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An intelligent system for energy management in smart cities based on big data and ontology

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Abstract

Purpose – This research paper aims at proposing a framework based on semantic integration in Big Data for saving energy in smart cities. The presented approach highlights the potential opportunities offered by Big Data and ontologies to reduce energy consumption in smart cities.

Design/methodology/approach – This study provides an overview of semantics in Big Data and reviews various works that investigate energy saving in smart homes and cities. To reach this end, we propose an efficient architecture based on the cooperation between ontology, Big Data, and Multi-Agent Systems. Furthermore, the proposed approach shows the strength of these technologies to reduce energy consumption in smart cities.

Findings – Through this research, we seek to clarify and explain both the role of Multi-Agent System and ontology paradigms to improve systems interoperability. Indeed, it is useful to develop the proposed architecture based on Big Data. This study highlights the opportunities offered when they are combined together to provide a reliable system for saving energy in smart cities.

Practical implications – The significant advancement of contemporary applications (smart cities, social networks, health care, IoT, etc.) requires a vast emergence of Big Data and semantics technologies in these fields. The obtained results provide an improved vision of energy-saving and environmental protection while keeping the inhabitants' comfort.

Originality/value – This work is an efficient contribution that provides more comprehensive solutions to ontology integration in the Big Data environment. We have used all available data to reduce energy consumption, promote the change of inhabitant's behavior, offer the required comfort, and implement an effective long-term energy policy in a smart and sustainable environment.

Keywords Big data, Energy saving, Multi-agent system, Ontology, Semantics integration, Smart cities

Paper type Research paper

Introduction

The term Big Data has appeared with the tremendous growth of online activities and network technology over the past two decades. The constant growth of computational power has produced an overwhelming flow of data. Usually, digital data is generated continuously from millions of smart devices and applications, e.g. (social networks,

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Amazon, smart-phones, sensors, etc.). *Gartner* defines *Big Data* as *a large information resource, high-velocity, and/or high-quality that requires new forms of processing to improve decision-making, discovery, and the optimization process* (Eine *et al.*, 2017). Big Data importance is highly raised in many vital areas, such as smart cities, IoT, healthcare, air traffic management, etc.

For fulfilling the inevitable need for Big Data applications especially data storage processing, various technologies have been allowed to handle Big Data (such as Hadoop and MapReduce), which offer more reliability, flexibility, scalability, and performance in a reasonable time and cost. However, the lack of interoperability between heterogeneous resources engenders an inherent issue, which makes data sharing and knowledge reuse a difficult task in Big Data applications (Rani *et al.*, 2017). To overcome this challenge, it becomes imperative to endow Big Data with semantics and allow a standard view to ensuring efficient interoperability between applications (Chandrasekaran *et al.*, 1999). Moreover, data could be shared and exchanged between individuals, systems, and organizations without any particular effort (Eine *et al.*, 2017).

For validating the contribution, this study focuses on smart cities as a contemporary example. We propose a variety of intelligent solutions to deal with urban challenges in citizens' real-life. Reducing energy consumption is one of the most relevant fields, which cope with smart cities development and sustainability. It aims at allowing an efficient strategy to save energy and reduce bills (Ejaz *et al.*,2017). In this context, we propose an architecture of various technologies cooperating together to provide efficient energy optimization. Not only for individual buildings, but also for the entire city as well. The proposed architecture is based essentially on Smart Building Ontology (Onto-SB), which is a powerful tool to represent the domain knowledge and provides a structural framework for organizing smart building data (Degha *et al.*, 2019). Onto-SB enables the reasoning by formally representing domain knowledge. In addition, we use the Multi-Agent System (MAS) to offer a reliable role, which provides efficient cooperation and autonomy needed to manage the enormous data generated and exchanged between the different actors of the system (Ma *et al.*, 2019). The use of Big Data technologies offers a reliable mechanism for data storage and processing. Therefore, the proposed system succeeds in reducing energy consumption and ensuring inhabitants' comfort in the context of smart environmental sustainability.

The rest of the paper is organized as follows. Background of the study reviews a background on Big Data, semantic integration, and smart cities. In Related work, some relevant related works are presented. Proposed multi-layer architecture is devoted to the presentation of the architecture. Implication presents system implementation of energy consumption in smart cities. Experimental results, discuss the experimental results. Finally, we conclude and mention some future works.

Background of the study

This section aims to present the main aspects involved in this work and helps the reader to establish the study in the context of the research. In addition, it provides a brief overview summarizing the main research topics used, such as Big Data, semantics, and MAS.

Big Data and semantic integration

In literature, Big Data is defined as a massive volume of both structured and unstructured data that is very difficult to store and process by using traditional database and software techniques, and it is characterized by the 5Vs model (Manyika *et al.*, 2011).

Big Data has recognized three generations in their development, as mentioned in (Jeong and Ghani, 2014), Big Data 1.0 (1994–2004), Big Data 2.0 (2005–2014), and Big Data 3.0 (2015-. . .). NoSQL databases and the Apache Hadoop are considered as the appropriate tool for Big Data management, which ensures scalability and high availability (Mehta and Buch, 2015). The new Big Data requirements in terms of data mining are increasingly changed from traditional data warehousing and mining systems. The heterogeneous and unstructured data involve novel technologies to ensure efficient data processing and analysis. To allow hidden patterns and derive value, various methods are used, such as decision trees, neural networks, and SVM. On the other hand, Big Data associated with cloud computing offer promising opportunities by providing high availability and elasticity with a low cost, low running time, and enables the deployment of new applications (Merizig *et al.*, 2019). Moreover, it allows computing resources sharing, including processing, storage, networking, and analytical software (Yang *et al.*, 2017).

Semantics integration in Big Data opportunities and challenges

A colossal evolution in data sources deluges the web by a wide variety of data in several areas. The challenges faced in modeling and managing systems in these areas appear with the 5Vs of Big Data. However, database researchers were anxious about how to combine different heterogeneous data sources by providing a standard query interface. Indeed, semantics integration offers many promising opportunities and harnesses the power of semantic knowledge bases (Beneventano and Vincini, 2019). It reduces comparatively the sources heterogeneity, offers data consistency, and warrants reliable interoperability among various systems (Abbes and Gargouri, 2018). Furthermore, it can share and reuse knowledge by standardizing vocabulary, providing pertinent information in retrieval, and executing queries in natural language. Moreover, it decreases information traffic through the network by mapping the ontology into the data sources and offers perceptual inference (Calvanese, 2015). Ontologies can deploy semantics security risk management tools.

However, when the ontologies grow, relatively many deficits appear, particularly the ratio between the size of the created instances and the working memory allowed, which can affect the performance and flexibility of the system (running time). Hence, the Big Data ecosystem offers the required tools to improve ontology-based systems. Whereas HDFS, HBase, and MongoDB permit to store a large volume of ontology instances and provide a sufficient running space regardless of their size (Bhadani and Jothimani, 2016). Besides, MapReduce, Storm, and Spark can ensure a quick processing framework. The use of NoSQL database and query languages, such as SPARQL, allows supporting the complicated structures of ontologies linked to Big Data applications. Furthermore, it offers reliable and efficient data management (Sayah *et al.*, 2018).

Energy-saving in smart cities

Scientists predict that by 2050, around 70 per cent of the world's population will reside in cities (Dritsa and Biloria, 2018). Hence, cities need smart technologies to address sustainability issues associated with the development of energy consumption (Wang and Moriarty, 2019). A smart city is considered as an integrated ecosystem endowed by the use of powerful technologies, which addressed to make cities more sustainable. In fact, smart cities are considered as one of the most important Big Data applications and an active domain of IoT (Shafik *et al.*, 2020). Researchers have been focused, as a part of their works, on smart cities, on reducing energy consumption (Soomro *et al.*, 2019). Especially with the daily growth of device usage in people's daily lives (Butt *et al.*, 2019). Knowing that the global demand for energy is continually increasing, it becomes necessary to find new solutions that ensure energy saving and offer a comfortable life for residents without affecting the environmental protection (Samuel, 2016).

Related work

The exponential growth in data volume obliges researchers to deal seriously with the new Big Data aspects (5 Vs). Various advanced technologies were developed to permit the easy management, storage, and analysis of data share. Otherwise, semantics help to facilitate interoperability among various systems (Ma *et al.*, 2019). These issues mainly characterize the smart cities. In our research, the works presented hereafter inquire into the topics dealing with intelligent technologies using ontologies, Big Data, and MAS for energy saving in smart homes and smart cities in general, which aim at ensuring sustainability and improve citizen's life.

Among the works focused on energy savings, the following used MAS as a principal paradigm thanks to their features, such as communication, autonomy, fault-tolerance, and high flexibility. (Anvari-Moghaddam *et al.*, 2017) proposed a practical framework of an ontology-driven MAS based energy management system (EMS) for monitoring and optimal control of buildings and micro-grid systems. In the same theme, the works presented in (Kofinas *et al.*, 2018) and (Harmouch *et al.*, 2019) discussed a real-time operation of the energy management system, which is based on MAS and fast converging T-Cell algorithm. These works aim to decrease the grid working cost and maximize the real-time response in the network. (Soetedjo *et al.*, 2019) Presented a hardware testbed for testing the building energy management system (BEMS) using MAS. Indeed, they employ both a genetic algorithm to find the optimal power required and the fuzzy logic controller to monitor the building devices. Otherwise, (Lejdel and Kazar, 2018) proposed a MAS to distribute the different tasks between agents when each agent can perform genetic algorithms to optimize energy consumption in real-time. Then, they develop a GIS system, which allows detecting the position of buildings and all the pertaining data.

For the same purpose, but with different means, authors choose an ontological approach for energy consumption (Kott and Kott, 2019). (Delgoshaei *et al.*, 2018) described an approach to monitor energy consumptions in an intelligent building by combining machine-learning techniques with semantics modeling and reasoning. A supervised learning algorithm with K-means clustering is integrated to identify and predict electricity consumption in buildings. More relevant work is reported in (Degha *et al.*, 2019) to manage and improve energy efficiency in buildings by considering resident behavior and building environment. Their works based on context-awareness with the aim of reducing energy consumption and allowing inhabitants comfort. The integrated Ontology offers a generic model to allow logical inference and a data mining classification algorithm, which used to obtain the rules representing normal energy consumptions (Lork *et al.*, 2019). Otherwise, (Saba *et al.*, 2019), based on the same parameters, as well as the occupants' behavior and activities, used OWL and SWRL for knowledge presentation and intelligent reasoning to reduce energy consumption in smart cities.

Otherwise, Big Data technology is used to offer a reliable, scalable, distributed data management, and storage. (Bokolo *et al.*, 2019) developed a layered architecture providing energy data that aims to facilitate energy prosumption with a renewable source. APIs were used as data adapters for prosumers, stakeholders, and real-time streaming to manage energy within smart cities. Moreover, in (Grolinger *et al.*, 2016), the authors used local learning with Big Data and support vector regression SVR to increase training speed and performing energy prediction scenarios.

In addition to the previous technologies, IoT, and other techniques are used to reduce energy in smart cities (Wala *et al.*, 2020). Mahapatra *et al.* (2017) developed a unifying framework for IoT in smart homes to build a green and sustainable smart city. A neural network-based *Q*-learning algorithm is applied to both reducing the demand and conserving energy during peak period while minimizing the resident's inconvenience. Papastamatiou *et al.* (2017) presented a methodology combining energy efficiency and energy management using multi-disciplinary data sources. The proposed approach contains two pillars: assessment and optimization of energy consumption in smart cities for short- and long-term periods. Another perspective based on cloud and fog for energy management in the smart cities employing meta-heuristic algorithm was tested by (Butt *et al.*, 2019), a VMs implemented to perform fast running of user's applications. However, the different components of the proposed system participate in providing the relevant information used to make more intelligent decisions and to help the consumers to reduce energy consumption all over the smart cities.

In the works cited above, we have perceived certain shortcomings:

(1) Some approaches intend to manage a single building and provide an individual solution.

(2) In the case of a system crash, the buildings lose the global energy consumption control.

(3) There is an overall high cost when we apply some system modifications in the smart cities.

(4) Some frameworks do not permit data collecting for the entire population.

(5) In several cases, we cannot predict the global consumption if we cannot know the general behavior.

(6) Lack of long-term consumption policy to avoid increasing energy production and environmental pollution.

(7) The majority of approaches do not ensure scalability and cooperation among various system components.

To overcome these drawbacks, we propose a new architecture that aims at performing the previous systems by using building ontology that offers a structural framework (Ma *et al.*, 2019). We employ the Big Data tool to manage a large number of buildings with multiple systems and devices, as well as to manage real-time interactions over storing a considerable amount of data from all resources of houses. Besides, it can ensure scalability, availability, sustainability, and greatly reduce the cost of hardware installed in each home. Our system employs the multi-agent system, which allows a high level of autonomy and cooperation; it significantly reduces data flow through the network (Howell *et al.*, 2017).

Through the data analysis offered by Big Data tools and inference rules, the system can understand the collective inhabitants' behavior, knows the appliances and peak periods. It can predict consumption for long-term and endows decision-making by a real overview to establish a global policy for reducing energy consumption in smart cities (Bokolo *et al.*, 2019).

Proposed multi-layer architecture

The following section describes the global system architecture and explains the different layers composing the system, where each layer contains a set of technologies that satisfy the requirements of the system.

System objective

The main objective of the proposed architecture is to allow efficient control of appliances and devices in smart buildings (air conditioning, heating, lighting, TVs, doors, etc.) to offer an appropriate energy-saving strategy, to ensure inhabitants' comfort and to reduce energy consumption overall the smart cities.

General architecture of the system

In this section, we present a description of different layers constituting our approach and the relationships between them. The Intelligent System for Energy Management in Smart cities (ISEM-SC) grounded on a Multi-Layer architecture by using agents. Each layer has its agents with a particular behavior and specific roles. The knowledge is distributed between cognitive agents, and we choose a peer to peer as a communication mode. Moreover, ISEM-SC uses a smart building ontology (Degha *et al.*, 2019). Further layers are added to meet smart cities' requirements, such as the high number of buildings served (speed of management and storage space), real-time interaction, autonomy services, etc. It also ensures scalability and extensibility by using Big Data infrastructure, autonomy and interoperability with MAS paradigm, flexibility, and prediction by integrating ontology and employing inference rules (Lork *et al.*, 2019).

ISEM-SC architecture is divided into four essential layers; each layer contains several components or modules that play a complementary role for each other and exchange data with adjacent modules to achieve ISEM-SC objectives. (Table 1 shows layers and the associated technologies).

Big Data tools are deployed to process thousands of data gigabytes, which are generated from a variety of devices installed in over the smart cities (Raghavan *et al.*, 2020). These tools offer promising solutions to manage volume, velocity, and variety of energy data. Likewise, a layered approach provides robustness, capability, and scalability in data processing, and analysis. Moreover, it can manage both real-time and historical energy data. These thematic tool becomes a talent solution to support a distributed management of energy consumption in smart cities and ensure sustainability by the good energy governance policy (Bokolo *et al.*, 2019).

In what follows, we provide a description of each layer, and a brief explanation is also included on the reason for each technology selected and its role (as shown in Figure 1).

End-User layer: Collects the data generated by different sensors and gathered into a supervised agent of each building that sends them to the Kafka for subsequent redirection to be processed (Alvarez *et al.*, 2019). Furthermore, it receives commands that are returned by the service provider layer via Kafka to enable and change device states to modify the environmental condition and reduce energy consumption.

Service provider (Backend agent) layer: Once Kafka receives data, it redirects each one to a chosen agent for processing by agent service, which imports knowledge from the database (MongoDB) and integrates the building ontology (Jena) by the communication with the storage layer. At this stage, agent service invokes SWRL rules and applies treatments on

Table 1. Architecture's layers and the associated technologies

Layer	Tools and Technologies
End User layer	Agents, sensors, devices
Service provider (Backend agent) layer	Agents, kafka
Storage layer	MongDB, Jena, ontology, SWRL
Hadoop infrastructure layer	Hadoop HDFS, MapReduce

knowledge to update the database and send commands and advice for the end-user layer. At this layer, Kafka used as a distribution event-streaming platform for building real-time data pipelines and streaming applications. It works as a cluster on multiple servers that can span many data centers; it can manage trillions of events a day (Le Noac'H *et al.*, 2017). Their uses in our architecture consist of the creating real-time streaming data pipelines that reliably transfer data among layers (End-User and service provider layer) and convert them to data streams.

Storage layer: Based on MongoDB and Jena are used to save information and knowledge providing from environmental resources, such as smart house devices, weather data, etc. (Chodorow *et al.*, 2019). It holds all data history and provides a framework for knowledge construction from data transformation combined with onto-SB ontology. This layer includes the inference rules engine, which is used to offer efficient management of smart cities' energy data (Yang *et al.*, 2018).

Hadoop infrastructure layer: In the smart city architecture, Huge amounts of data are collected from millions of sensors deployed in each building (Jawhar *et al.*, 2018). In our model, the Hadoop layer communicates directly with the storage layer via MongoDB and Jena to perform fast data processing and provides effective management of storage, availability, performance, and scalability, etc. (by HDFS and MapReduce).

AUML sequence diagram of the proposed architecture

This diagram summarizes the sequence of events and the interactions between the different components used in the proposed system (see Figure 2).

System scheduling

The house represents a dynamic environment where appliances' parameters and states have a frequent change. Once the sensors detect any modification, they send data to the user agent who receives and collects all data coming from appliances, sensors, and the environment (Estrada *et al.*, 2019). Each agent invokes ontology and executes the rules to manage local devices and sends data (environment parameters, home circumstances, etc.) to the service agent for processing. A large number of tasks are sent from various home agents redirected via Kafka to end service agents. These save the new information of each smart building database and update the smart building ontology with the real-time state of the smart building. The service agents invoke the Reasoning Engine Module (REM) and generate decisions and new knowledge based on the current context. At this step, the agent checks the database and ontology stored at the storage layer (MongoDB and Jena) to provide adequate decisions for the current context. Hadoop tools

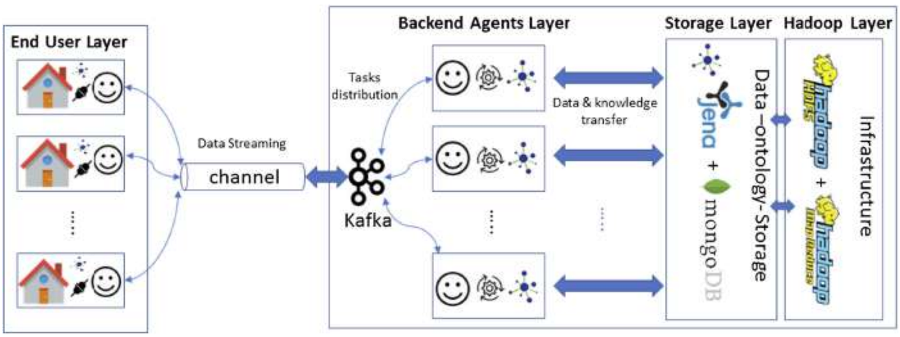


Figure 1.
Presents a multi-layer architecture for ISEM-SC

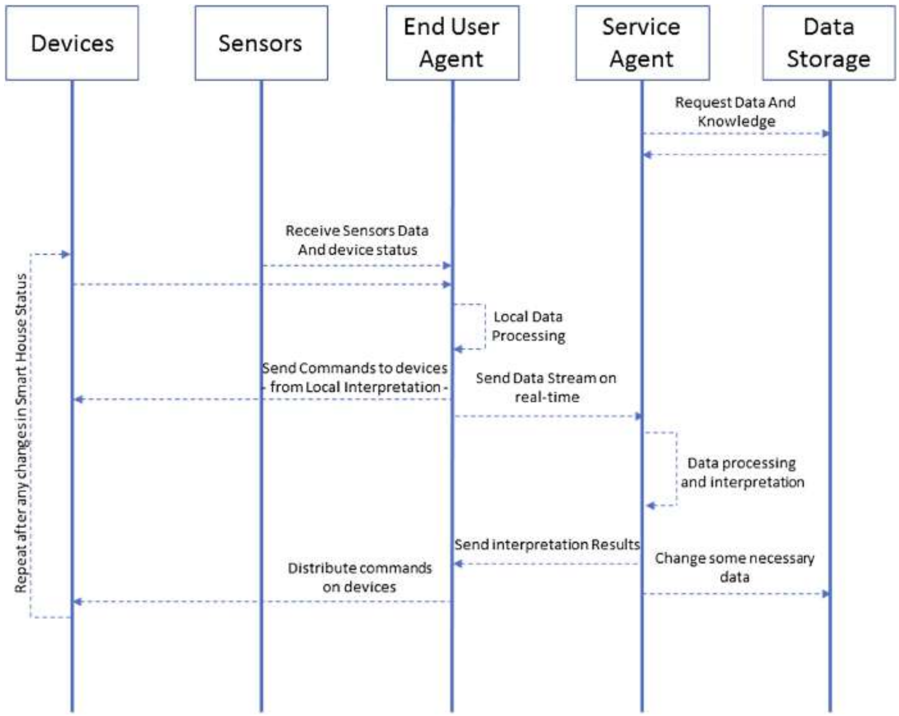


Figure 2.
AUML sequence diagram of ISEM-SC architecture

deployed to manage parallel processing and achieve storage via (HDFS MapReduce). Afterward, Service agents send commands and decisions to the end-user agents, which instruct actuators and appliances infrastructure to change their state to reduce energy consumption.

In addition, the service agents provide general control over the entire smart city by verifying the total energy demand and compared with the available energy produced by the energy supplier. Two cases appear: if the available energy is sufficient to meet the demand, there is no intervention. Otherwise, the service agent sends the decision to all household agents to reduce energy by modifying the operating threshold of the active appliances. In this case, the system contributes greatly to manage peak hours, ensures an equal policy for all consumers, and avoids energy crash. As a result, the proposed architecture achieves an important objective by reducing energy consumption, reducing consumers' bills, ensuring energy availability, and saving energy production without affecting the comfort of the inhabitants.

Smart building ontology Onto-SB

Figure 3 shows our ontological knowledge model called Onto-SB that is intended to serve ISEM-SC architecture. It is proposed to offer a structural framework of smart building data. It contains definitions of elementary concepts that are used and their relations. OWL used to represent concepts and relationships employed in the ontology. Onto-SB provides a structural framework for organizing smart building data. It contains a comprehensible definition of most basic concepts used in smart homes and their relations. Onto-SB includes

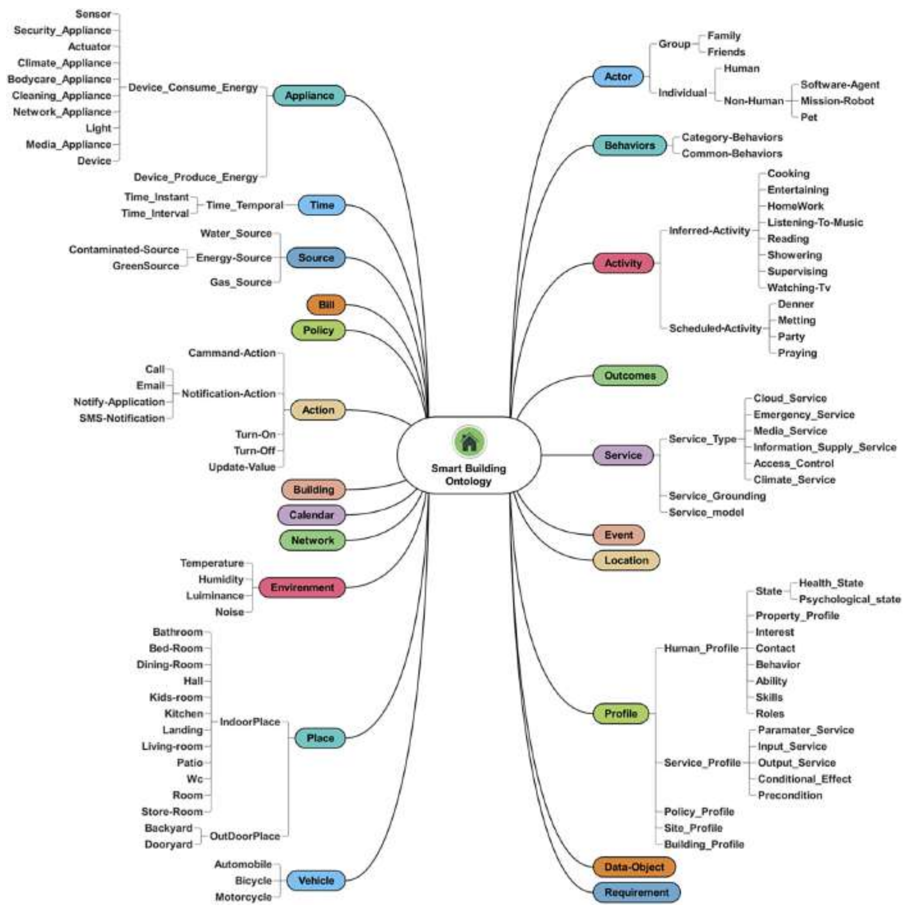


Figure 3. Presents the taxonomy used in Onto-SB concepts (Degha *et al.*, 2019)

more than 200 concepts, representing humans, devices, places, environment, services, etc. Also, SWRL is deployed to apply rules for different purposes where the structured relationships between concepts and the formal representation of domain knowledge enable reasoning (Degha *et al.*, 2019).

In the following sections, we briefly introduce some Onto-SB concepts with their description and some instances. For each attribute, we illustrate the relationship between the concepts (Table 2).

This section is devoted to present the environment of the buildings implicated in this study, and it emphasizes on the elements that are consuming energy (appliances and devices). As well, we highlight the parameters influencing the energy consumption (climate data, activities of inhabitants, etc.).

Reasoning Engine Module (REM)

This module that is integrated at the service layer is deployed to generate decisions by using the knowledge available on smart homes. It has a vital role in the implementation and efficiency of the proposed system. REM based on SWRL rules and represented as

Concept	Description	Instances	Attribute	Relationships
Actor	Represents building inhabitants	Mother, father, sister, child, grandfather, etc.	Occupant Name Occupant Role	Occupant Has Activity Occupant Has place
Building	Represents the home	Home ID, location, size, profile, etc.	Building Name Building Size	Building Has Action Building Has Place
Appliance	Represents home devices and appliances	Light, laptop, TV, iron, air conditioner, etc.	Appliance Name Appliance Power	Appliance Has Action Appliance Has Place
Place	Represents the different home places	Room, kitchen, WC, garage, Living room, etc.	Room Size Room Name	Place Has Appliance Place Has Event
Activity	Represents inhabitants' activities	Sleep, watch TV, cook, eat, wake up, enter, etc.	Behavior Name Activity Time	Activity Has Place Activity Has Time

Table 2.
Smart home concepts, instances, attributes, and relationships

conditional logic, where each rule uses a conjunction of predicate clauses to a list of executable actions. Through these rules, REM can detect energy waste and provide measures to save energy. The inferred decisions are used to update the knowledge base and send commands to the end-user agents, which act on the actuators installed at the smart building to reduce energy consumption. The following figure shows some rules, which are used to manage and monitor energy waste in the smart building (Figure 4 and Figure 5).

Environment presentation

Our study occurred at El Oued city in Algeria. El Oued is located in the southeast of Algeria around 600 km from the capital Algiers. It is characterized by latitude: 33°, 22′, 00″

Rule 1 switch off the lights in a place (room, garage, kitchen, etc.) in case of the external lighting (sun) is suitable (in our case, greater than 22 Linux):
Lighting-Sensor (?j) ˆ Appliance-Value (?j , ?val) ˆ swrlb : greaterThan (? val , ?22) ˆ Appliance-LocatedInPlace (?z , ? j) ˆ Lighting-appliance (h) ˆ Appliance-LocatedInPlace (?z , ? h) -- > Appliance_State (?h, "off") ˆTurn-of(?h)
Rule 2 stops lighting appliance fonction when it detects the absence of inhabitant in a given place:
Moving-Sensor (?x) ˆ Appliance-State (?x , ?stat) ˆ swrlb : equal (? Stat,? on) ˆ Appliance-Value (?x , ?val) ˆ Appliance-Value (?x , ? 0) ˆ Appliance-LocatedInPlace (?x , ? z) ˆ Appliance- LocatedInPlace (?l , ?val) ˆ Place (?z) ˆ Light (?l) ˆ Appliance-State (?l , ?stat2) ˆ swrlb : equal (? Stat2 , "on") -- > Appliance_State (?l, "off") ˆTurn-of(?l)
Rule 3 stops cooling appliance fonction when it detects the absence of inhabitant in the room:
Moving-Sensor (?x) ˆ Appliance-State (?x , ?stat) ˆ swrlb : equal (? Stat, ?on) ˆ Appliance-Value (?x , ?val) ˆ Appliance-Value (?x , ? 0) ˆ Appliance-LocatedInPlace (?x , ? z) ˆ Appliance- LocatedInPlace (?l , ?val) ˆ Place (?z) ˆ aircondition (?l) ˆ Appliance-State (?l , ?stat2) ˆ swrlb : equal (? Stat2 , "on") -- > Appliance_State (?l, "off") ˆTurn-of(?l)
Rule 4 used to stop cooling appliance (air condition) if the ambient temperature in the room reach 26 C :
Temperature-Sensor (?t) ˆ Appliance-Value (?t , ?val) ˆ swrlb : lessThan (? val , ?26) ˆ Appliance-LocatedInPlace (?z , ?t) ˆ Cooling-appliance (h) ˆ Appliance-LocatedInPlace (?z , ? h) -- > Appliance_State (?h, "off") ˆTurn-of(?h)
Rule 5 used to turn off the water pump if the user turns it on and leaves their place (in the bathroom, WC or kitchen):
Moving-Sensor (?x) ˆ Appliance-State (?y , ?stat) ˆ swrlb : equal (? Stat , ?on) ˆ Appliance-Value (?y , ?val) ˆ Appliance-Value (?y , ? 0) ˆ Appliance-LocatedInPlace (?y , ? v) ˆ Appliance- LocatedInPlace (?l , ?val) ˆ Place (?v) ˆ pump (?l) ˆ Appliance-State (?l , ?stat2) ˆ swrlb : equal (? Stat2 , "on") -- > Appliance_State (?l, "off") ˆTurn-of(?l)
Rule 6 turn off the air exchanger in the kitchen when the relative humidity (produced in cooking) less than 30 per cent, so the mother finish cooking:
Humidity-Sensor (?h) ˆ Appliance-Value (?h , ?val) ˆ swrlb : lessThan (? val , ?30) ˆ Appliance-LocatedInPlace (?z , ?h) ˆ Airexchanger-appliance (h) ˆ Appliance-LocatedInPlace (?z , ? h) -- > Appliance_State (?h, "off") ˆTurn-of(?h)
The ***Rule 7*** shut off every selected useless devices when bedtime comes (in our case 10:30) except the exempted appliances such as refrigerator, camera, clock, etc.:
Time-instant (?t) ˆ swrlb : equal (?t , "10:30 PM") ˆ applianceSleepMode (?x , ?m) ˆ swrlb : equal (?m , "on") ˆ -- > Appliance_State (?x, "off") ˆTurn-of(?x)

Figure 4.
SWRL rules used to manage the energy of appliances

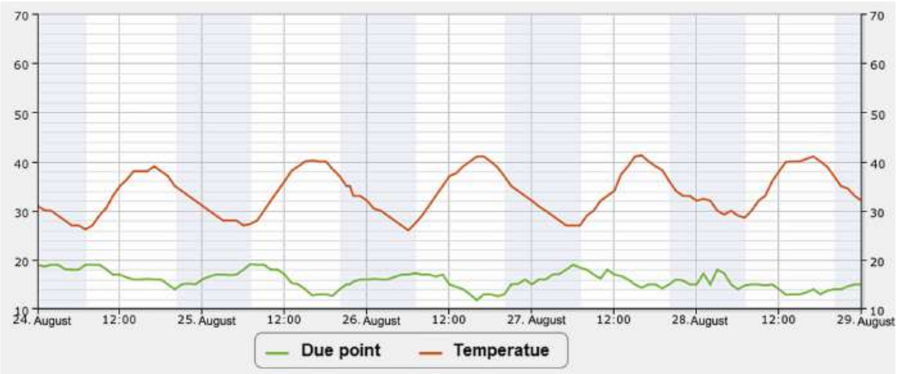


Figure 5.
The real temperature of August 26, day ("Infoclimat", 2020)

N and a longitude: 06°, 51′, 00″ *E* with 85 m elevation above sea level. A family of nine members occupied the house (grandfather, grandmother, mother, father, and five children), the home designed in local architecture (in our model, home with three rooms, kitchen, bathroom, and garage). El Oued is characterized by a hyper-arid hot desert climate with scorching and a very long summer and a short and cold winter. The average of maximum temperatures in summer are 46–48 ℃ in July, it is considered as one of the hottest cities in Algeria (Infoclimat, 2020). These characteristics engender a high-energy demand, which is used in air-conditioning. For more than 120 days per year, the Mercury exceeds 40 ℃. In winter, temperature becomes warm in the day but cold during the night, which requires heating sources. On most days of the year, the sky is clear, and the sun is omnipresent; the average duration of sunstroke is about 3,978 h per year, which offer a perfect environment for solar energy source. The relative humidity is generally low over the year, with an annual average of around 26 per cent. The experimental home includes a variety of electrical appliances. To get a clear view of the energy consumed in the home, we present hereafter an example of electrical appliances and its power ratings (see Table 3).

The following table illustrates the various sensors used in smart building and explains the role of each one (Kertiou *et al.*, 2018). The number of each sensor's kind is also given. All the sensors are set up according to the role intended for the various sensors. Every sensor generates periodically (1 s, 5 s, 1 min, etc.) data and sends them to the local agent. The produced measurements and detections express the various events that happened by inhabitants or environmental changes, which directly affect energy consumption in the smart home. The proposed system is based essentially on these data to analyze and apply the decisions to update the knowledge base and save energy over the entire smart city (see Table 4).

Scenarios description

To test the system, we hypothesized the following scenario: we suppose a summer day (August 26, 2019) in El Oued city for a period of 24 h (see Figure 5). The scenario is characterized by some properties: duration, event, actor, location, and appliance. The sequence of events affects appliances states (turn-on/turn-off), and therefore, the energy consumption throughout the building. Table 5 demonstrates the scenario steps.

After creating a scenario, we should know the energy consumption in each smart home. For this reason, we calculate the rate of consumption of each appliance over the experimental day. Table 6 presents the obtained values.

Place	Electrical appliance	Appliance Number	Consumption W/h
Kitchen	Light	2	25
	Refrigerator	1	200
	Dishwasher	1	1,300
	Microwave	1	1,150
	Electric mixer	1	300
	Coffee maker	1	700
	Vacuum cleaner	1	800
	Ceiling fan	1	70
	Air exchanger	1	370
Living room	Light	3	25
	Air conditioner(8000 BTU)	1	900
	TV LCD	1	150
	Demodulator	1	25
Room 1	Light	2	25
	Air conditioner(6000 BTU)	1	700
	Iron	1	850
	Laptop	1	70
Room 2	Light	2	25
	Air conditioner(6000 BTU)	1	700
	Clock	1	5
Bedroom	Light	3	25
	Air conditioner(6000 BTU)	1	700
	Clock	1	5
	Desktop PC	1	80
Bathroom and WC	Light	4	25
	Washing machine	1	350
	Electric shaver	1	15
	Water pump	1	1,200
Garage	Light	4	25
	Camera	1	25

Table 3.
Illustration of used appliances at smart house model

Sensor	Sensor function	Number
Temperature sensor	A device used to measure temperature (indoor/ outdoor)	12
Humidity sensor	A device measures Relative Humidity in an atmosphere	10
Optical sensor	Used to measures the physical quantity of light rays	16
Pressure sensor	A device that senses pressure	6
Proximity sensor	A device that detects the presence or absence of a nearby object	14
Open/Close Sensor	Used to detect close/open objects (window, door, etc.)	32
Gas sensor	A device used to detect the presence of various gases	10
Smoke sensor	A device that senses smoke (airborne particulates and gases)	10

Table 4.
Illustrates the used sensors and their roles in the smart home

To get the total energy consumed per each appliance, we use the following formula (1):

$$E_{di}(wh) = \sum_{i=1}^{n} (\text{end time } d_i - \text{start time } d_i) \times P \tag{1}$$

To calculate the total energy consumed in each smart home, we apply the next formula (2):

$$E_t(wh) = \sum_{i=1}^{n} E_{di}(wh) \tag{2}$$

Where "E" energy (Wh), "di" is appliance type, "P" appliance consumption.

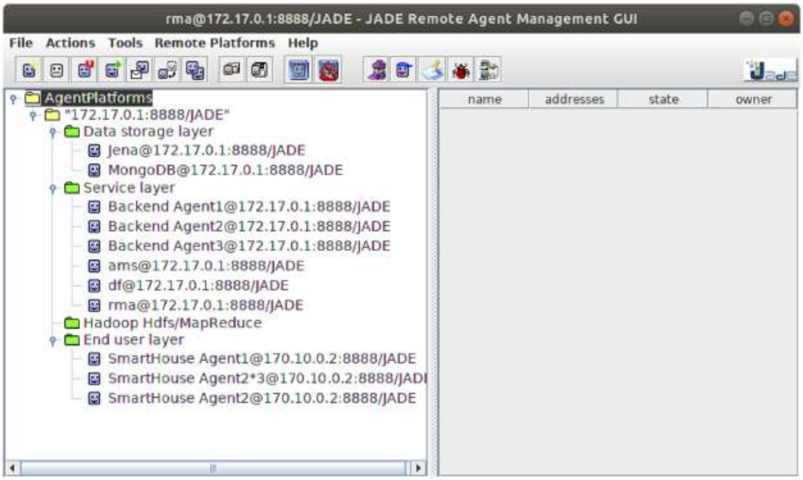


Figure 6.
Presents JADE implementation of different agents layers.

A general overview in the previous table shows that high electrical consumption is engendered by the air conditioning (more than 55 per cent). Since the temperature remains high throughout the day, residents prefer staying at home to avoid the high heat outside and require a suitable temperature, which expresses the huge consumption in this scenario.

Implementation

We used JAVA to develop the system modules and Eclipse IDE editor. To manipulate and translate ontology to OWL, we used Protégé5 API. After creating classes with their properties and relationships, we added SWRLTab to apply SWRL rules and SQWRL queries, the reasoning module (it is a step to deduce new contextual knowledge based on available contexts) that aims at deriving new knowledge by exploiting available data and exploring the ontology context, such as (human profile, personal presence, appliance consuming energy, etc.). This knowledge used to reduce energy consumption and maximize resident comfort.

Moreover, Figure 6 presents JADE remote agent management GUI, which describes the different agents created in each layer, whereas every layer holds an agent responsible for communicating with other agents by sending a message. They can cooperate and leverage their autonomy, modularity, distribution, and intelligence to reduce the high computational time required to manage a large amount of data.

The environment used for the implementation is a cluster with five machines (Master 4 GB Ram, 250 GB Hard-Disk, 4 Slaves 2 GB RAM, and 100 GB Hard Disk). Apache Hadoop installed as an infrastructure in this cluster, and other frameworks, such as Kafka, MongoDB, and Jena installed over them. Jade Platform is also installed in this cluster. In every smart house, there is a machine with low performance (1 GB RAM and 100 GB Hard-Disk) that is used as a client for the Big Data server, and the Jade platform is installed in this machine (see Table 7).

The local agent in each house achieves the process concerning data collection from devices and sensors in every house. Then, data annotation is done by using the ontology before sending them to the service agent in synchronized mode. Afterward, the end-user agents receive a return back message containing the command that will

Time	Events	Actors	location	Appliances activated
00:00 a.m.-06:00 a.m.	Sleeping	All	Bedroom, room 1 and 2	Air conditioner
06:00 a.m.-06:20 a.m.	Weak up	Mother	Bedroom	Lights, water pump
06:20 a.m.-06:45 a.m.	Preparing breakfast	Mother	Kitchen	Lights, coffee maker
06:45 a.m.-07:00 a.m.	Weak up	All other	Bedroom, room 1 and 2	Lights, water pump
07:00 a.m.-07:20 a.m.	Take breakfast	All	Kitchen	–
07:20 a.m.-07:50 a.m.	Preparing to go out	Father, children	Bathroom, room	Lights, water pump, shaver
07:20 a.m.-08:50 a.m.	Cleaning house	Mother	All	Vacuum, water pump
08:50 a.m.-10:00 a.m.	Watch TV	All staying	Livingroom	Air conditioner, TV
10:00 a.m.-11:20 a.m.	Preparing lunch	Mother	Kitchen	Microwave, Electric mixer,..
10:00 a.m.-11:30 a.m.	Reading books	Grand father	Livingroom	–
11:30 a.m.-01:00 p.m.	Eating lunch	All	Kitchen	Lights, microwave
01:00 p.m.-02:30 p.m.	Watch TV	All staying	Livingroom	Air conditioner, TV, lights
02:30 p.m.-03:00 p.m.	Return to home	Father, children	All	–
03:00 p.m.-03:30 p.m.	Take a shower	Father, children	Bathroom	Pump water, shaver, lights
03:30 p.m.-06:30 p.m.	Repose	All	Livingroom	Air conditioner, TV
06:30 p.m.-08:30 p.m.	Prepare/ eat dinner	Mother/ All	Kitchen	Microwave, Electric mixer,..
08:30 p.m.-10:30 p.m.	Watch TV/ revise lessons	All/ children	Livingroom, room 1and 2	Air conditioner, TV, lights
10:30 p.m.-06:00 a.m.	Go to sleep	All	Bedroom, room 1 and 2	Air conditioner

Table 5. Simple scenario of daily routines in a smart home

be executed later. If there is no message due to any reason, the local agent reacts according to their local behavior. On the other hand, the service agent reloads the ontology at the start-up phase, preparing to receive messages from all the houses, and then starts to analyze the coming data by using the knowledge base and their stored rules according to the current context. It invokes a solution for each house and sends a message to the end-user agent, which acts in order to reduce energy consumption at their level.

The proposed system not only provides a local energy-saving solution for each smart home but also offers general monitoring of the entire electricity network. In this context, the service agent uses its reasoning skills and performs a cyclical check on the ratio between the total energy demand and the available energy offered by the supplier. When consumption exceeds the supply, the agent service sends a message to the end-user agents to increase the cooling threshold. After repetitive tests, energy consumption reaches an equilibrium level and prevents a grid crash. The following algorithm demonstrates the used strategy:

Table 6. Energy consumption in one smart home during the period of 24 h

Operating device	Power (W/h)	Device number	Operation time (m)	Energy consumed (*W*)
Light	25	20	360	3,000
Air conditioner 9000 BTU	900	1	570	*8,550*
Air conditioner 6000 BTU	700	3	450	*15750*
Refrigerator	200	1	1,440	4,800
Dishwasher	1,300	1	90	1950
Microwave	1,150	1	80	1,533
Electric mixer	300	1	80	399
Coffee maker	700	1	50	583
Vacuum cleaner	800	1	90	1,200
Ceiling fan	70	1	210	245
Air exchanger	370	1	240	1,480
TV LCD	150	1	280	700
Demodulator	25	1	280	116
Iron	850	1	30	425
Laptop	70	1	120	140
Clock	5	2	1,440	240
Desktop PC water pump	80	1	90	120
Electric shaver	1,200	1	155	3,100
Camera	15	1	30	7.5
Light	25	1	1,440	600

Table 7. Illustrates hardware used for the implementation

Environment	Machine	Number	Description
Environment 1	Master	1	2 CPU Core 4 GB RAM 250 GB HDD
	Slave	4	1 CPU Core 2 GB RAM 100 GB HDD
Environment 2	Low performance machine	In each home	1 CPU Core 1 GB RAM 100 GB HDD

```
Algorithm adjust total consumption
   Total Powered Energy;
   Total Required Energy;
   ACLMessage reply;
   Response response;
      Cyclic Behavior (this)
      {for (house in houses)
         Total Required Energy = house. Energy Consumed;
         If (Total Required Energy > Total Powered Energy)
         response. Actions. add("Decrease Air Condition:1");
      else
         response. Actions. add("Increase Air Condition:1");
         for (house in houses)
            {reply.add Receiver (house.Agent);
            reply.set Content (response)
            reply.send();}
      }
```

Experimentation and results

To validate the proposed architecture, we look at two basic metrics. First, the rate of energy consumption and the execution time of the tasks. Two simulation experiments have been established for this purpose.

First simulation

The first experiment deals with energy consumption in the smart city, where we used the previous scenario. After applying rules in several cases, the proposed approach allows significant energy saving in various devices, such as air conditions, light, TV, water pump, etc. To switch off the device, we use another criterion when the light or outside temperature becomes adapted to the preferences of the inhabitant (Figure 7). For total consumption, the system intervenes to adjust the preference threshold for reducing the total demand. Table 8 shows the energy saved in various devices by using certain rules, which give a significant result in reducing consumption. Approximately 15.62 per cent of energy saved in this experiment compared to the consumption of the MAS-GA system (without ontology and Hadoop).

Figure 8 shows the obtained results in several scenarios (presented in red color) we used 20 smart houses, where the energy consumption is reduced in each case with an average of 1,300 Kw/h.

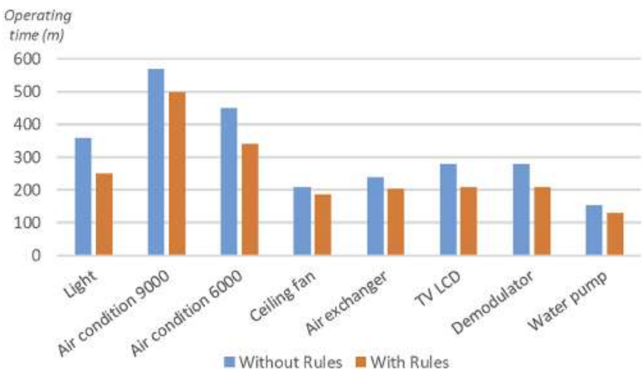


Figure 7.
Appliances operating time with and without rules

Table 8.
Energy saved in various appliances with the rules used

Appliance	Operation time (m)	Energy consumed (W)	Switch off time (m)	Energy saved (W)	Energy saved Ratio %	Used rule
Light	360	3,000	100	830	27.66	Rule 1,2
Air conditioner 9000 BTU	570	*8,550*	70	1,050	12.28	Rule 3,4
Air conditioner 6000 BTU	450	*15750*	90	2,700	17.14	Rule 3,4
Ceiling fan	210	245	25	29.16	11.90	Rule 3
Air exchanger	240	1,480	33	203.5	13.75	Rule 6,7
TV LCD	280	700	40	100	14.28	Rule 7
Demodulator	280	116	40	16.66	14.36	Rule 7
Water pump	155	3,100	2	500	16.12	Rule 5,7

Second simulation

The second phase of experimentation aims to validate the treatment time criterion. For this reason, we applied the simulation of our framework on the hypothesized cluster (5 machines: Master with 4 GB Ram, 100 GB Hard-Disk, and 4 Slaves with 2 GB RAM, and 250 GB Hard Disk) the selected scenarios suppose an environment in various cases: one, 5, 10, and 20 smart houses.

For simulation purposes, it is performed by using the CloudSim software, which is a Framework for modeling and simulating of heterogeneous environments with cloud computing interfaces and services (Alwasel *et al.*, 2019).

It provides the required infrastructures and capacities to evaluate and analyze Big Data applications with MapReduce features (interactions, distributed-task, and data workflows). We have created a data center, which contains a host with virtual machines (1 master and 4 slaves). However, each smart home is represented by a cloudlet (task). The broker allocates and sends the tasks to the master VM in which it redirects them to the slaves' VM. Then the slaves execute the tasks in parallel and transmit the results. The next figure presents some of the simulation results (Figure 9):

To evaluate the processing time, we compare the efficiency of the architecture in terms of execution time with ICA-BEMS in different cases. Figure 10 shows the obtained results that demonstrate the effectiveness of the proposed system (thanks to Big Data tools) and maintains an approximately short duration (of 1 s) contrary to the evolutional duration of the other system.

Discussion

The configuration of the simulation environment was created according to the criteria discussed above. The obtained results clearly prove the utility of combining technologies (ontology, Big Data, and MAS) to reduce energy consumption without affecting the inhabitants' comfort. These tools reduce the cost of the hardware used in each building, ensure a high level of system availability, offer scalability to smart cities by leveraging Big Data environment, which can process large data volume in real-time and addresses mainly the volume and velocity challenge. It provides autonomy and reduces data flow over the network by using MAS. Moreover, the system monitors the energy demand in peak time and offers for the supplier a good opportunity to deal with the distribution strategy and ensure a sustainable and long-term policy by exploiting knowledge and analyzing data history. Therefore, it helps to reduce environmental pollution and promote environmental sustainability (see Table 9).

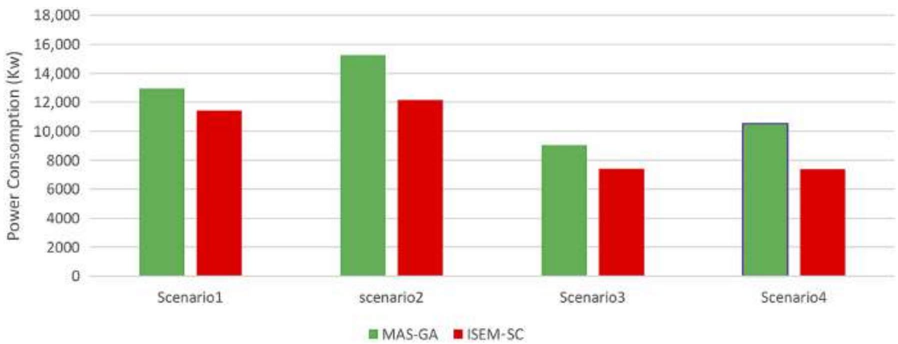
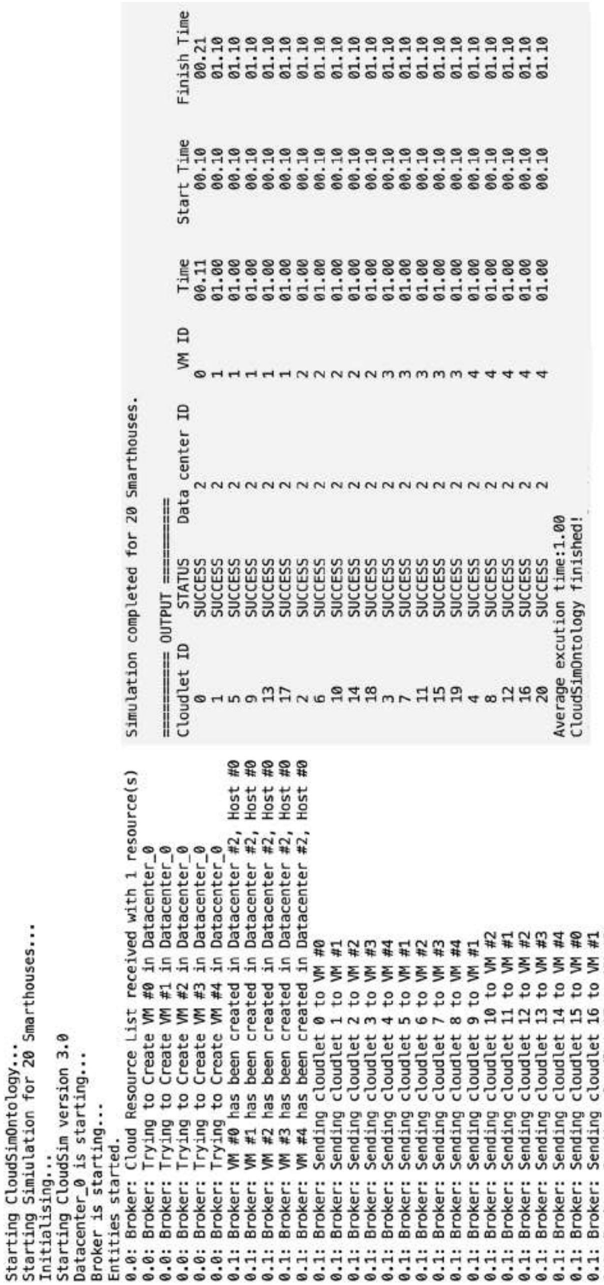


Figure 8.
Energy consumption in the smart city for various scenarios



```
Starting CloudSimOntology...
Starting Simiulation for 20 Smarthouses...
Initialising...
Starting CloudSim version 3.0
Datacenter_0 is starting...
Broker is starting...
Entities started.
0.0: Broker: Cloud Resource List received with 1 resource(s)
0.0: Broker: Trying to Create VM #0 in Datacenter_0
0.0: Broker: Trying to Create VM #1 in Datacenter_0
0.0: Broker: Trying to Create VM #2 in Datacenter_0
0.0: Broker: Trying to Create VM #3 in Datacenter_0
0.0: Broker: Trying to Create VM #4 in Datacenter_0
0.1: Broker: VM #0 has been created in Datacenter #2, Host #0
0.1: Broker: VM #1 has been created in Datacenter #2, Host #0
0.1: Broker: VM #2 has been created in Datacenter #2, Host #0
0.1: Broker: VM #3 has been created in Datacenter #2, Host #0
0.1: Broker: VM #4 has been created in Datacenter #2, Host #0
0.1: Broker: Sending cloudlet 0 to VM #0
0.1: Broker: Sending cloudlet 1 to VM #1
0.1: Broker: Sending cloudlet 2 to VM #2
0.1: Broker: Sending cloudlet 3 to VM #3
0.1: Broker: Sending cloudlet 4 to VM #4
0.1: Broker: Sending cloudlet 5 to VM #1
0.1: Broker: Sending cloudlet 6 to VM #2
0.1: Broker: Sending cloudlet 7 to VM #3
0.1: Broker: Sending cloudlet 8 to VM #4
0.1: Broker: Sending cloudlet 9 to VM #1
0.1: Broker: Sending cloudlet 10 to VM #2
0.1: Broker: Sending cloudlet 11 to VM #1
0.1: Broker: Sending cloudlet 12 to VM #2
0.1: Broker: Sending cloudlet 13 to VM #3
0.1: Broker: Sending cloudlet 14 to VM #4
0.1: Broker: Sending cloudlet 15 to VM #0
0.1: Broker: Sending cloudlet 16 to VM #1
0.1: Broker: Sending cloudlet 17 to VM #2
0.1: Broker: Sending cloudlet 18 to VM #3
0.1: Broker: Sending cloudlet 19 to VM #4
```

```
Simulation completed for 20 Smarthouses.

========== OUTPUT ==========
Cloudlet ID    STATUS    Data center ID    VM ID    Time     Start Time    Finish Time
    0          SUCCESS        2            0        00.11       00.10         00.21
    1          SUCCESS        2            1        01.00       00.10         01.10
    5          SUCCESS        2            1        01.00       00.10         01.10
    9          SUCCESS        2            1        01.00       00.10         01.10
    13         SUCCESS        2            1        01.00       00.10         01.10
    17         SUCCESS        2            1        01.00       00.10         01.10
    2          SUCCESS        2            2        01.00       00.10         01.10
    6          SUCCESS        2            2        01.00       00.10         01.10
    10         SUCCESS        2            2        01.00       00.10         01.10
    14         SUCCESS        2            2        01.00       00.10         01.10
    18         SUCCESS        2            2        01.00       00.10         01.10
    3          SUCCESS        2            3        01.00       00.10         01.10
    7          SUCCESS        2            3        01.00       00.10         01.10
    11         SUCCESS        2            3        01.00       00.10         01.10
    15         SUCCESS        2            3        01.00       00.10         01.10
    19         SUCCESS        2            3        01.00       00.10         01.10
    4          SUCCESS        2            4        01.00       00.10         01.10
    8          SUCCESS        2            4        01.00       00.10         01.10
    12         SUCCESS        2            4        01.00       00.10         01.10
    16         SUCCESS        2            4        01.00       00.10         01.10
    20         SUCCESS        2            4        01.00       00.10         01.10
Average excution time:1.00
CloudSimOntology finished!
```

Figure 9.
Simulation of execution time scenarios in 20 smart homes

Conclusion

Energy management in smart cities has become one of the most critical issues emerging in sustainability solutions. The intensive data evolution generates a huge distributed and heterogeneous dataset, which creates a serious challenge to deal with the volume and the heterogeneity of data. For addressing these issues, Big Data tools and ontologies technologies have been used to achieve efficient energy saving in smart cities. In this article, we proposed an Intelligent System for Energy Management in Smart cities (ISEM-SC) that aims at reducing energy consumption. In this context, we reviewed first, the background of Big Data and semantics integration followed by related work. Then, we presented a layered architecture. The proposed system combines various technologies (Big Data, ontology, and MAS) used to reduce energy consumption without affecting the inhabitants' comfort.

This framework provides several opportunities. For instance, it:

(1) Reduces energy consumption in each smart home and therefore throughout the smart cities;

(2) Reduces hardware cost used in each building and process data in a short time;

(3) Ensures a high level of system availability;

(4) Offers scalability by leveraging Big Data environment, which can process huge data in real-time;

(5) Provides autonomy and reduces data flow over the network by using MAS;

(6) Monitors the energy demand in peak time and avoids grid crash;

(7) Provides an effective long-term energy distribution policy;

(8) And it helps to reduce environmental pollution and promotes environmental sustainability.

The obtained results in different scenarios show efficient energy savings with a rate of 15.62 per cent. Besides, the system maintains an approximately short duration (of 1 s) in the processing time, unlike the evolutionary duration of the other systems.

In future work, we will focus on the capabilities provided by the Big Data, ontology, and MAS to model an efficient architecture capable of combining energy management, water use, and road traffic in smart cities. In order to convert the huge raw data into intelligent knowledge used later by decision-makers, to provide smart sustainability and easy life for citizens.

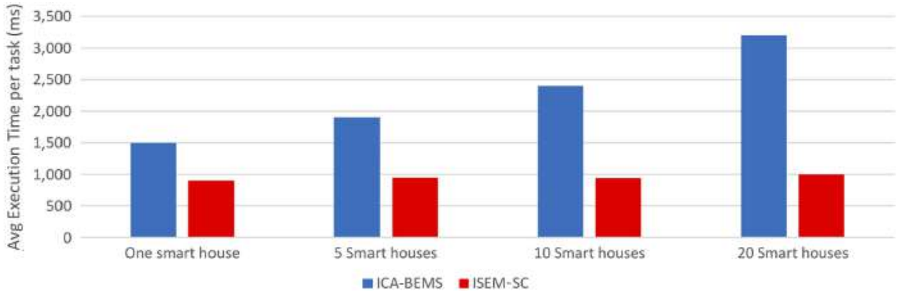


Figure 10.
The execution time in various scenarios

Table 9. Comparison of the main characteristics of energy saving in experienced works

Features works	Ontology	MAS	Big data	Reduce energy	Material cost	Resident comfort	Efficiency
MAS-GA	No	Yes	No	Medium	Medium	High	Medium
ICA-BEMS	Yes	No	No	Medium	High	Medium	Low
ISEM-SC	Yes	Yes	Yes	High	Low	High	High

Benefits Works	Intelligence	Understand behavior	Cooperation	Data flow	Autonomy	Prediction	Streaming	Process time	Scalability	Availability
MAS-GA	Yes	Yes	Yes	Medium	Yes	Yes	No	Medium	Yes	Medium
ICA-BEMS	Yes	Yes	No	High	No	Yes	No	High	No	Low
ISEM-SC	Yes	Yes	Yes	Low	Yes	Yes	Yes	Low	Yes	High

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