of their current work in which an enriched ontological model is used to improve the effectiveness of a recommender system. In particular, authors go through all the characteristics that make an ontology effective, selecting among them the ones more relevant for the task at hand. Also, (Maarala et al., 2017) introduces a new semantic technology reasoner to be applied to the Internet of Things (IoT) domain. Their intention is to make the reasoner and data collection as scalable as possible with the idea of implementing the technology into real-life scenarios. It is worth mentioning that they focus on showing the performance data and point out possible bottlenecks of the technology.

3 DOMAIN ONTOLOGIES FOR SMART GRIDS

As a first step, we collected existing ontologies in the SG domain. We have focused on a series of SG domain ontologies reported in previous research as well as some that are used in industry and are yet to be reported in research venues. All these ontologies can be seen in Table 1. Some of the ontologies are not available, despite their description and applicability being reported in research papers — this is mostly due to a fair share of broken URLs or missing references, which hinders the adoption of the ontologies.

The OEMA ontology was introduced in (Cuenca et al., 2017) to provide a modular approach ontology for the SGs domain. In this case, we are using the complete ontology so we consider it to be able to tackle the network as a whole. The SEPA's is the ontology developed by the Smart Electric Power Alliance for controlling buildings; this includes registering energy usage, the base for any SG application. The Open Energy Ontology is intended for modelling the whole energy system with an interest in the open source model. Facility Ontology was designed to control the production of any facility, and for this reason, it provides control over the energy usage, crucial for SGs. SSG, introduced in (Salameh et al., 2019), aims at modeling the SG components, their features and properties, allowing the achievement of the SG objec-

Table 1: Smart Grids Ontologies.

Name	Aim	URL
OEMA Ontology network	Whole Network Ontology	http://www.purl.org/oema/ontologynetwork
SEPA's Smart Grid Ontology	System to control buildings	https://github.com/smart-electric-power-alliance/Electric-Grid-Ontology
Open Energy Ontology	Energy System Modelling	https://openenergy-platform.org/ontology/
Facility Ontology	SG Components	https://github.com/usnistgov/facility
DABGEO	Energy Management Applications	https://innoweb.mondragon.edu/ontologies/dabgeo/index-en.html
SSG (Salameh et al., 2019)	SG Components	N.A.
Prosumer-oriented (Gillani et al., 2014)	Prosumer Ontology	N.A.
N.A. (Schachinger et al., 2016)	SG Integration	N.A.
N.A. (Zhou et al., 2012)	SG Demand / Response Applications	N.A.
N.A. (Catterson et al., 2005)	SG Health Monitoring	N.A.

tives. The ontology of (Catterson et al., 2005) focuses on monitoring the health of the components of a SG, in particular, that of any given transformer. DABGEO is the natural continuation of the OEMA Ontology: introduced in (Cuenca et al., 2020) is aimed at providing complete control to energy management applications.

An explanation for the ontologies of (Gillani et al., 2014), (Schachinger et al., 2016) and (Zhou et al., 2012) can be found in Section 2.

4 ANALYZING THE ONTOLOGIES

In this section we provide a description of the process we adopted to obtain the metrics regarding the description and performance of the main ontologies from Table 1. For this task we have used the Protégé[1] software in its *5.0.0* Linux version. As for the reasoners we are using HermiT, version *1.4.3.456*, and Pellet, version *2.2.0*.

First of all, we begin by downloading the ontology from the corresponding repository (Fig. 1). Once we have acquired the ontology, we proceed to load it into Protégé. As it is loaded, it might occur that the ontology itself tries to import some other ontologies. If these are readily available, Protégé will load them automatically, but in the case they are not, we load them manually. Once the main ontology and all the imported ones are loaded into Protégé, they are merged into one final ontology that represents what we will be measuring. This allows us to work with a real-world ontology as well as makes the workflow easier.

[1] https://protege.stanford.edu/products.php

After the final ontology is obtained, we annotate the metrics of the ontology that are listed by Protégé. In this case we are going for the metrics that are labelled as Axiom, Logical Axiom Count, Declaration Axiom Count, Class Count, Object Property Count, Data Property Count, Individual Count, and Annotation Property Count. To this list we also add how much time Protégé has taken to load the ontology.

Once we have the metrics we proceed to start the associated reasoner in Protégé and get the reasoning time. Afterwards it is the moment to extract any conclusions from the data collected.

4.1 Ontology Metrics

The results and the metrics of each of the selected main SG ontologies that were analyzed can be seen in Table 2. These metrics have been obtained accordingly to the process described in Section 4. All the measurements were done on an Intel i7-3537U CPU @ 2.00GHz, with 8GB of RAM, running Ubuntu 20.04.2 LTS. The metrics regarding time are extracted by performing five different times the same task in a completely new instance of Protégé and obtaining the mean.

We also measured the memory and CPU usage for each ontology as it can be seen in Figures 3 to 7. To capture these plots we used a script, based on Python's libraries `psrecord` and `matplotlib`, that is:

```
psrecord $(pgrep process_name)
--interval 1 --plot file_name.png
```

Finally, a comparative of the times of each ontology can be seen in Figure 2. It is important to mention that the missing bars, indicate that the time is not available for some or other reason.

Table 2: Metrics.

	OEMA Ontology network	SEPA's SG Ontology	Open Energy Ontology	Facility Ontology	DABGEO
Axiom	24738	5491	8563	15248	11678
Logical Axiom Count	9577	2426	1614	11904	4349
Declaration Axioms Count	5686	111	1215	691	2590
Class Count	3502	250	928	431	1964
Object Property Count	941	70	83	107	270
Data Property Count	712	28	N.A.	43	204
Individual Count	47	234	104	1722	69
Annotation Property Count	32	117	95	52	43
Loading time	7241.2ms	12284.6ms	1296.2ms	3726ms	1973.2ms
Reasoning time (HermiT)	N.A.	1106ms	331.8ms	N.A.	56051.2ms
Reasoning time (Pellet)	26406.6ms	788.2ms	N.A.	N.A.	N.A.

4.2 Issues

Despite our best work, obtaining all the metrics after analyzing all the ontologies has been challenging, and have encountered multiple issues that we proceed to list below. These issues are something to take into account when analyzing the ontologies, but not something that makes impossible to work with them. They are, therefore, questions that need to be taken into account when deploying any of these ontologies in a real-world scenario.

The issues that have aroused when analyzing the ontologies are:

- OEMA cannot be loaded as it was intended. During the process of loading it, it tries to import certain ontologies that are no longer available online.
- The loading time of OEMA when tracking its use gets too big (287516 ms) without any reason.
- OEMA does not reason with HermiT because the reasoner does not support built-in atoms, something that the ontology has.
- Open Energy Ontology does not reason with Pellet because of issues with the transitive rules.
- Facility Ontology does not reason with HermiT nor Pellet. For the first it states that there is a Non-simple property at Cardinality restriction. For the latter, it flags an error related to the TransitiveObjectProperty axiom. Let us state that it actually reasons with ELK (with an average time of 2576.4ms) after several warnings.
- For DABGEO ontology an error happens while running the Pellet reasoner and the process has to be killed. It is due to trying to use a literal as an individual.

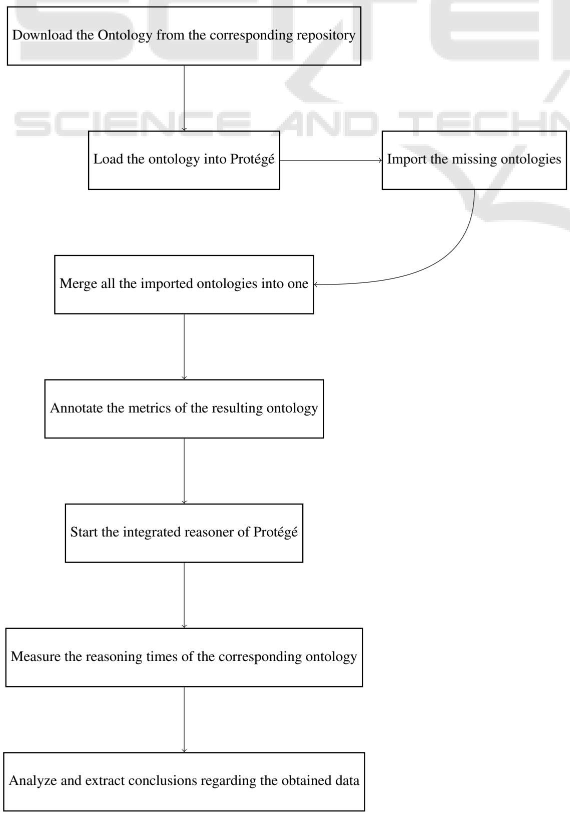

Figure 1: Process Model.

5 TECHNICAL RESULTS

As the figures and tables show, there is a trend between the ontologies OEMA and SEPA, as OEMA

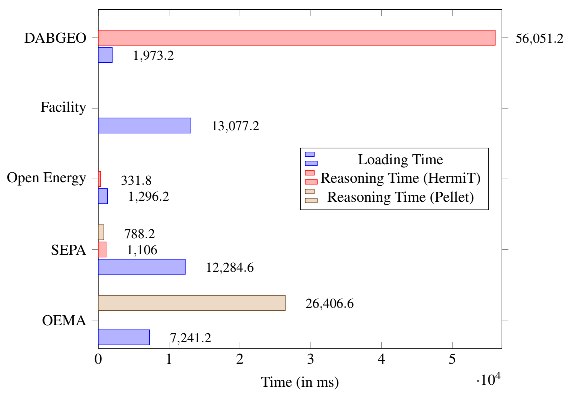

Figure 2: Performance comparison of ontologies.

appears to be the one with the highest count of Axioms and Classes, while SEPA is the one with the lowest number of those. Nevertheless, there is no reason to believe that these numbers actually affect performance in any way as, particularly, SEPA appears as the one with the highest loading time. The only two metrics that are higher for SEPA in comparison with OEMA are the Individual Count and the Annotation Property Count. Interestingly enough, the Open Energy Ontology has a higher Individual Count than SEPA (actually, the highest of them all), but at the same time, the Open Energy Ontology has the lowest loading time of all the ontologies. Therefore, if we were to link the high loading time of SEPA to anything, it, necessarily, would be linked to the Annotation Property Count, where SEPA has the highest of all the ontologies.

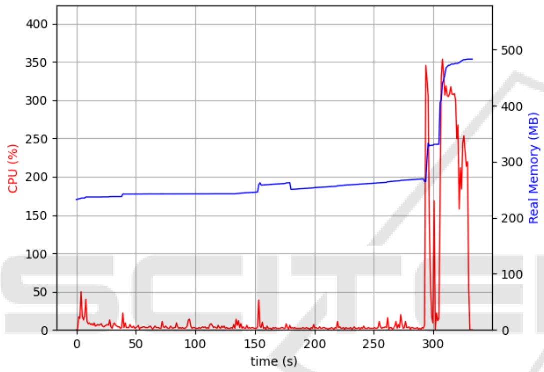

Figure 3: OEMA Performance.

When looking to the reasoning time while using HermiT we found that DABGEO has the highest time by a wide margin, while the Open Energy Ontology has the lowest. When comparing the metrics of ontologies we discover that DABGEO has a higher count on all categories except for Individual Count and Annotation Property Count. We can assume that having a higher value in most of the metrics affects the performance of DABGEO within the reasoner. The fact that aside these two ontologies only SEPA is able to reason with HermiT sheds some light into the Annotation Property Count issue that we pointed out for SEPA and its high loading time. It comes to show that, despite taking longer to load, its performance with respect to the reasoner is way better than that of DABGEO. We could conclude that having a high Annotation Property Count damages the performance while loading the ontology, but not as much while reasoning with it.

In regards to the reasoning time using Pellet we found that OEMA has the highest reasoning time while SEPA has the lowest. This comes in accordance

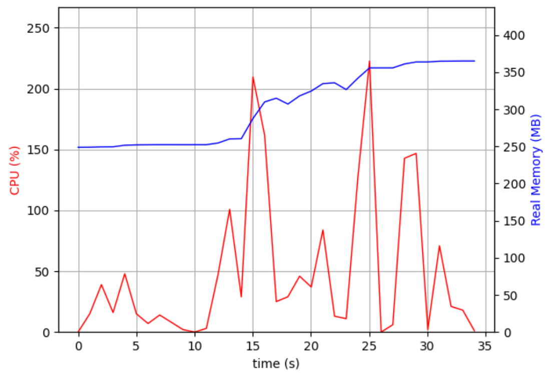

Figure 4: SEPA's Ontology Performance.

to the data that we have regarding the metrics of the characteristic of each ontology: The biggest ontology takes longer to reason and the smallest takes the less to reason (as it would seem intuitively before the analysis). This points out to the possible conclusion that the size of the ontology actually matters when setting up an ontology in a time-constrained situation. This is even more important if we take into account that the difference in time is an order of magnitude 33 times larger.

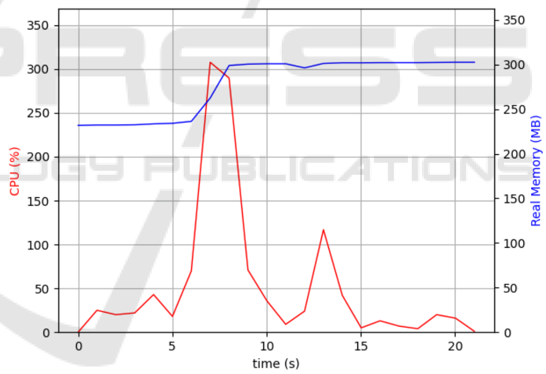

Figure 5: Open Energy Ontology Performance.

Finally, when taking a look at the memory and CPU usage metrics of each ontology, we found out that OEMA appears as the more demanding ontology. Nevertheless, we are not able to take out any strong conclusions as there were issues when trying to plot the OEMA performance. With that in mind, if we leave OEMA aside, we have found that the highest memory and CPU consumption is attributed to DABGEO. This might be enough to point out that a higher reasoning time, could potentially lead to a higher resource cost. Let us remember that DABGEO has the highest reasoning time of any ontology on any reasoner. Therefore, when dealing with a resource-constrained platform, we need to take into account the reasoning time so less resources are required.

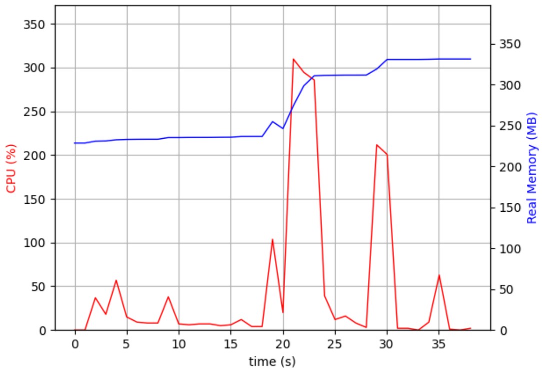

Figure 6: Facility Ontology Performance.

On the other hand, the less resource-consuming ontology is the Open Energy Ontology. This might come across as unexpected, as the ontology only metrics that are to be highlighted are the Data Property Count, it has none, and the reasoning time. The only conclusion that we could draw is that, as we pointed above, the reasoning time is linked directly to the resource usage.

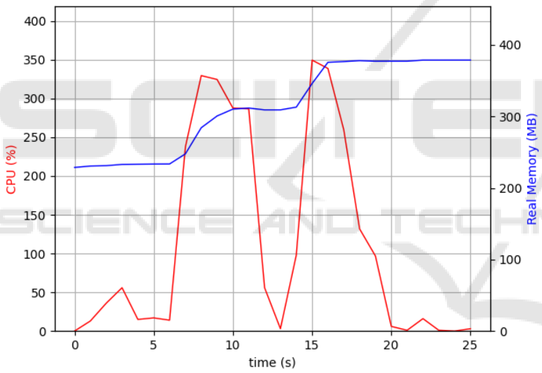

Figure 7: DABGEO Performance.

6 CONCLUSIONS

In this paper we have shown the state of the art regarding semantic web reasoning in the domain of SGs. After finding the most representative ontologies of the domain, we have analyzed those that are available and established a comparison between them, trying to point out possible bottlenecks and points of improvement. We have found that a higher loading time seems to be linked to a higher reasoning time. In the same way, a high reasoning time seems to be tied to a higher resource consumption. These conclusions are specially important in the domain because of their intended implementation in resource-constrained platforms such as smart meters.

About the different ontologies analyzed in the paper, we can point out that the most resource consuming and higher metrics in general is OEMA, while in the other side of the spectrum we find Open Energy Ontology as the less resource-consuming ontology, and SEPA as the ontology with the lowest metrics overall. Despite that, regarding loading times, SEPA is the one with the highest and Open Energy Ontology the one with the lowest time. The highest time when reasoning is that of DABGEO, while the lowest is the one of the Open Energy Ontology.

Furthermore, it is worth noting that, despite an almost overflowing amount of references on the semantic web technologies in the domain of the SGs, most of these technologies are not readily available: There are many broken URLs, ontologies that are no longer available, outdated platforms. It is even more evident when, after finding the few available ontologies, these will not work properly with some staples of the semantic web reasoning such as Protégé.

At this point, there are many possible lines on which to expand the work already done. We intend to provide a solid common platform, based on the Jena[2] framework, to extend the comparison beyond the readily available tools. We also want to provide approaches to improve the loading and reasoning times as well as the resource load of the available ontologies. Finally, it is our intention to also provide a comparison of the performance of the ontologies and reasoning methods in a real-world environment such as a resource-constrained device.

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[2] https://jena.apache.org/index.html

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