Towards Cognitive Cities in the Energy Domain

Javier Cuenca, Felix Larrinaga, Luka Eciolaza and Edward Curry

Abstract Current cities address efficiency challenges for optimizing the use of limited resources. City sustainability and resilience must also be improved through new learning and cognitive technologies that change citizen behavioural patterns and react to disruptive changes. These technologies will allow the evolution of current cities towards the so called "Cognitive Cities". This chapter highlights the importance of Semantic Web and semantic ontologies as a foundation for learning and cognitive systems. Energy is one of the city domains where learning and cognitive systems are needed. This chapter reviews Information and Communication Technologies (ICT)-based energy management solutions developed to improve city energy efficiency, sustainability and resilience. The review focuses on learning and cognitive solutions that improve energy sustainability and resilience through Semantic Web technologies. In addition, these solutions are evaluated from level of acceptance and use of semantics perspectives. The evaluation highlights that the Cognitive City approach is in the early stages in the energy domain and demonstrates the need for a standard energy ontology.

Key words: Cognitive Cities, Energy domain, Semantic Web, Semantic ontology, Energy sustainability, Energy resilience.

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1 Introduction

Cities are complex socio-technical systems that are on the edge of chaos. The amount of different actors and domains involved in the normal performance of a city, together with the challenge of responding to exponentially growing demands (energy, water, transportation, etc.) with limited resources, need sophisticated solutions that go beyond existing technological developments and innovations. Cities represent an ecosystem where the relationships between its different parts give rise to collective behaviours (Caragliu et al, 2011; Batty et al, 2012). In such a scenario, any uncertainty may produce rapidly escalating and compounding errors in the prediction of the system's future behaviour. Different actors are constantly changing their inner properties to better fit in the current environment, thus the analysis of the relations and interactions between them represents a non-trivial challenge that needs global/inter-sectorial solutions.

In this sense, we fully agree with the view in Finger and Portmann (2016), that "*urban problems cannot be reduced only to efficiency problems*" addressed by smart cities. In the scenario where technology, institutions and organizations co-evolve, the need of learning and cognitive technologies in order to address sustainability and resilience challenges are clear. The constant dynamic interplay between order and disorder need creative systems solutions. Cognitive Cities will address the current urban challenges of efficiency, sustainability and resilience. Efficiency refers to optimizing the use of limited resources; sustainability is about increasing humans' ecology awareness, while resilience implies the successful adaptation to changes. As defined by Finger and Portmann (2016), "*cognitive cities build on learning cities, which in turn build on smart cities*".

In order to improve cities sustainability and resilience, future cognitive solutions for cities must make data available to different city actors and must detect and react to external shocks (i.e., economic crisis, epidemics, heat waves, water shortages, etc.). Another key feature of cognitive systems is human involvement. Human-machine interactions are needed as human-machine collaboration allows reacting to disruptive situations (Finger and Portmann, 2016). The Semantic Web (Berners-Lee et al, 2001) enables all these capabilities. Semantic Web provides tools for relating and making inferences from large amounts of data from different domains. Semantic Web also provides standardized machine-readable vocabularies for data exchange and common vocabularies for human-machine interaction. Hence, we argue that Semantic Web must be the base of future cities' cognitive solutions.

In this chapter, we will focus on the situation of the energy domain within cities. Cities account for around 70% of global energy consumption and over 70% of energy-related carbon emissions (Field et al, 2014). The integration of renewable energy sources (RESs) as distributed generation is an attractive solution to deal with the dependency on fossil fuels, the constant increment of the energy consumption and the poor energy quality supplied by a conservative and aged power network. This distributed/decentralized solution represents an enhanced complexity for the management of city energy systems. Meeting the requirement for enhanced outcomes in terms of quality of life on the one hand and greater resilience (successful adaptation to fast and slow moving shocks and stressors) on the other, needs greater sophistication of governance (Moyser and Uffer, 2016). While the advancement in technology has been scaled up to support cities (e.g., sensor embedded energy grids), there is still very limited demonstration of integrated information communication systems across city departments and between stakeholders. City energy management is a potential niche of application of smart, learning and cognitive systems. The purpose is to improve the current grid in terms of efficiency, sustainability and resilience to create a future Smart Grid (Fang et al, 2012).

This chapter provides a review and an evaluation on developed Information and Communication Technologies (ICT)-based solutions for improving cities energy management within recent research projects and initiatives. In the review, solutions are classified by the energy aspect (efficiency, sustainability, or resilience) on which they impact. The greatest part of the review focuses on semantic models for representing energy data and ontology-based learning and cognitive systems for improving energy sustainability and resilience. These solutions are evaluated from two perspectives: level of acceptance and use of semantics. The first perspective expresses the level of acceptance of reviewed solutions from the research and market perspectives. The second perspective identifies how the use of Semantic Web can be improved in order to accelerate the adoption of energy management cognitive solutions in future cities. Finally, the chapter enumerates short and long-term steps for achieving mass market deployment of ICT solutions towards Cognitive Cities in the energy domain.

The structure of the chapter is as follows: Section 2 explains the future Cognitive Cities vision and required layers. Section 3 highlights Semantic Web as the base for future cities' learning and cognitive solutions. Section 4 introduces the Cognitive Cities energy scope and provides a literature review about developed ICT-based solutions within this scope. Section 5 provides an evaluation of energy management ICT-solutions. Finally, in Section 6 conclusions and the future work in cities energy management solutions are presented.

2 Cognitive Cities Overview

Smart Cities integrate ICT in order to improve efficiency, addressing environmental, economic and social issues. Within the Smart Cities approach, ICT gather and analyse urban infrastructures data, such as energy, traffic, public safety or water. The purpose is to optimize these infrastructures, making possible an efficient use of usually limited resources and easing or simplifying life for citizens. On top of that, cities have to address sustainability and resilience challenges. These challenges can not only be tackled with technical solutions, but also human involvement and the ability to deal with disruptive changes (Finger and Portmann, 2016). Thus, city actors must change their working habits, social relations and consumption patterns in order to improve cities economic, social and ecological sustainability. Both citizens and organizations should be provided with access to urban data analysis results so that they can learn from this information. The knowledge obtained in this stage will be used to change the city actors' behaviour. This stage is known as *Learning Cities*. City resilience requires taking a step further as technologies and actors must collaborate in order to withstand disruptive changes and external shocks (i.e., economic crisis, water/energy shortages, transport breakdowns, etc.); this requires what is known as *Cognitive Cities*.

Efficiency can be addressed by managing data generated by current ICT through smart systems that optimize the use of city infrastructures. However, sustainability and resilience require both technological improvements and human involvement (Finger and Portmann, 2016). New learning and cognitive systems that change citizens' behavioural patterns and adapt to disruptive changes must be developed. Learning and cognitive systems learn about different urban environments and make decisions to improve city sustainability and resilience. This requires a set of technologies for exchanging, analysing and making inferences about data from different domains (Finger and Portmann, 2016). We consider a data domain as a set of related concepts that belong to a specific area of interest (Hebeler et al, 2011). Urban data are stored at individual silos and heterogeneous devices. These factors are a very significant barrier for developing new learning and cognitive systems for cities. Semantic Web (Berners-Lee et al, 2001) is considered as the solution for overcoming interoperability problems that arise due to data heterogeneity and data silos. Semantic Web provides a set of technologies for representing, exchanging and processing data from different domains in a standardized way. Hence, semantic models for representing this data must be created as a base of Learning and Cognitive Cities.

To sum up, we can consider the paradigm of Cognitive Cities as the targeted evolution path of current cities, that will have to evolve in successive steps through Smart and Learning Cities (Finger and Portmann, 2016) (see Fig. 1).

Delivering a Cognitive City requires a set of technologies that conform to the so called *Cognitive Cities' technology stack* (Finger and Portmann, 2016). This stack is made up by four layers as shown in Fig. 2. Each layer is built above the previous layer and adds new technologies. All these technologies together conform *cognitive systems*.

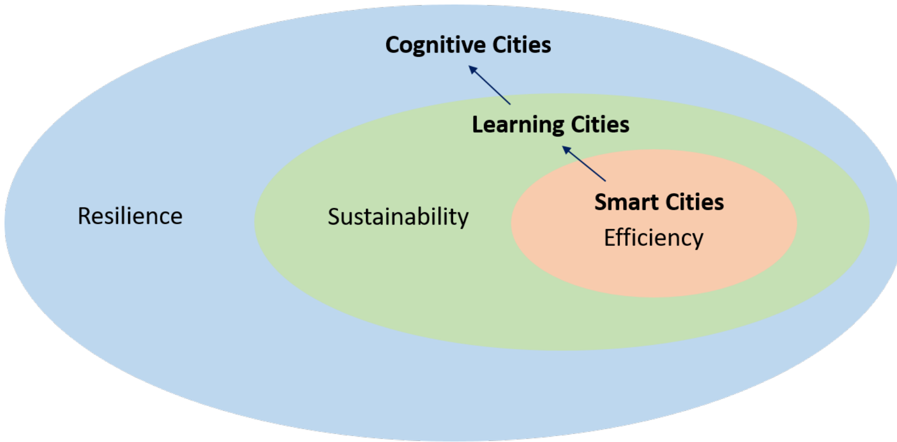

Fig. 1 Cities evolution towards Cognitive Cities

- **ICT infrastructures layer:** this layer includes ICT-based systems that gather and exchange data from urban infrastructures using sensors and communication technologies.
- **Data layer:** this layer adds data representation standards and optimization techniques. Data representation standards are used to represent urban infrastructures data collected by the ICT infrastructure layer. Optimization techniques are used for city resources optimization purposes. Hence, standards and optimization techniques along with ICT-based systems form smart systems.
- **Data analysis and display layer:** this layer adds tools for urban infrastructure data exchange and analysis (i.e., Big Data (Cavanillas et al, 2016)). It also adds intuitive and user-centered display and social media tools for human-machine interaction. All these tools together conform *learning systems*. These systems are oriented to assist different actors on changing their behavioural patterns.
- **Dynamic layer:** this layer adds dynamic systems that detect real-time environmental changes. These systems react to environmental changes in collaboration with humans. This collaboration is enabled by new soft computing methods (i.e., natural language processing, pattern recognition algorithms, etc.) that provide a human-computer automatic interaction.

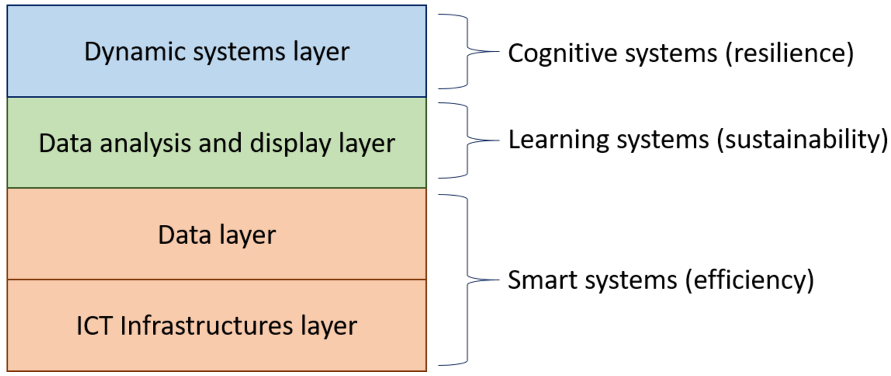

Fig. 2 Cognitive Cities' technology stack

3 Semantic Web Role in Cognitive Cities

Both learning and cognitive systems must learn from different urban environments in order to assist actors in changing their behavioural patterns and adapting to disruptive changes in collaboration with humans. In other words, learning and cognitive systems are required to exchange, extract knowledge and make decisions about different domains for large volumes of data collected at high rates and in most cases in real time (Finger and Portmann, 2016). ICT-based systems have traditionally operated in functional silos and rely on heterogeneous technologies. These factors hinder the integration among devices (Moyser and Uffer, 2016) and human-machine interaction. Hence, in order to facilitate knowledge extraction and decision making from urban environment data, learning and cognitive systems must address the following interoperability (Serrano et al, 2015) challenges:

1. There is the need of creating a model or representation of urban data from different domains (Finger and Portmann, 2016).
2. Urban data must be represented and exchanged in a standardized and machine-readable way (Moyser and Uffer, 2016).

Semantic Web provides the necessary technologies for addressing these challenges. Semantic Web was defined in 2001 by Berners-Lee et al (2001) as "*an extension of the current web in which information is given well-defined meaning, better enabling computers and people to work in cooperation*." It adds metadata to the information available on the Web, creating vocabularies that describe additional information such as the content, meaning and data relationships. This information should be meaningful and manageable by both humans and computers.

Formal representations of the Semantic Web vocabularies are called ontologies. Ontologies represent web data as a set of standard classes and objects and relations between them (Berners-Lee et al, 2001). Additionally, ontologies can include inference rules when describing and relating web data, improving intelligent agents' performance when deductions over web data. Semantic Web encompasses a set of standards and technologies used to describe and relate data on the Web. The set of best practices of using these standards and technologies is called Linked Data. Bizer et al (2009) define Linked Data as "*data published on the Web in such a way that it is machine-readable, its meaning is explicitly defined, it is linked to other external data sets, and can in turn be linked to and from external data sets*". Hence, the Linked Data approach allows the connection of data from different domains and data stored in different systems in order to create a global knowledge base. Future cities' learning and cognitive capabilities will benefit from Semantic Web technologies in several ways:

- Semantic Web provides standardized and machine-readable data representation, exchange and processing mechanisms for systems that rely on heterogeneous data formats as well as data access interfaces and protocols.
- As data relationships are specified, data can be linked across different domains, eliminating data silos.
- By means of using the Semantic Web humans can communicate with machines using a common vocabulary, a common set of rules and even natural language.
- Thanks to semantics, machines are capable of inferring knowledge from explicit facts.

All these benefits together result in a better performance of intelligent agents and data analysis applications used for knowledge extraction and decision making within cities learning and cognitive systems. Taking this into account, the Semantic Web should be considered as an intermediate layer between the data layer and the data analysis and display layer (see Fig. 3). It provides a bridge between Smart systems and Learning systems, and by extension, cognitive systems. Semantic representation of different urban domains is a key requisite in the Smart Cities evolution process towards Cognitive Cities.

4 Cognitive Cities in the Energy Domain

Energy is one of city domains where ICT based solutions are being applied. The aim is to improve energy resources management and to integrate buildings and infrastructures (i.e., smart homes, public buildings, organization facilities, etc.) in the future Smart Grid. According to Fang et al (2012), the

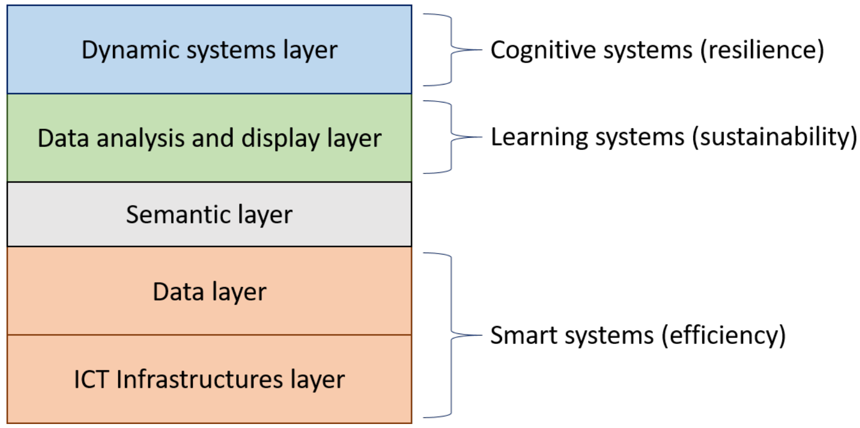

Fig. 3 Cognitive Cities' technology stack (II)

"*Smart grid is envisioned to meet the 21st century energy requirements in a sophisticated manner with real time approach by integrating ICT to the existing power grid with monitoring and control purposes*". ICT will enable a two-way communications network between energy stakeholders, namely customers, utilities and energy operators (i.e., markets, energy service providers, Distribution System Operators (DSOs), etc.) (Locke and Gallagher, 2010). This network is called Advanced Metering Infrastructure (AMI). AMIs will improve demand side management and the knowledge that energy stakeholders have about energy usage.

Furthermore, by adding ICT to the current energy grid, a scalable and reliable integration of distributed energy resources (DERs) like RESs (i.e., photovoltaics), energy storage systems (ESSs) (i.e., batteries) and Electric Vehicles (EVs) can be performed. This will lead to new scenarios such as microgrids or Virtual Power Plants (VPPs). Both microgrids and VPPs are networks that will replace conventional power plants and will improve current grid efficiency and flexibility by integrating distributed generation, ESSs and loads (Unamuno and Barrena, 2015; Fang et al, 2012). Both AMIs and DERs integration require future Smart Grid applications such as, home and building energy management systems (HEMs), energy Demand Response (DR) applications, power outage management systems (OMSs), advanced power distribution management, asset management, etc. (Gungor et al, 2013). The current state of the art of these applications in different Smart Grid scenarios (Smart Homes, microgrids, etc.) is discussed in later sections.

Through these applications, Smart Grid aims to improve current grid efficiency, sustainability and resilience. Regarding efficiency, the objective is to optimize the use of both non-renewable and renewable energy sources through smart systems. Regarding sustainability, the objective is to provide citizens (i.e., energy consumers, energy auditors, building designers, etc.) a complete assessment of the energy performance of different city infrastructures (i.e., homes, public buildings, organizations), and suggest actions to change their energy management behavioural patterns for economic, social and ecological purposes through learning systems. Regarding resilience, the objective is the use of cognitive systems in collaboration with humans in order to prevent, avoid and react to power outages caused by power peak periods or natural disasters. In order to develop learning and cognitive systems within cities energy scope, energy data from different domains must be collected, exchanged, processed and analysed efficiently in real time (Rusitschka and Curry, 2016). According to Corrado et al (2015), energy data can be classified into the following categories:

- **Energy performance data:** it includes energy quantities (i.e., energy consumption, renewable energy production, etc.) energy performance indicators (i.e., CO2 emissions, energy cost, etc.) and energy systems data (i.e., RESs, appliances, Heating, ventilation and air conditioning (HVAC) systems, etc.).
- **Energy-related and contextual data:** it includes buildings and infrastructures technical data (i.e., building construction, building geometry, etc.), geographical data (i.e., latitude and longitude, height above sea level, etc.), weather data (i.e., temperature, humidity, precipitation, etc.), environmental data (air pollutants of the urban area such as nitrogen dioxide, ozone, etc.,) socio-economic data (i.e., population income and poverty, economic activity, etc.), demographic data (i.e., population density, age, learning and education, etc.), legislative constraints (current or new infrastructures performance requirements) and land and buildings registry data (i.e., land value, land tenure, etc.).

As can be seen, these data are relevant to many domains (weather, building technical data, etc.) and are stored in heterogeneous and non-integrated devices. The ICT-based systems interoperability issues explained above are also present in the Smart Grid scope. Thus, a semantic representation of energy data is needed as an enabler/bridge to progress from Smart Grids towards learning and cognitive systems.

The following subsections provide a literature review on existing ICT-based solutions for improving cities energy efficiency, sustainability and resilience within energy management research projects and initiatives. These solutions are classified by the *Cognitive Cities' technology stack* layers on which they impact.

4.1 ICT Infrastructure Layer and Data Layer

In this layer, ICT solutions are used for data metering, data transmission, data storage and energy optimization.

Smart Grid energy data metering is performed by AMI systems, Automatic Meter Reading (AMR) systems and smart meters. These systems are used to create a two-way communication network between energy consumers and utilities. Other type of sensors and sensors networks (i.e., Phasor measurement units, Wireless Sensor Networks (WSNs)) are also used to measure and monitor Smart Grid mechanical state (Fang et al, 2012).

The energy data transmission is performed by a set of communication technologies. These technologies can be wireless or wired (Gungor et al, 2011). The main Smart Grid wireless communication technologies are the following: ZigBee, 6LoWPAN, Z-wave, Wireless Mesh and Cellular Network Communication (i.e., 3G, WiMAX) (Mahmood et al, 2015). The main Smart Grid wired communication technologies are the following: Power Line Communication (PLC) and Digital Subscriber Lines (DSL). Transmitted data are represented under a set of Smart Grid standards. These standards can be classified according to Smart Grid application where there are used (Gungor et al, 2011): Revenue metering information model (i.e., ANSI C12.19, M-Bus, etc.), building automation (i.e., BACnet), substation automation (i.e., IEC 61850), powerline networking (i.e., HomePlug, PRIME, etc.), home energy measurement and control (i.e., U-SNAP, IEEE P1901, Application-Level Energy Management Systems (i.e., IEC 61970, OpenADR), Inter-control and Inter-operability Center Communications (i.e., IEEE P2030, ANSI C12.22), Cyber Security (i.e., IEC 62351) and Electric Vehicles (i.e., SAE J2293, SAE 2836).

Smart Grid energy data can be stored in different repositories: Relational Database Management Systems (RDBMS) (i.e., Oracle, MySQL, Microsoft SQL Server, etc.), NoSQL databases (i.e., Cassandra, HBase, MongoDB, etc.) and cloud-based distributed file systems (i.e., Google File Systems, Hadoop Distributed file system, Disco Distributed File System, etc.).

Energy optimisation at this level is concerned with finding optimal solutions for contexts where maximization and minimization techniques can be applied. An example of an optimization problem can be to minimize as much as household energy consumption while maintaining a specific comfort temperature. When applying optimization techniques, the optimization problem is represented mathematically through an objective function. This function is subject to a set of constraints represented as equations or inequalities (Snyman, 2005). In the previous example, the objective function would be to *minimize the energy consumption while the constraint would be maintaining a specific comfort temperature*.

In the energy scope, optimization techniques have been applied with different ecological, environmental, and operational objectives: maximize the revenue, minimize carbon emissions, maximize reliability, maximize energy production, minimize operation cost, minimize investment cost, etc. Optimization techniques allow optimizing some of these aspects at a time and taking into account several constraints (a minimum energy production, a maximum operation cost, etc.). (Iqbal et al, 2014). Iqbal et al (2014) and Fathima and Palanisamy (2015) provide insights about the application of different optimization techniques for improving Smart Grid energy efficiency. These optimization techniques are classified into two main categories: Linear optimization techniques or Linear Programming (LP) and nonlinear optimization techniques or Nonlinear Programming (NLP). LP is applied when the optimization problem is represented as a linear function and constraints (linear optimization problems). NLP is applied when the optimization problem is represented as a non-linear function and constraints (nonlinear optimization problems) (Luenberger et al, 1984). Linear and nonlinear optimization techniques applied for improving energy efficiency include: Simplex algorithm (Luenberger et al, 1984), Nelder-Mead algorithm (Singer and Nelder, 2009), meta-heuristics (Glover and Kochenberger, 2006) and Artificial Neural Networks (ANNs) (Fathima and Palanisamy, 2015). Apart from previous algorithms, there are also sets of optimization tools that have been used for improving Smart Grid energy efficiency. The most commonly used tools are HOMER (Lambert et al, 2005), GAMS (Fathima and Palanisamy, 2015) and HYBRID2 (Baring-Gould et al, 1996).

4.2 *Semantic Layer*

The concern of this review in the semantic layer is to identify the different ontologies used to represent the energy domain. From the beginning of the current decade, Semantic Web technologies were applied for creating ontologies that represent energy data of different Smart Grid scenarios such as Smart Homes, buildings, organizations or microgrids. These ontologies are aimed to be the energy knowledge base for Smart Grid applications that are in the conceptual or design phases.

On the one hand, Kofler et al (2012) and Daniele et al (2016) present Smart Homes energy data representation models. Kofler et al (2012) present an ontology design created within the ThinkHome project[1]. The ontology represents, in a machine-readable way, home energy consumption, production and energy-related contextual data. The ontology is made up by several ontologies that represent different domains data:

- *Building ontology:* it represents building architecture data i.e., layout, spaces data, etc.
- *User information ontology:* it represents user comfort preferences, user schedules, etc.

[1] http://www.eui.eu/Projects/THINK/Home.aspx

- *Processes ontology:* it represents home system processes, user activities data, etc.
- *Exterior ontology:* it represents weather and climate conditions.
- *Energy and resource parameter ontology:* it represents home equipment or devices (i.e., home appliances, energy measurement sensors) data, home energy demand and supply data and energy providers and energy tariffs data.

Furthermore, the authors suggest how represented data can be used combined with a multi-agent system in order **to improve energy efficiency at future smart homes.** The proposed use cases are:

- Select energy providers depending on produced energy type or energy tariffs (i.e., consume only energy produced by RESs or select a provider which has an excess of energy and sells it cheaper).
- Disconnect unnecessary equipment according to occupancy or customer behaviour patterns (i.e., disconnect from the electricity grid entertainment equipment such as the TV when user is unlikely to return more to the living room).

Daniele et al (2016) present the ontology SAREF (Daniele et al, 2015) and its current version, SAREF4EE. The objective of the ontology SAREF4EE is **to improve interoperability among electrical appliances of different manufacturers** allowing them to be connected with customer energy management systems used for Smart Grid DR optimization strategies. The SAREF4EE ontology represents the following information: home appliances, sensors and actuators data (i.e., device manufacturer, device state, device function, energy flexibility, etc.), building spaces (i.e., rooms), home energy production and consumption data, associated costs, energy performance data time intervals and home weather conditions and home occupancy data.

On the other hand, Blomqvist et al (2014) and Andreas Fernbach and Kastner (2015) present building energy data representation models. Blomqvist et al (2014) publishes as published as Linked Data the data about energy efficiency improvements, energy saving recommendations and energy measures taken from previous energy audits are within DEFRAM and DEFRAM-2 projects[2]. The linked dataset published represents the following data: energy audits and measures of industrial organizations and recommendations for improving energy management given after previous audits. It also represents data about investment cost of applying such recommendations, achieved energy saves and additional information about the organization (i.e., organization location, organization facility size, etc.). The final purpose is to use the previous linked dataset as a knowledge base for future ICT-based solutions **to help organizations for saving energy based on energy audits performed over similar organizations, to facilitate researches**

[2] http://www.ida.liu.se/~evabl45/defram.en.shtml

and policy makers comparing and analysing data from different audits and to facilitate third parties' applications that use energy audits data.

Andreas Fernbach and Kastner (2015) present an ontology that describes building features and Building Automation Systems (BASs). BASs monitor and control automatically HVAC systems of indoor environments (Kastner et al, 2005). The ontology is presented as a first step of using Semantic Web technologies for the **automated integration of BASs developed by different manufacturers,** and represents the following information: static building information (i.e., architectural, geometrical, building topology, building physics properties, etc.) and building equipment technical information (HVAC systems as well as lighting applications). The ontology also represents BASs configuration data such as device (i.e., measurement equipment, HVAC systems controllers and actuators, etc.) locations, functionalities and datapoint descriptions.

The ontology OntoMG (Salameh et al, 2015) represents a microgrid energy data. A microgrid is a set of RESs, ESSs and loads that can operate autonomously or connected to the main grid. The ontology OntoMG is presented as the knowledge base of a microgrid energy management system that is being developed. The ontology encompasses renewable and non-renewable generators, storage equipment, electrically connected loads and their properties, which include mobility, economical, operational and ecological aspects. The purpose of this ontology is to be used by computational and optimization techniques aiming **to achieve different microgrid objectives (i.e., minimizing transmission losses, generating good power quality, minimization of green-house effect gases, etc.).**

Finally, Hippolyte et al (2016) and Gillani et al (2014) present energy data representation models for Smart Grid wider areas. Hippolyte et al (2016) provide a general approach of Semantic Web application for representing Smart Grid prosumers energy data within the MAS2TERING European project[3]. A prosumer is a Smart Grid stakeholder that consumes and produces energy. Specifically, the ontology MAS2TERING is aimed **to facilitate the representation the data of different Smart Grid domains and provide interoperability among different Smart Grid agents and stakeholders.** The MAS2TERING ontology links concepts of data representation standards used in different energy domains. These concepts are the following: home area networks (smart appliances, power profiles, renewable energy generation, smart meters and smart user interfaces), energy DR concepts (i.e., market context, dynamic pricing and event descriptions, etc.) and Smart Grid stakeholders' information and their roles and responsibilities within both the energy supply value chain and the flexibility value chain. The authors' final purpose is to use this ontology as a base for Smart Grid multi-agent systems for an energy market coordination process for improving energy flexibility among energy prosumers and DSOs.

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[3] http://www.mas2tering.eu/

Gillani et al (2014) present an ontology for representing energy data of prosumer oriented Smart Grids. The ontology is aimed to be complemented with an inductive reasoning layer. This layer is in the design phase and will contain applications for detecting the energy consumption patterns of consumer appliances, energy production patterns and energy producers' performance (i.e., efficiency, impact to the environment) patterns. The objective is **to improve Smart Grid DR and sustainability by predicting Smart Grid energy consumption and production.** The prosumer oriented Smart Grid ontology represents the following data: infrastructures data (type of operation, time and geographical location, and power critical premises), electrical appliances data (consumption and temporal data, power consumption rating and operational patterns), electrical generation systems data, power storage systems data (type, produced power, charge and discharge efficiency, etc.), weather report data, events (i.e., electrical appliance events, weather events, storage events and generator events, etc.), energy production and consumption services contractual information and connectivity relationships between producers and consumers.

4.3 Data Analysis and Display Layer

The review in this layer presents ICT solutions that go one step further enabling the construction of learning systems focused on improving Smart Grid sustainability. These systems use different data analysis techniques and display tools over semantically represented energy data models. Learning systems provide citizens a holistic view of infrastructures energy performance and suggest actions for changing their energy management behavioural patterns. With these systems home energy consumers and both public and private organizations will see their energy bills slashed. They also will be able to choose between a wide variety of energy vendors depending on their energy tariffs. Public and private organizations will also be benefited, as they will perform a more efficiency management of their energy consumption sources (i.e., facilities, business travel, etc.) with both economic and ecological purposes (Curry et al, 2012).

On the one hand, the solutions proposed by Curry et al (2012) Hu et al (2016), Niknam and Karshenas (2015) and Pont et al (2015) are oriented to assess citizens about urban infrastructures energy performance. Curry et al (2012) present an enterprise energy observatory system. The aim of this system is **to improve enterprise energy management at different levels from both economic and ecological perspectives.** The enterprise energy observatory system includes data analysis and display applications that provide an enterprise energy performance view at organizational, function and individual level:

- *Organizational level:* executives can view the real-time consumption of energy across all enterprises domains, IT, facilities, travel, etc.
- *Function level:* the system provides a fine-grained understanding of what business activities are responsible for IT energy usage, and can enable IT to bill appropriately.
- *Individual level:* it gives an employee real-time energy consumption data on their IT, Facilities, Travel, etc.

The system includes also internal applications (i.e., a Complex Event Processing (CEP) engine, data search and query engines, etc.) that ease the knowledge extraction of enterprise Linked Data by energy analysis applications. All system applications are underpinned by energy related data from different enterprise domains that have been published as Linked Data. . This data includes enterprise business entities (i.e., employees, products, customers, equipment, assets, buildings, rooms, etc.), direct electricity consumed by Office IT and Data centers, energy consumption measurement sensors and business information (i.e., enterprise Resource Planning (ERP), finance, facility management, human resources, asset management and code compliance, etc.).

Hu et al (2016) present a building Energy Performance Assessment (EPA) system developed within the SuperB project[4]. This system **shows the performance gap between building predicted and measured energy performance data.** The EPA system includes tools that measure, analyse and show building or particular zones energy performance data. The energy performance data are expressed as energy metrics that include Energy Use Intensity (EUI), energy cost, normalised atmospheric emissions, etc. These metrics are compared with building predicted energy performance data. A building energy performance simulation model makes these predictions. Data used by the EPA system analysis and display tools is represented under an ontology (Corry et al, 2015) that contains and links/fuses building data of different domains. Each domain is represented by an individual ontology:

- *IfcOWL ontology*: it includes building geometry data, material properties, as-built construction details and HVAC systems specifications.
- *SIMModel ontology*: it includes building performance simulation data.
- *SSN ontology*: it contains building sensors data (i.e., consumption metering sensors, temperature sensors).
- *Performance assessment ontology*: it contains building energy performance quantitative metrics needed to compare current with predicted energy performance.

Sensor measurements values and corresponding time intervals are stored in relational databases due to performance reasons and a mapper module is used to link previous ontologies with measurement and time values.

[4] http://cordis.europa.eu/project/rcn/187015_en.html

Niknam and Karshenas (2015) and Pont et al (2015) also present building EPA systems, but in this case these systems are focused on the design stage. The EPA system developed by (Niknam and Karshenas, 2015) **shows building designers the building energy performance corresponding to a building specific design.** The objective is to optimize the building design for a better energy performance. Specifically, a prototype of the EPA system was developed that predicts building heating cost based on its design and simulated environmental conditions data through a heating cost calculation algorithm. The EPA system is underpinned by four ontologies that represent the following data respectively: building properties (i.e., surface area, thickness, heat transfer coefficient, etc.), mechanical equipment specifications (i.e., capacity, type of fuel, and energy consumption, etc.), historical weather information of building geographic location and energy cost information based on the type of energy required for mechanical equipment.

Pont et al (2015) present a web decision support and optimization platform for building designers. The purpose of the web platform is to make buildings energy performance-oriented designs within the SEMERGY project[5]. This platform **shows building designers' suggestions about different building components alternatives according to user preferences and technical constraints for optimizing heating demand, environmental impact and investment cost.** These suggestions are made by a reasoning interface that makes inferences through building design and simulated environmental conditions data. These data are represented by an ontology that captures building geometry and material data, building equipment data, building materials data and historical and simulated weather data of building geographic location.

An integrated platform[6] that shows energy related data about cities to different actors is presented within the SEMANCO project[7]. The aim of this platform is to **provide a complete view of city energy performance in order to help different city actors** (i.e., energy policy makers, building designers, citizens, etc.) **to make informed decisions for reducing cities carbon emissions.** The platform includes visualization tools that display energy data and analysis tools that perform different analysis tasks (i.e., make energy performance predictions, classify buildings according to their consumption or carbon emissions, etc.) over cities energy data at different scales (building, neighbourhood, municipality or region). The integrated platform is underpinned by an ontology that captures energy efficiency concepts of urban areas (Corrado et al, 2015). The objective of this ontology is to provide models for urban energy systems to be able **to assess the energy performance of an urban area.** The ontology represents the following information: building energy consumption data, associated energy performance indicators (i.e., en-

[5] http://www.semergy.net/

[6] http://www.semanco-project.eu/index_htm_files/SEMANCO_D5.4_20131028.pdf

[7] http://semanco-project.eu/

ergy savings, energy costs, etc.) and timestamps, consumed energy sources, building features, building equipment features and services. The ontology also represents external factors such as weather conditions, building geographical location, demographic, environmental and socio-economic data.

The solutions presented by Burel et al (2016), Fensel et al (2014), Sicilia et al (2015), Yuce and Rezgui (2015) and Stavropoulos et al (2016), apart from offering energy assessment, are oriented **to offer citizens suggestions for improving urban infrastructures energy performance.** Burel et al (2016) present the EnergyUse collaborative web platform. The purpose of this platform is **to raise home end-user climate change awareness.** The platform collects home appliances energy consumption data from smart plugs and allows end users viewing and comparing the actual energy consumption of various appliances. Users can also share energy consumption values with other users and create open discussions about energy saving tips. Discussions are described and classified by tags defined by users. These tags correspond to energy appliances and topics related with the discussed energy saving tips.The EnergyUse platform includes tools that analyse and extract concepts from discussions created. These tools link extracted concepts with appliance and environmental terms included in external semantic repositories in order to create new tags and descriptions for discussions. The purpose of these additional tags and descriptions is to improve user navigation experience among discussions. Finally, the EnergyUse platform also exports appliance consumption and community generated energy tips as linked data to be used by third parties, such as other users or websites. The EnergyUse platform is supported by the ontology EnergyUse, which represents the following information: user profiles of users that use the platform, home appliances and HVAC systems data, home sensors and actuators data, home appliances energy consumption measures and energy tips discussion data.

Fensel et al (2014) present a home energy management platform developed within SESAME and SESAME-S[8] projects. The aim of this platform is **to help home users making better decisions in order to reduce their energy consumption.** The platform allows users defining energy saving policies and it generates its own energy saving policies through an ontology reasoning engine. Specifically, this ontology reasoning engine generates schedules and rules for turning on and off home devices based on tariff plans and desired indoor environmental conditions. Energy saving policies are presented through different user interfaces aimed to stimulate and facilitate users to use energy more responsibly. Home energy data are represented under the following ontologies (Fensel et al, 2013):

- *SESAME Automation Ontology:* it represents general concepts (e.g. resident data, location data) and home automation and energy domain data (i.e., device, configuration).

[8] http://sesame-s.ftw.at.

- *SESAME Meter Data Ontology:* it represents metering equipment data.
- *SESAME Pricing Ontology:* it represents available energy types and tariffs data.

Sicilia et al (2015) present a web-based Decision Support System (DSS) prototype developed within the framework of the OPTIMUS project[9]. The objective of the DSS is **to support users and organizations decision-making process for improving buildings energy efficiency.** The DSS uses machine learning algorithms to predict building energy performance and environmental conditions. Predictions take into account seven different energy data domains. These domains are represented and linked by the ontology OPTIMUS: building/equipment features data, weather forecasting data, energy and environmental values measured by sensors, building occupants notion of comfort, building occupants comfort patterns, energy prices data and renewable energy production data.

Yuce and Rezgui (2015) present a building energy management system that **assists users to save energy** developed within the KnoholEM Project[10]. This system is underpinned by a semantic knowledge database which contains building information and devices metering data. These data are used by an ANN that learns building consumption patterns, and a genetic algorithm (GA)-based optimization tool that generates optimized energy saving rules taking into account learned energy consumption patterns and different objectives (including comfort) and constraints. These rules are presented to facility managers as energy saving suggestions through a graphical user interface (GUI).

Stavropoulos et al (2016) present a building energy management system that combines energy assessment, energy advice and building automation. This system **monitors building energy performance and shows this information to allow users taking actions to increment energy savings.** Intelligent agents within the system also devise short-term and long-term energy saving policies that are automatically generated and enforced. Furthermore, the system is also designed to receive energy providers' instructions in future Smart Grids. This system is supported by the ontology BOnSAI (Stavropoulos et al, 2012), which represents the following energy data: building appliances and sensor/actuators data, building structure data, user location and energy and environmental condition measures.

4.4 Dynamic Layer

Finally, the ICT solutions identified in the review and related to the dynamic layer concentrate on improving Smart Grid resilience. Specifically, these so-

[9] http://www.optimus-smartcity.eu/

[10] http://www.knoholem.eu/page.jsp?id=2

lutions are focused on improving Smart Grid DR by detecting disruptive situations (i.e., power peak periods) over semantically modelled data. These systems react to disruptive situations in collaboration with humans.

Zhou et al (2012b) present a CEP engine (Zhou et al, 2012c) developed within the Los Angeles Smart Grid Demonstration Project[11]. The CEP engine purpose is **to enable dynamic DR applications that detect power peak situations and perform actions to improve DR**. The CEP engine is supported by a Smart Grid semantic information model (Zhou et al, 2012a) that is made up of different ontologies in order to represent different energy data domains:

- *Electrical equipment ontology:* it contains electrical equipment features and power consumption details collected from smart meters.
- *Organizations ontology:* it contains different organizations information, people involved in the organization as well, as their roles within the organization.
- *Infrastructures ontology:* : it contains environment concepts including transportation networks, buildings and so on, besides the Power Grid infrastructure.
- *Weather ontology:* it contains weather information.
- *Spatial ontology:* it contains building equipment or infrastructure spatial location information.
- *Temporal ontology:* it contains power consumption time data, scheduling information of infrastructure, electrical equipment data and individual people data.

Shi et al (2014) present a **microgrid energy management and control system that combines both sustainability and resilience actions is presented.** Hence, this system impacts on both data analysis and display and dynamic layers. On the one hand, the microgrid energy management system includes a Human Machine Interface (HMI) for microgrid monitoring and control. Apart from that, the system includes a microgrid scheduling algorithm and a microgrid DR optimization algorithm. The DR optimization algorithm adapts microgrid demand to real-time energy prices. The energy-scheduling algorithm schedules microgrid DERs and loads with both economic and ecological optimization purposes. Both algorithms use semantically represented data that includes: microgrid devices information (i.e., DERs, smart meters, smart appliances, EVs charging station, PVs and batteries, etc.), weather forecast information, Automated Demand Response (ADR) signals received from utility and energy market information.

Finally, (Zhang et al, 2016) present an energy management platform for VPPs. VPPs are groups of DERs and controllable loads that act as a single energy stakeholder within the Smart Grid. Within VPPs energy prosumers sell

11 https://www.smartgrid.gov/project/los_angeles_department_water_and_power_smart_grid_regional_demonstration.html

their surplus energy during energy curtailment or energy consumption peak load periods. The energy management platform adapts VPPs energy production and consumption to peak loads that occur both either in the VPP or the Smart Grid. The energy management platform includes algorithms that **select the best energy storage systems scheduling strategy among energy prosumers for facing energy peak load periods in Smart Grid and VPP in a distributed manner.** The selection of the strategy is based on energy generation sources and loads, respective energy generation and consumption forecasting performed by machine learning algorithms (i.e., Dynamic Bayesian Networks). All information used by the platform to manage VPPs energy DR is represented by an ontology. This information includes: buildings and facilities data, buildings spatial-use patterns, energy production, consumption and storage systems (i.e., renewable energy generation units and controllable loads) data, ICT based sensors and actuators data. The ontology also represents weather conditions of areas where systems are deployed, events (i.e., prosumer energy consumption or generation changes, weather condition changes and loads operation changes, etc.) and services offered by prosumers for improving VPP or Smart Grid DR such as energy supply or energy curtailment.

5 Evaluation

This section presents the evaluation of the literature survey in relation to semantics and the advances towards Cognitive Cities for the energy domain. These solutions are evaluated from two perspectives: level of acceptance and use of semantics.

5.1 Level of Acceptance

This perspective expresses the level of acceptance of reviewed solutions from the research and market perspectives. According to Curry et al (2016), city ICT-based solutions development are divided into two cycles. These solutions includes solutions developed for the energy domain. The first cycle corresponds to a research phase that includes experimental design and pilot deployment. The second cycle is focused on citywide deployments of ICT solutions to drive mass market adoption. Curry et al (2016) also point out that Smart City ICT based solutions have reached this second cycle, as current Smart City projects are focused on key innovation characteristics (i.e., relative advantage, compatibility, cost efficiency, risk level, etc.) for mass market adoption.

This cyclic approach can be also extended to learning and cognitive systems for the energy domain. Regarding Learning Cities, there is a lot of literature about ontology-based learning systems focused on changing citizens' energy management behavioural patterns. All these systems are limited to pilot demonstrators that in some cases were implemented in specific Smart Grid scenarios. For example, the EPA system developed by Hu et al (2016) has been implemented in a sports centre in order to measure its energy operation against previously predicted performance by a BEPS model; the enterprise energy observatory system has been implemented within the Irish Insight Centre for Data Analytics (formerly DERI: Digital Enterprise Research Institute); the DSS developed by Sicilia et al (2015) has been validated in three different buildings in order to predict their energy performance; the building energy management system developed by Yuce and Rezgui (2015) has been tested in a care home; and the integrated platform developed within SEMANCO project has been tested in three cities for analysing energy performance data. The next step is to evaluate the impact, compatibility, cost efficiency, feasibility and benefits of these systems in citywide deployments (Curry et al, 2016). After evaluating these aspects, learning systems shall be marketed to consumers. There is less literature about cognitive systems focused on improving Smart Grid resilience. These solutions are still in the experimental design (Zhou et al, 2012b) or pilot demonstrator implementation phases: the microgrid energy management and control system developed by Shi et al (2014) has been implemented in a pilot microgrid and VPP energy management platform developed by Zhang et al (2016) has been tested in a pilot VPP.

In conclusion, we can say that the scientific community investigating ICT-based solutions is evolving towards Cognitive Cities and is in the early stages in the energy domain. From the market point of view, only Smart City initiatives are tackling ICT-based solutions innovation aspects (see Fig. 4).

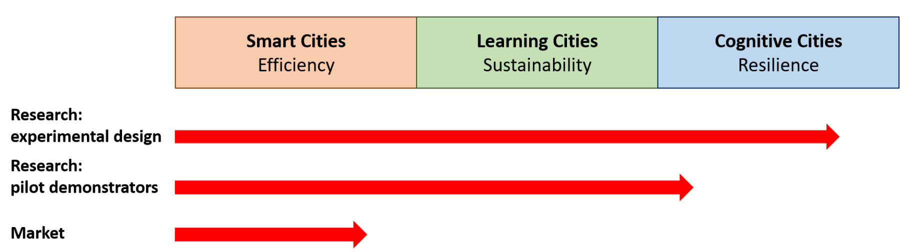

Fig. 4 Evaluation of Cognitive Cities' energy scope ICT solutions progress

5.2 Use of Semantics

The second perspective identifies how the use of Semantic Web can be improved in order to accelerate the adoption of energy management cognitive solutions in future cities. As said in Sections 4.2–4.4, the ontologies reviewed in this chapter are/will be the knowledge base of a wide variety of Smart Grid energy management applications. All these applications can be grouped into five high-level categories. Each category corresponds to a Smart Grid scenario on which the Smart Grid application impacts: Smart Home energy management, building/district/city energy management, organization energy management, microgrid energy management and Smart Grid DR management.

Within previous categories, each Smart Grid application belongs to a specific scope of application. For example, within Smart Home energy management, there are applications that are focused on energy assessment and device control, energy saving collaborative advice, etc. In many cases, represented energy data domains are repeated among developed ontologies. This is particularly true when ontologies are/will be the knowledge base of applications that belong to the same category. For example, most of ontologies developed within the reviewed Smart Grid applications represent the building technical equipment data. Table 1 illustrates which energy data domains have been included in ontologies according to Smart Grid application category and scope of application.

Table 1 shows that *Basic energy related concepts* are represented in most ontologies. External factors such as climate and geographical data are also present in most ontologies. We cannot say the same about other external factors such as environmental, demographic and socio-economic data. Specific equipment (Non-renewable energy sources, RESs and ESSs) data are mainly represented at microgrid and Smart Grid DR energy management applications ontologies. There are some exceptions as building and Smart Home energy management applications use RESs and ESSs data. Almost all Smart Grid stakeholders are represented in DR management applications ontologies. Other applications only use specific stakeholder data depending on their scope of application. Smart Grid DR data is limited to Smart Grid DR management applications. Energy performance data (apart from energy consumption and production) is present at building and Smart Grid DR management applications. Organization related data is limited to organization energy management applications with the exception of Smart Grid DR management applications. Some Smart Home energy management applications include concepts such as home processes data in their ontologies. Finally, energy saving tips and recommendations are included in Smart Home and buildings energy saving applications. Table 1 also shows that applications which ontologies belong to a specific category introduce new concepts in their ontologies. For example, all ontologies of Smart Home energy management applications represent home user data. Other concepts, on the

Energy data domains	Application categories and scopes of application	Smart Home energy management			Building/district/city energy management			Organization energy management		Microgrid energy management	Smart Grid DR energy management	
		Energy assessment and device control (Kofler et al, 2012)	Energy saving collaborative advice (Burel et al, 2016)	Energy saving advice and control (Fensel et al, 2014)	BASs integration (Andreas Fernbach and Kastner, 2015)	Building EPA (Hu et al, 2016) (Niknam and Karshenas, 2015) (Pont et al, 2015) (Corrado et al, 2015)	Energy saving advice (Sicilia et al, 2015) (Yuce and Rezgui, 2015) (Stavropoulos et al, 2016)	Energy saving advice (Blomqvist et al, 2014)	Energy assessment (Curry et al, 2012)	Microgrid multi-objective energy optimization (Salameh et al, 2015) (Shi et al, 2014)	Smart Grid energy market coordination process (Hippolyte et al, 2016) (Gillani et al, 2014) (Zhou et al, 2012b) (Daniele et al, 2016)	VPP energy market coordination (Zhang et al, 2016)
Basic energy related concepts	Building/infrastructure technical data	X	X	X	X	X	X	X	X	-	X	X
	Energy consumption systems data	X	X	X	X	X	X	X	X	X	X	X
	Energy production/ consumption data	X	X	X	X	X	X	X	X	X	X	X
	Sensors/actuators data	X	X	X	X	X	X	-	X	X	X	X
Specific equipment data	RESs data	X	-	-	-	-	X	-	-	X	X	X
	ESSs data	-	-	-	-	-	-	-	-	X	X	X
	BASs devices data	-	-	-	X	-	-	-	-	-	-	-
External factors	Weather/climate data	X	X	X	X	X	X	-	-	X	X	X
	Geographical data	X	X	X	X	X	X	X	X	X	X	X
	Environmental data	-	-	-	-	X	X	-	-	-	-	-
	Demographic and socio-economic data	-	-	-	-	X	-	-	-	-	-	-
Smart Grid users/ stakeholders data	Home user data	X	X	X	-	-	-	-	-	-	-	-
	Building occupants data	-	-	-	-	-	X	-	-	-	X	-
	Employees data	-	-	-	-	-	-	-	X	-	X	-
	Energy suppliers/utilities data	X	-	X	-	X	X	-	-	X	X	X
	DSOs data	-	-	-	-	-	-	-	-	-	X	-
Smart Grid DR data	DR operations	-	-	-	-	-	-	-	-	X	X	-
	Events data	-	-	-	-	-	-	-	-	-	X	X
	Services offered by prosumers	-	-	-	-	-	-	-	-	-	-	X
Energy performance data	Energy Key Performance Indicators (KPIs) data	-	-	-	-	X	-	-	-	-	X	-
	Economical, operational and ecological objectives	-	-	-	-	-	-	-	-	-	-	X
	Building energy performance simulation data	-	-	-	-	X	-	-	-	-	-	-
Organization-related data	Organization facilities data	-	-	-	-	-	-	X	X	-	X	-
	Organization assets data	-	-	-	-	-		-	X	-	X	-
	Business processes data	-	-	-	-	-	-	-	X	-	-	-
	Investment cost of energy saving plans	-	-	-	-	-	-	X	-	-	-	-
	Energy audits data	-	-	-	-	-	-	X	-	-	-	-
Other concepts	Home processes data	X	-	-	-	-	-	-	-	-	-	-
	Energy saving tips and recommendations data	-	X	-	-	-	X	-	-	-	-	-

Table 1 Represented energy data domains depending on Smart Grid application category and scope of application

other hand, are only included in applications that belong to a specific scope of application. For example, only the energy saving collaborative advice application includes home energy tips data in its ontology.

A common data representation model is one of Smart Grid key challenges that can be addressed by Semantic Web technologies (Wagner et al, 2010). The energy data domains repetition among reviewed ontologies evidences a convergence towards a standard energy ontology. One single ontology can be used in a wide variety of Smart Grid scenarios and energy management applications with minimal changes. A standard energy ontology should include at first Basic energy related concepts enumerated in Table 1. Other energy domains that can be present in more than one Smart Grid scenarios should be also included. These energy domains are: RESs and ESSs data, external factors (i.e., weather/climate data, environmental data, etc.), Smart Grid users/stakeholders (i.e., home users, organizations, building occupants, etc.) data, Smart Grid DR operations data, energy Key Performance Indicators (KPIs) and energy saving tips and recommendations data. Then, applications that belong to a specific scope of application (i.e., home energy collaborative advice) can add application specific concepts (i.e., energy tips discussions) to the standard energy ontology. Looking further ahead, as cognitive energy management applications evolve and settle in cities, a nearly fully standard energy ontology can be developed. There will be no need to add new data as new energy management applications arise.

A standard energy ontology would also help to represent energy domains in a common manner. Energy data domains are represented with different levels of detail among reviewed ontologies. This is particularly true for *Basic energy related concepts*. Table 2 shows the level of detail some of reviewed energy ontologies represent *Basic energy related concepts*.

When considering energy consumption systems data, ThinkHome, EnergyUse and ProSGV3 ontologies are candidates to represent this domain. However, one of these ontologies may be not enough to represent the whole energy consumption systems domain. One ontology may include energy systems data that other ontology does not. For example, the EnergyUse ontology represents heating systems while BOnSAI ontology does not. Fig. 5 shows which concepts include each ontology regarding energy consumption systems domain. ThinkHome, EnergyUse and ProSGV3 are the ontologies that include more concepts. However, each ontology (except BOnSAI) includes its own concepts. All these concepts should be merged in a standard ontology. In addition, different terms are used to represent the same energy data.

[12] https://www.auto.tuwien.ac.at/downloads/thinkhome/ontology/

[13] http://www.ida.liu.se/projects/semtech/schemas/energy/2013/09/efficiency.owl

[14] http://ontology.tno.nl/saref4ee/

[15] http://lpis.csd.auth.gr/ontologies/bonsai/BOnSAI.owl

Ontology / Energy domains	ThinkHome ontology[12]	DEFRAM project ontology[13]	SAREF4EE ontology[14]	BOnSAI ontology[15]	EnergyUse ontology[16]	ProSGV3 ontology[17]
Building/ infrastructure technical data	H	-	L	M	H	H
Energy consumption systems data	H	-	M	L	H	H
Energy production/ consumption data	H	M	H	H	H	H
Sensors/ actuators data	H	-	M	M	-	M

Table 2 Basic energy related concepts representation level of detail (H=High/M=Medium/L=Low)

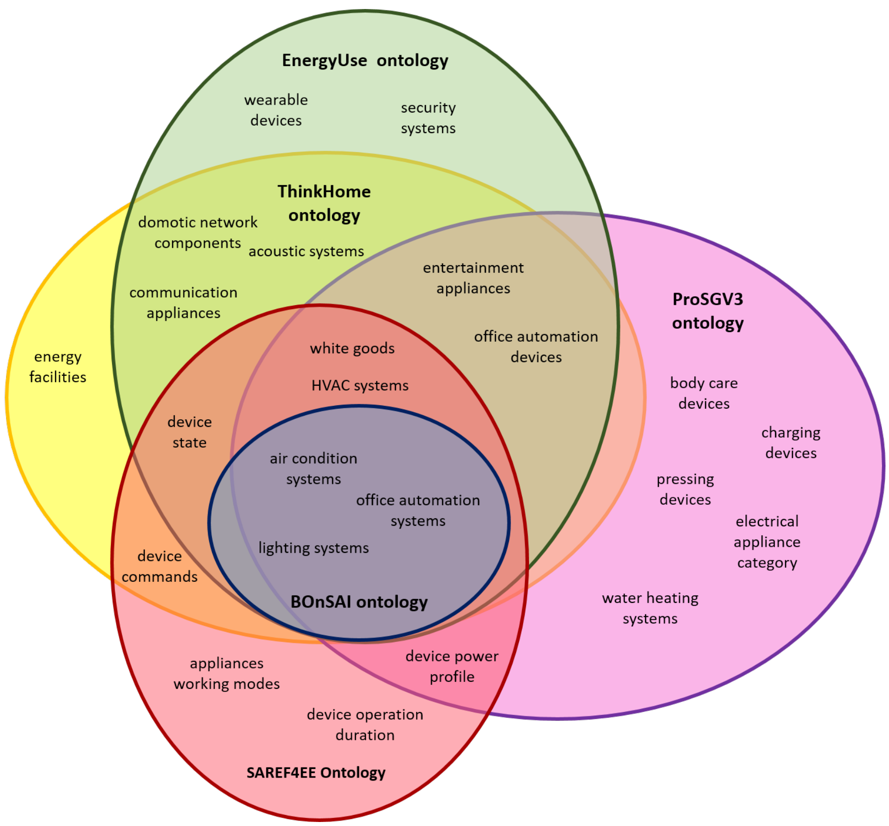

Fig. 5 Energy consumption systems data representation

This term and domain representation diversity, called *semantic heterogeneity*, leads to an interoperability problem that hinders the full adoption of these ontologies in real scenarios (Maree and Belkhatir, 2015). Hence, there is the need of creating a unified ontology that represents all energy domains providing a common terminology. This ontology could be a standard knowledge base of energy management solutions in any Smart Grid scenario or even energy management solutions applied in various scenarios at the same time, i.e.,, organizations that include microgrids. Moreover, a unified ontology would reduce energy management application developers' effort when creating energy ontologies and to be more focused on application implementation.

Apart from energy data ontologies standardization, Smart Grid applications should include more energy concepts that they do. Energy recommendations are only included in energy saving applications. These recommendations should be also oriented to avoid undesired situations within Smart Grid applications focused on improving grid resilience. Energy performance indicators should also be included at organizational level. Finally, in Smart Grid DR applications more stakeholders should be included; i.e., Energy Services Companies (ESCOs), Balance Responsible Parties (BRPs), etc.

6 Conclusions and Future Work

The evolution of current cities will take them to the so-called Smart Cities. Smart Cities are aimed to optimize urban infrastructures through smart systems, making possible an efficient use of the usually limited resources and a high quality of life for citizens. Apart from efficiency, cities address sustainability and resilience challenges. These aspects are addressed by learning and cognitive systems that change the citizens' behavioural patterns and adapt to disruptive changes in collaboration with humans. Cities that include learning and cognitive systems are called "Cognitive Cities". We can consider Cognitive Cities as the targeted evolution path of current cities.

Both learning and cognitive systems must learn from different urban environments in order to assist actors in changing their behavioural patterns and adapting to external shocks (i.e., economic crisis, epidemics, heat waves, water shortages, etc.) in collaboration with humans. The Semantic Web enables these capabilities. Semantic Web provides tools for relating and making inferences from large amounts of data from different domains. Semantic Web also provides standardized machine-readable vocabularies for data exchange and common vocabularies for human-machine interaction. Hence,

[16] http://eelst.cs.unibo.it/apps/LODE/source?url=http://socsem.open.ac.uk/ontologies/eu

[17] http://data-satin.telecom-st-etienne.fr/ontologies/smartgrids/proSGV3/ProSG.html

in this chapter we argue that Semantic Web must be the base of future cities' cognitive solutions.

City energy management is a potential niche of application of smart, learning and cognitive systems. The purpose is to improve current grid efficiency, sustainability and resilience within the future Smart Grid. In recent years, Information and Communication Technologies (ICT)-based systems applied in city energy management have evolved considerably. In this chapter, a review and evaluation of existing ICT-based solutions for improving city energy management is presented. The main part of the review is focused on sustainability and resilience aspects.

This chapter provides a review and an evaluation on developed ICT-based solutions for improving cities energy management within recent research projects and initiatives. In the review, solutions are classified by the energy aspect (efficiency, sustainability, or resilience) on which they impact. The greatest part of the review focuses on semantic models for representing energy data and ontology-based learning and cognitive systems for improving energy sustainability and resilience. Current energy efficiency solutions correspond to smart systems. These systems include energy data metering infrastructure, energy data exchange communication technologies and standards and energy data storage repositories. Then, optimization techniques are applied over energy data in order to optimize city energy management from ecological, economic and operational perspectives. Learning systems are focused on improving city energy sustainability. These systems use different data analysis techniques and user-centered display tools over energy data. Learning systems provide citizens a holistic view of infrastructures energy performance and to suggest actions for changing their energy management behavioural patterns. Energy resilience solutions correspond to cognitive systems. These systems are focused on improving Smart Grid Demand Response (DR) by detecting disruptive situations (i.e., power peak periods) and interacting with energy users.

The chapter also evaluates these solutions from two perspectives: level of acceptance and use of semantics. The first perspective expresses the level of acceptance of reviewed solutions from the research and market perspectives. According to this evaluation, development of smart systems in the energy domain is in the advanced stages as Smart Cities projects are now focusing on mass market adoption. Although there is a wide literature about learning systems in the energy domain, these systems are limited to pilot demonstrators. In some cases, the pilot demonstrators were implemented in specific Smart Grid scenarios (i.e., Smart Homes, microgrids, etc.). Before marketing energy management learning systems, they must be evaluated in citywide deployments. There is less literature about cognitive systems in the energy domain. These solutions are still in the experimental design or pilot demonstrator implementation phases.

The second perspective identifies how the use of Semantic Web can be improved in order to accelerate the adoption of energy management cognitive solutions in future cities. Semantic Web technologies application in cities energy scope within recent research initiatives has supported a breakthrough in Smart Grid energy data representation, exchange and processing. The developed ontologies within these initiatives link and represent energy performance data and energy-related data from different domains (i.e., energy performance, weather/climate data, building technical data, etc.). The representation of these energy domains depends on the Smart Grid scenario where ontologies are applied. This, along with terminological differences when representing energy data, evidences the need for a standard energy ontology. This ontology will be used in a wide variety of Smart Grid energy management applications (i.e., Smart Home energy management, microgrid energy management, etc.). In addition, a standard energy ontology will allow representing different energy domains using a common terminology.

Taking into account previous evaluations, in order to reach mass market deployment of ICT-based solutions towards Cognitive cities in the energy domain, a number of steps are necessary:

- Semantic technologies adoption in the form of ontologies as support to upper layers.
- Deployment of pilot demonstrators based on the semantic layer and providing ICT-based solutions to deal with resilience.
- Thorough test of those demonstrators.
- Include technology capabilities in commercial devices.

This vision of the future has a short-term plan, a mid-term plan and a long-term plan. The previous first two points are framed in the short term while the third and the fourth steps are vision as actions for the mid-long term.

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